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Abstract

Electricity markets are increasingly influenced by variable renewable energy such as wind and solar power with a pronounced weather-induced variability and imperfect predictability. As a result, the evaluation of the capacity value of variable renewable energy, i.e. its contribution to security of supply, gains importance. This paper develops a new methodology to endogenously determine the capacity value in large-scale investment and dispatch models for electricity markets. The framework allows to account for balancing effects due to the spatial distribution of generation capacities and interconnectors. The practical applicability of the methodology is shown with an application for wind power in Europe. We find that wind power can substantially contribute to security of supply in a decarbonized European electricity system in 2050, with regional capacity values ranging from 1 - 40 %. Analyses, which do not account for the temporal and spatial heterogeneity of the contribution of wind power to security of supply therefore lead to inefficient levels of dispatchable back-up capacity. Applying a fixed wind power capacity value of 5 % results in an overestimation of firm capacity requirements in Europe by 66 GW in 2050. This translates to additional firm capacity provision costs of 3.8 bn EUR per year in 2050, which represents an increase of 7 %.

Keywords: Reliability of supply, Capacity adequacy, Multi-regional power system, Wind power, Power system modeling

JEL classification: C61, C63, D47, L50, Q42, Q48

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1. Introduction

The Paris climate agreement aims at holding global warming to well below 2 degrees Celsius (United Nations (2015)), creating the need for a deep decarbonization of the global electricity sector. Recent cost reductions suggest that the optimal pathway will to a substantial part be based on variable renewable energy sources (VRE). As a consequence, global electricity markets are increasingly influenced by generation technologies based on VRE such as wind and solar energy. Electricity generation from VRE differs from dispatchable power generation in its pronounced dependency on weather conditions. These weather-induced variations show spatial dependencies and are not perfectly predictable. Accordingly, there arise important implications for reliability of supply in power systems as electricity is only storable at comparatively high cost and the supply-demand balance has to be maintained at all times in order to prevent outages.

Reliability of supply has always been a major concern in electricity systems as outages incur high economic losses. With increasing shares of VRE, reliability issues gain further importance due to the variability, spatial dependency and imperfect predictability of electricity generation based on VRE and the resulting risk of unavailability during times of stress (e.g. Cramton et al. (2013)). VRE resources are typically less correlated on a wider geographical scope, which enables balancing effects because of imperfectly correlated generation patterns at different locations. Hence, markets can benefit from these balancing effects via interconnections and cross-border cooperation. Envisaged reliability levels can thereby be reached at lower costs compared to reliability measures restricted to national borders (e.g., Cepeda et al. (2009) and Hagspiel (2017)). Against this background, the following research question arises: What is the optimal mix and allocation of VRE capacity in order to benefit from balancing effects both in generation and contribution to security of supply to reach an envisaged reliability target?

Assessing the contribution of VRE to security of supply is complex, because of the stochasticity of electricity generation based on weather-dependent resources. The ability of an additional VRE generation unit to provide secure capacity depends on the correlation of its electricity generation with electricity demand and with electricity generation from other units. To give intuition for this dependency, consider a simple example for wind energy: An electricity system has an off-peak demand of one and a peak demand of two with off-peak periods being more frequent compared to peak demand situations. Additionally, there are two possible sites A and B for investment into wind capacities. Wind generation at site A is perfectly correlated with off-peak demand and wind generation at site B is perfectly correlated with peak demand hours. In this setting, wind capacities at site A generate more electrical energy because off-peak situations are more frequent. Nevertheless, wind investments at site B can be preferable because wind generation capacities at site B generate electricity in the critical peak demand situations. Thus, one unit of wind capacity at site B reduces the need for one unit of dispatchable capacity and therefore contributes to security of supply. Now consider the situation where there is already one unit of wind capacity in place at site B, which generates one unit of electricity in peak demand hours. The remaining residual demand, which must be supplied by dispatchable generation capacity, is one in off-peak and one in peak demand periods. As a result, installing one additional unit of wind capacity at site B cannot contribute to security of supply because firm capacity is still required in the off-peak demand period and thus cannot be substituted. However, if there were wind capacities of one unit installed at both sites, investing in one additional unit of wind capacity at site B would indeed contribute to security of supply.

The highly stylized example clarifies that the marginal contribution to security of supply from additional generation capacities based on VRE depends on all existing installed capacities within the system, because these capacities and their weather-dependent generation determine the critical residual demand situations. Typically, generation patterns of wind and solar power plants at different locations are positively correlated. Therefore, the ability of one unit of VRE generation capacity to substitute firm capacity, which is referred to as its capacity value (or capacity credit)[1], declines as the share of VRE in total generation increases.[2] Nevertheless, economic long-term simulation models for electricity markets, which are widely used in scientific and political practice, often assign fixed exogenous capacity values to wind and solar generation and neglect cross-border effects for reasons of simplification and computational tractability. Similarly, adequacy studies and capacity mechanisms often do not or only crudely allow for participation of VRE and are often confined to national borders.[3]

Against the described backdrop, this paper develops a new methodology to endogenously determine the contribution of VRE to security of supply in a long-term partial equilibrium

[1]In literature, capacity value and capacity credit are used as synonyms. Throughout this paper we will stick to the term capacity value. It is important not to confuse a technology´s capacity value with its capacity factor describing its yearly average capacity utilization.

[2]See IRENA (2017) for an overview of empirical studies showing this decreasing return to scale effect.

[3]See e.g. Cepeda et al. (2009) and Hobbs and Bothwell (2017) for a discussion. An overview on how U.S. and European capacity mechanisms credit VRE contributions to reliability is given in Byers et al. (2018) and European Commission (2016a). Furthermore, there are efforts to coordinate European adequacy assessments and foster cross-border cooperation (European Commission (2016b)).

model for electricity markets. The proposed methodology builds on an iterative approach, which captures the non-linear dependency of the capacity value of VRE on installed capacity and its spatial distribution considering cross-border cooperation via interconnectors. The methodology therefore determines cost-minimal investment into power plants taking into account electricity generation as well as provision of security of supply of VRE, while keeping computational tractability in a large-scale application. After introducing our methodology, we apply it in a first step to a simple two-country example. Building on that, we extend it to the European electricity system to determine an optimal decarbonization pathway until the year 2050, starting from the existing power plant fleet. Our analysis focuses on wind power, however the presented approach can be applied to all VRE technologies. We build the analysis on a new dataset, which is based on meteorological reanalysis data featuring a high spatial and temporal resolution. The data is therefore well suited to optimally capture the stochastic properties of wind generation and the resulting contribution to security of supply.

We show that the proposed methodology is capable to endogenously determine the capacity value of wind power in large-scale investment and dispatch models for electricity markets. The results of the large-scale application imply that wind power can substantially contribute to security of supply in a decarbonized European electricity system cooperating with respect to reliability, with an average wind power capacity value of 13 % in 2050. Additionally the results show that the capacity value of wind power is heterogeneous across different regions and years, which is a result of varying wind conditions as well as increasing total installed capacities and technological innovation over time. Existing modeling approaches, which typically assign constant exogenous capacity values for wind power, therefore result in inefficient levels of dispatchable capacities, which are required to guarantee security of supply in electricity systems with high shares of VRE. In our application for the European electricity system, the additional yearly costs for firm capacity provision[4] when applying exogenous fixed wind power capacity values of 5 % compared to endogenous capacity values amount to 1.5 and 3.8 bn EUR in 2030 and 2050, respectively, which represents additional costs of 3 % and 7 %. Finally our results suggest that European market integration can substantially improve the contribution of wind power to security of supply due to cross-border balancing effects.

Our paper is mainly related to two streams of literature. The first relevant stream

[4]The yearly costs to provide firm capacity are calculated by summing the annuitized investment costs and the fixed operation and maintenance costs of all dispatchable power plants. Thereby, the fixed costs to hold available dispatchable capacity are represented.

examines system adequacy and reliability of supply in electricity systems. Reliability of supply in electricity systems has been subject to extensive scientific research effort, both from a technical as well as an economic point of view.[5] In particular, the contribution of individual technologies to system adequacy, i.e. the capacity value, has been a focus of interest. The probability theory of the capacity value of additional generation for the cases of statistical independence and dependence is presented in Zachary and Dent (2012). Based on these theories, various contributions investigate empirical methods to evaluate the capacity value of wind power in electricity systems.[6] Cepeda et al. (2009) investigate the positive implications of connecting different electricity systems on reliability and ways to internalize cross-border effects in a two-zone model. Hagspiel et al. (2018) introduce a comprehensive framework to investigate reliability in power systems consisting of multiple technologies and interconnected regions. All the mentioned studies focus on static analyses for given power systems. Consequently, the capacity value is not evaluated within a dynamic model, which determines the optimal future structure of an electricity system.

The second relevant literature stream focuses on the analysis of electricity systems with high shares of VRE based on long-term dynamic partial equilibrium models. Typical research questions within this literature are optimal decarbonization pathways for electricity systems or optimal allocation of renewable generation capacites. However, the contribution of VRE to security of supply is often only crudely accounted for by assigning fixed exogenous capacity values.[7] Grave et al. (2012) address this issue by varying the capacity value of wind power exogenously in order to determine sensitivities in the resulting amount of required dispatchable back-up capacity. The endogenous dependency of the capacity value on total installed capacity of VRE and the impact of interconnections are not accounted for. Welsch et al. (2015) integrate a stepwise linear function for the capacity value into an optimization model. As a result, the capacity value declines endogenously. However, balancing effects of imperfectly correlated wind power generation in different geographical areas and technological innovation over time are not captured by this approach. Hobbs and Bothwell (2017) use a market equilibrium model for the ERCOT system to endogenously assess the capacity value of wind and solar power. However, they apply a greenfield approach with a limited regional representation of wind and solar power generation. The scalability of the

[5]Early contributions in the two fields include e.g. Billinton (1970) and Telson (1975).

[6]See e.g. Keane et al. (2011) for a discussion of different methodologies including capacity value approximation techniques and Milligan et al. (2017) for a recent review of research into the capacity value of wind power.

[7]See for example Hagspiel et al. (2014) or Fürsch et al. (2013).

applied methodology to more complex models with various years and a higher geographical resolution is computationally limited.

In summary, our contribution with respect to the above mentioned literature is to (i) endogenously evaluate the capacity value of wind power within a dynamic investment and dispatch model for electricity markets, while (ii) accounting for the statistical properties of wind power in interconnected systems and (iii) keeping computational tractability in a large-scale application.

The remainder of the paper is structured as follows. Section 2 introduces our methodology. Section 3 illustrates the proposed approach based on a simple example with two countries. Section 4 discusses a large-scale application for the European electricity system. Section 5 concludes.

2. Methodology

In order to develop a consistent economic framework to investigate the system adequacy of future electricity systems and the contribution of VRE generation to reliability, we will start with a brief revision of the reliability metrics, in particular the well-known loss of load expectation, expected energy unserved and equivalent firm capacity measures, and a definition of the capacity value (Section 2.1). We will then describe a framework to calculate the contribution of a single supplier to reliability, i.e. its capacity value, based on an optimization framework (Section 2.2). Subsequently, we will revisit the optimization problem for planning and operation of power systems in order to show how the capacity value of individual technologies is typically accounted for in long-term investment and dispatch models (Section 2.3). Finally, we will discuss how the two economic modeling frameworks are linked by means of an iteration procedure developed in this work (Section 2.4).

We will use the notation as listed in Table 1. Unless noted differently, we will use capital letters for random variables, bold capital letters for sets, lower case letters for parameters and bold lower case letters for optimization variables.

2.1. Reliability metrics

Different methodologies have been proposed to determine generation adequacy and the capacity value of individual technologies. Hereby, the two measures loss of load expectation ($LOLE$) and expected energy unserved (EEU) are often applied to depict the ability of a system to cover expected load levels (Allan and Billinton (1996)). The contribution of individual technologies to system adequacy, i.e. its capacity value, has been investigated using different approaches, whereof the most commonly used are the effective load carrying

Sets	
$i \in \mathbf{I}$	Generation technologies
$m, n \in \mathbf{M}$	Markets
$t \in \mathbf{T}, \mathcal{T}$	Time ($\mathbf{T}$: complete data set, $\mathcal{T}$: time slices)
Random variables	
L	Load
X	Availability of existing capacity
Y	Availability of extra capacity
K	Availability of import capacity
Parameters	
$LOLP$	Loss of load probability
$LOLE$	Loss of load expectation
EEU	Expected energy unserved
EFC	Equivalent firm capacity
$\bar{x}$	Nominal capacity of existing generator
x	Availability of existing generator
$\bar{y}$	Nominal capacity of extra generator
v	Capacity value of extra capacity $\bar{y}$
$\bar{k}$	Transmission capacity
η	Transmission efficiency
l	Load
l_{peak}	Peak demand
δ	Fixed costs
γ	Variable costs electricity generation
Optimization variables	
$\mathbf{z}$	Overall equivalent firm capacity needed
$\mathbf{z}^y$	Equivalent firm capacity of extra capacity $\bar{y}$
$\mathbf{u}$	Load curtailment
$\mathbf{k}$	Capacity / electricity transmission between markets
$\bar{\mathbf{x}}$	Generation capacity
$\mathbf{g}$	Electricity generation

Table 1: Model sets, parameters and variables

capability ($ELCC$) and the equivalent firm capacity (EFC) approaches (Keane et al. (2011), Madaeni et al. (2013), Zachary and Dent (2012)). Following Hagspiel et al. (2018), we apply the EFC approach.[8] Note that the EFC approach provides consistent results with the $ELCC$ approach (Amelin (2009)).

In the following, we will briefly revisit the derivation of the well-known $LOLE$ and EEU

[8]Amelin (2009) define the equivalent firm capacity of a generating unit as the capacity of a fictitious 100 % reliable unit, which results in the same loss of load probability decrease as the respective unit.

measures. We define the loss of load probability ($LOLP$) at a specific instant in time t as

$$LOLP_t = P(X_t < L_t), \tag{1}$$

i.e., as the probability that the available existing capacity X_t is smaller than load L_t (Allan and Billinton (1996)).[9]

The well-known reliability level measure loss of load expectation is then derived by summing up probabilities over some time-period T:

$$LOLE = \sum_{t \in \mathbf{T}} LOLP_t. \tag{2}$$

To calculate the expected energy unserved EEU, the $LOLPs$ are weighted with the expected load level that cannot be served:

$$EEU = \sum_{t \in \mathbf{T}} E(L_t - X_t) * LOLP_t. \tag{3}$$

The contribution of individual technologies is then determined by applying the EFC approach. Our focus of interest is the amount of equivalent firm capacity $\mathbf{z}^y$ by which the available existing capacity X_t can be reduced when installing some new capacity $\bar{y}$ with availability $Y_t \in [0, 1]$, such that the initial (target) reliability level EEU is achieved. Thus, by replacing X_t by its equivalent $(X_t + \bar{y}Y_t - \mathbf{z}^y)$ and applying Equation (1), the modified equation that needs to be solved for $\mathbf{z}^y$ then writes as

$$EEU = \sum_{t \in \mathbf{T}} E(L_t - (X_t + \bar{y}Y_t - \mathbf{z}^y)) * P(X_t + \bar{y}Y_t - \mathbf{z}^y < L_t). \tag{4}$$

Based on the resulting $\mathbf{z}^y$, the capacity value v of a technology with capacity $\bar{y}$ can be calculated according to

$$v = \frac{\mathbf{z}^y}{\bar{y}} \tag{5}$$

with $0 \leq v \leq 1$.

In practice, Equation 4 is typically solved by means of numerical iteration: after $\bar{y}$ has been added to the system, in each iteration step $\mathbf{z}^y$ is increased by some small amount until the reliability target EEU is reached.

The above equations describe a self-contained system without interconnections to neighboring systems. In interconnected systems, the $LOLP$ and $LOLE$ depend on the statistical

[9] Note that in Equation (1), we implicitly assume that load is inelastic with no adjustment when capacity is scarce, e.g., due to the lack of real-time pricing.

characteristics of the random variables involved, i.e. their joint distributions. If we consider dependent stochastic variables such as load and wind profiles in neighboring countries, the problem becomes analytically highly complex and thus not tractable in a large-scale application.[10] Thus we apply a framework that endogenously determines the level of equivalent firm capacity by means of numerical optimization, as described in the following section.

2.2. A framework for endogenous equivalent firm capacity in multiple interconnected markets

In contrast to the above introduced reliability metrics, which typically build upon *exogenously* given existing capacities X_t and demand levels L_t, the framework at hand *endogenizes* the level of equivalent firm capacity by minimizing the firm capacity $\mathbf{z}$ that needs to be available in the system to achieve the target reliability level EEU. Following Hagspiel et al. (2018), we formulate the deterministic equivalent of the probabilistic problem by replacing probabilities and random variables by their deterministic counterpart based on data covering a large range of possible outcomes, which is typically referred to as hindcast approach in the literature. Hereby, the probability measure P models the distributions of the random variables, approximated via sums over historic time series. The validity of the hindcast approach may be justified by the central limit theorem (Zachary and Dent (2012)).

The general idea of the optimization framework is the following: A central authority (social planner) minimizes the required firm capacity over all markets to reach a certain market-specific target reliability level EEU, taking into consideration load, solar and wind characteristics as well as interconnection constraints.[11] Alternatively, the social planner problem can be interpreted as a representation of multiple interconnected markets, which perfectly cooperate with respect to reliability. The resulting planning problem can then be formulated as the integrated optimization problem (6).[12]

The objective function (6a) minimizes the sum of firm capacity $\mathbf{z}_m$ over all markets, subject to four constraints: The adequacy constraint (6b) states that the required firm capacity has to be greater or equal to the market-specific and time-varying load $l_{m,t}$ minus

[10]See Zachary and Dent (2012) for a thorough discussion of the probability theory of the capacity value of additional generation considering independent and dependent variables.

[11]It is straightforward to reformulate the problem for reliability targets based on the $LOLE$ measure instead of EEU (see Hagspiel et al. (2018)). Note however, that, as this approach includes binary load shedding variables, the problem becomes a mixed integer optimization problem as opposed to the linear program optimization at hand.

[12]The reader is referred to Hagspiel et al. (2018) for a comprehensive derivation of the methodology. Note that for notational simplicity, the capacity additions $\bar{y}$ in Equation (4) were dropped and all capacities exogenously given to the system were aggregated by their nominal capacities $\bar{x}_i$ and their capacity availabilities $x_{i,t}$.

the load curtailment variable $\mathbf{u}_{m,t}$, minus the sum of the available generation capacity, plus the sum over electricity exchanges $\mathbf{k}_{m,n,t}$ and $\mathbf{k}_{n,m,t}$ between market m and market n at every instant of time t. Thereby, we charge electricity imports with an efficiency loss $\eta_{m,n}$ in order to account for transmission losses. The reliability constraint (6c) requires the sum of load curtailment activities $\mathbf{u}_t$ not to exceed a certain reliability target, specified as expected energy unserved EEU within the considered period of time T. Hence, the load curtailment variable $\mathbf{u}_t$ allows for a relaxation of the load serving requirement (Equation (6b)) by shaving off load peaks until the reliability level EEU is reached. And finally, the electricity exchange constraint (6d) limits $\mathbf{k}_{m,n,t}$ to the installed transmission capacity $\bar{k}_{m,n}$.

$$\min \sum_m \mathbf{z}_m \tag{6a}$$

$$\text{s.t.} \quad \mathbf{z}_m \geq l_{m,t} - \mathbf{u}_{m,t} - \sum_{i\in\mathbf{I}} \bar{x}_{i,m} x_{i,m,t} + \sum_{n\in\mathbf{M}} \mathbf{k}_{m,n,t} - \sum_{n\in\mathbf{M}} \eta_{m,n}\mathbf{k}_{n,m,t} \qquad \forall m,t,m\neq n \tag{6b}$$

$$\sum_t \mathbf{u}_{m,t} \leq EEU_m \qquad \forall m \tag{6c}$$

$$\mathbf{k}_{m,n,t} \leq \bar{k}_{m,n} \qquad \forall m,n,t,m\neq n \tag{6d}$$

for $i \in \mathbf{I}, m,n \in \mathbf{M}, t \in \mathbf{T}$.

Solving Problem (6) yields the required firm capacity in each market $\mathbf{z}_m^+$ to reach the specified level of reliability, assuming cooperation with respect to reliability. In order to determine the capacity value of technology i in market m under perfect cooperation, we set the corresponding capacity $\bar{x}_{i,m}$ to zero and resolve the model, which yields $\mathbf{z}_m^-$.

Based on the result we then calculate the technology- and region-specific capacity value under perfect cooperation according to

$$v_{i,n,m} = \frac{\mathbf{z}_m^- - \mathbf{z}_m^+}{\bar{x}_{i,n}} \qquad \forall i,m,n. \tag{7}$$

This framework can be applied to derive the local capacity value $v_{i,m,m}$ of technology i with capacity $\bar{x}_{i,m}$ with respect to market m where the technology is located ($n = m$), but also to derive the cross-border capacity value $v_{i,n,m}$ of a technology $\bar{x}_{i,n}$ located in market n with respect to a neighboring market m.

Note that in this formulation, the capacity value represents the marginal contribution of a technology to reliability, given the contribution of all other technologies. Or, framed as a coalition game, it depicts the marginal contribution of a single coalition member to the total coalition of suppliers, e.g. wind and solar generators.[13] Additionally, note that each market m can consist of more than one region for solar and wind generation to account for their spatial heterogeneity. Thereby, we implicitly assume no internal network constraints inside a market.[14]

2.3. Accounting for the contribution to reliability in an investment and dispatch model

To pursue our objective of investigating allocational effects of different ways to account for contributions to reliability, we apply an investment and dispatch model based on optimization problem (8). The problem at hand is similar to the integrated problem for investment and operation as formulated e.g. in Turvey and Anderson (1977). By assuming inelastic demand, e.g. due to the lack of real-time pricing, and market clearing under perfect competition - which is common in electricity market modeling literature - we are able to treat the problem as a cost minimization problem. It can be interpreted as a social planner problem where a social planner with perfect foresight minimizes total system costs for investment in generation capacity and the operation of generation and transmission between markets.

$$
\begin{aligned}
\min \quad TC &= \sum_{i,m} \delta_{i,m} \bar{\mathbf{x}}_{i,m} + \sum_{i,m,t} \gamma_{i,m,t} \mathbf{g}_{i,m,t} && && \text{(8a)} \\
\text{s.t.} \quad l_{m,t} &= \sum_{i} \mathbf{g}_{i,m,t} + \sum_{n} \mathbf{k}_{n,m,t} && \forall m, t, m \neq n && \text{(8b)} \\
\mathbf{g}_{i,m,t} &\leq x_{i,m,t} \bar{\mathbf{x}}_{i,m} && \forall i, m, t && \text{(8c)} \\
|\mathbf{k}_{m,n,t}| &\leq \bar{k}_{m,n} && \forall m, n, t, m \neq n && \text{(8d)} \\
\mathbf{k}_{m,n,t} &= -\mathbf{k}_{n,m,t} && \forall m, n, t, m \neq n && \text{(8e)} \\
l_{m,peak} &\leq \sum_{i,n} v_{i,n,m} \bar{\mathbf{x}}_{i,n} && \forall m && \text{(8f)}
\end{aligned}
$$

for $i \in \mathbf{I}, m, n \in \mathbf{M}, t \in \mathcal{T}$.

[13] Such a coalition game, namely the allocation of the joint contribution of a set of multiple interdependent suppliers to reliability has been analysed by Hagspiel (2018). He finds that the Shapley value represents a unique additive consistent allocation rule. While the Shapley value represents the average marginal contribution of a single supplier over all possible permutations to form a coalition, our approach captures the marginal contribution of the analyzed supplier to the full coalition (see Equation (7)). Because of the decreasing returns to scale of the capacity value with respect to total installed capacity, our approach can be interpreted as a conservative estimate in comparison to the Shapley value.

[14] Our approach generally allows for consideration of internal network constraints. It could be extended in this direction, e.g. by applying a load flow approach with multiple nodes per market.

The objective function (8a) minimizes total system costs over all markets m, technologies i and time steps t. It consists of a fixed costs term and a variable costs term. Generation capacity $\bar{\mathbf{x}}$, electricity generation $\mathbf{g}$ and transmission between markets $\mathbf{k}$ are optimization variables. Additional generation capacities can be installed at the costs of $\delta_{i,m}$ and electricity generation incurs variable costs of $\gamma_{i,m,t}$. The cost minimizing objective function is subject to various constraints: The equilibrium constraint (8b) states that the load level $l_{m,t}$ has to be satisfied at all times by the sum of generation in market m and electricity exchanges between markets m and n. Constraints (8c) and (8d) mirror that generation and transmission are restricted by installed generation and transmission capacities.[15] Furthermore, electricity trades from market m to market n are necessarily equal to negative trades from market n to market m (Equation (8e)). Finally, the peak capacity constraint (8f) requires the sum of generation capacities $\bar{\mathbf{x}}_{\mathbf{i},\mathbf{n}}$ weighted with their capacity values $v_{i,n,m}$ to be greater or equal than the market-specific annual peak load $l_{m,peak}$. Note that both local capacity ($n = m$) as well as capacity from a neighboring market n can contribute to the peak constraint in market m. The peak constraint is typically introduced in models that apply a time slices approach in order to represent the full variability of demand and VRE supply, as well as unavailabilities of dispatchable generation.

The investment and dispatch model (8) is formulated as a linear program. However, as discussed above, the capacity value $v_{i,n,m}$ is a function of generation capacity $\bar{x}$. Hence, if the capacity value in the peak capacity constraint (8f) would be formulated as a function of generation capacity $\bar{\mathbf{x}}_{i,m}$, e.g. by applying the analytical expression introduced by Voorspools and D'haeseleer (2006) for the capacity value of wind, the problem would become non-linear. While solution algorithms exist to solve non-linear problems, the applicability of non-linear problems in real-world, large-scale electricity market applications often suffers from prohibitively high solving times. Alternatively, piece-wise linearization would represent a way to deal with non-linear analytical expressions in linear problems. However, analytical expressions so far only exist for systems without interconnections and are thus not suited to address our research question. Against this background, we solve the non-linear problem by means of iteration, as discussed in the following section.

[15] Note that in this formulation, we neglect a market's internal transmission constraints. Like in the capacity value framework introduced above, the model at hand could be extended to account for internal transmission constraints, e.g. by applying a load flow approach with multiple nodes per market.

2.4. A framework to endogenize the capacity value in a large-scale electricity market model

In order to endogenize the capacity value of VRE in a large-scale electricity market model, we introduce the iteration algorithm depicted in Figure 1 and discuss its application for the example of wind power: after running the investment and dispatch model (8) with exogenous start values for the region-specific capacity values of wind generation, the capacity value framework (6) is applied based on the resulting optimal region-specific wind generation capacities. In the next iteration step, the updated capacity values $v_{i,n,m}$ calculated in Equation (7) are passed to the peak capacity constraint (8f) of the investment and dispatch problem. Subsequently, updated capacity values are calculated considering the new wind capacities. This iteration algorithm is continued until convergence is reached.

Note that the investment model is solved based on a dataset with reduced temporal resolution (time slices) in order to keep the model computationally tractable. We apply a two-stage spatial and temporal clustering algorithm in order to derive a reduced dataset, which captures the relevant properties of wind and solar generation as well as load.[16] The capacity value on the other hand is calculated based on the full temporal resolution in order to allow for a correct evaluation of security of supply.

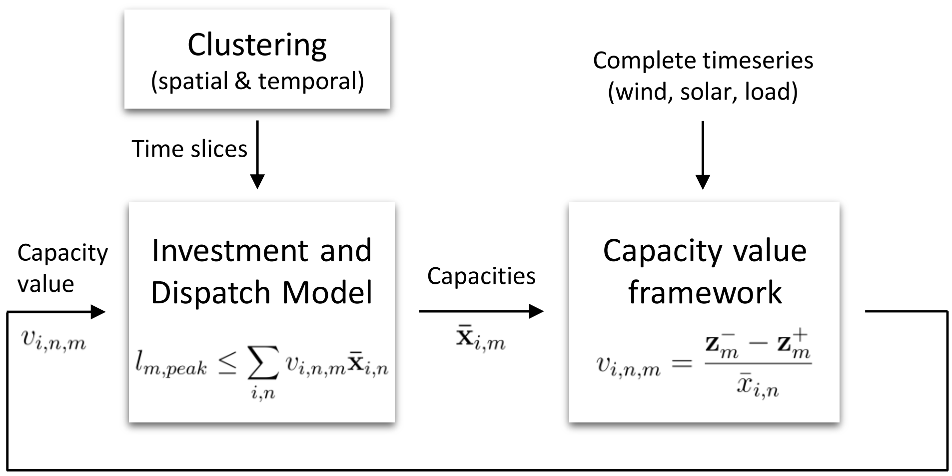


Figure 1: Iteration algorithm

The procedure depicted in Figure 1 successively linearizes the non-linear properties of the capacity value by iteratively solving two corresponding linear problems. Hence, this novel framework allows to endogenously account for the non-linear dependency of the capacity

[16]See section 4.2 and Appendix B for a description of the comprehensive high-resolution data set and the clustering algorithm.

value of wind power on the amount and spatial distribution of installed wind capacity, as well as resulting system effects via interconnectors. Building on that, effects on system costs and optimal allocation of capacities resulting from different ways of crediting the contribution of wind power to reliability can be quantified. Despite the iterative linearization, the non-linearity of the problem remains. As a result, existence and uniqueness of a global optimum can not generally be guaranteed.[17] In order to address this issue, we numerically test optimality by comparing model runs for a wide range of start values.[18]

From a practical perspective, the social planner in the presented capacity value framework can be interpreted as a central authority, e.g. the European Commission, which assesses the required firm capacity in each market in order to reach market-specific target reliability levels, taking into consideration load, solar and wind characteristics as well as interconnection constraints. This centralized assessment of market-specific required dispatchable capacity is then taken as a basis for the amount of capacity procurement in each market. Consequently, the capacity value framework determines the required quantity of dispatchable generation capacity, while the specific cost-minimal structure of back-up capacities to meet this requirement is determined in the investment and dispatch model.

In the following, we apply the presented methodology to a simple two-country system for illustrative purposes (Section 3), followed by a large-scale application covering the European electricity system (Section 4).

3. Illustrative example: Two-country system

In order to illustrate the basic functioning of the proposed methodology, this section presents an application to a simple case with only two countries, namely France and Germany. The example follows a greenfield approach, which optimizes the system configuration in both countries for the year 2030. For reasons of simplification, only investments into gas-fired power plants, battery storage and onshore wind power capacities are allowed with each country consisting of only one wind region. The interconnection between both countries is assumed to have a capacity of 5 GW. The remaining data assumptions for example on costs, electricity demand and CO_2 reduction targets are equivalent to the large-scale application and are described in detail in Section 4.2.

[17]Global unique optima can be guaranteed for convex minimization problems. A formal proof of the convexity of the problem is out of the scope of the paper. Nevertheless the decreasing returns to scale of the capacity value with respect to installed capacity, which is observed in empirical studies, suggest convexity.

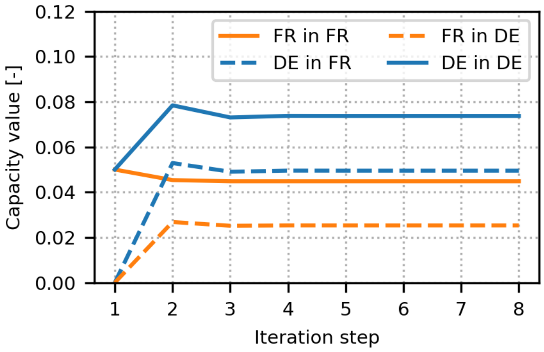
[18]See Sections 3 and 4.

By solving the integrated problem (6), it is assumed that the two countries perfectly cooperate with respect to reliability. As such, they take full advantage of balancing effects in capacity supply and demand. In this illustrative example, for simplification, the reliability target expected energy unserved is set to perfect reliability ($EEU = 0$) in both countries, which means that load must be fully served in all hours as no peak shaving is allowed. Thus, the problem reduces to the analysis of the hour with peak residual load in each country and derives the minimally required firm capacity, considering capacity exchanges via the interconnector. The resulting firm capacity requirement is then applied as minimal capacity procurement level in the electricity market investment and dispatch model (8).

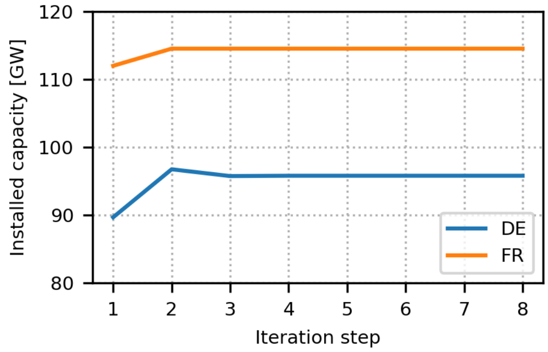
We start the iteration by running the investment and dispatch model with a start value of 5 % for the local capacity value of wind power and 0 % for cross-border contributions of wind to security of supply. The resulting capacity values, installed capacities for wind power and required firm capacity as well as total system costs are depicted in Figure 2 for the first eight steps of the iteration. Figure 2(a) shows the local capacity value of wind power (e.g. 'FR in FR' for the capacity value of French wind power in France) as well as the cross-border capacity value via the interconnector from France to Germany ('FR in DE') and vice versa. In the first iteration step, the electricity market model determines the optimal wind power capacities based on the start values for the wind power capacity values. The resulting wind power capacities are then used in the capacity value framework to calculate capacity values based on actual wind infeed and load time series. As shown in Figure 2(a), the local capacity value of wind in Germany increases in the second iteration step, while the French capacity value slightly decreases. Moreover, the cross-border capacity values both increase to non-zero values.

Based on the updated capacity values the electricity market model determines new optimal wind power investment, taking into consideration the adjusted contribution to security of supply from wind power. As shown in Figure 2(b), optimal wind power capacities increase in the second iteration step because of the higher capacity value. The corresponding required firm capacity to reach the reliability target decreases, as shown in Figure 2(c). Consequently, the required firm capacity provided by dispatchable capacities is reduced as the contribution of wind power to security of supply is increased. In the third iteration, the capacity values are slightly reduced because increased wind capacities decrease the relative contribution to security of supply. After the fifth iteration, convergence is reached and the model results remain constant in the following iterations.[19]

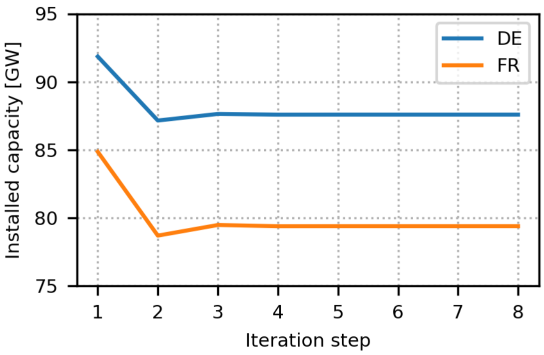
[19]In order to test for robustness, the calculations were conducted for a wide range of start values.



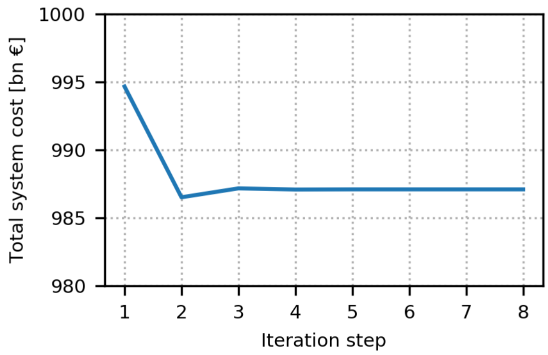
(a) Capacity value of wind power in FR and DE (national and cross-border)



(b) Installed wind power capacity in FR and DE



(c) Required firm capacity in FR and DE



(d) Total system costs for two-country system FR-DE

Figure 2: Iteration results in 2030 for the illustrative two-country system FR-DE

The two country case shows the basic interactions of the key model variables throughout the iteration process. In the following section, the methodology will be applied to a real-world large-scale application. The basic logic of the model interactions is identical to the discussion in this section.

4. Large-scale application: European electricity market

This section presents an application and extension of the previously developed methodology to the European electricity system. A large-scale investment and dispatch model for the European electricity market is applied in order to determine the optimal pathway to a low-carbon electricity system in 2050. Based on the presented methodology, the development of regional capacity values of wind power over time and the corresponding implications on optimal allocation of wind power capacities are assessed.

The analysis is structured as follows: Sections 4.1 and 4.2 give a brief description of the applied electricity market model as well as assumptions and data sources. Section 4.3 presents the model results.

4.1. Electricity market model and scenario definition

The applied model is a partial equilibrium model that determines the cost minimal configuration of the European electricity system, considering investment decisions as well as dispatch of power plants. Cost minimization over several years reflects perfect competition and the absence of market distortions as well as perfect foresight as fundamental model assumptions. The model is an extended version of the linear large-scale investment and dispatch model presented in Richter (2011), which has been applied for example in Bertsch et al. (2016) and Knaut et al. (2016). The basic model structure follows the same logic as in Problem (8), however additional constraints are included in order to improve the representation of politically implied restrictions and technical properties of electricity systems. These constraints include for example ramping or storage constraints as well as politically imposed CO_2 reduction targets to decarbonize the power sector.[20]

The model represents a total of 27 European countries.[21] Transmission between countries is represented by net transfer capacities (NTC), which are assumed to be extended according to the ENTSO-E Ten-Year Network Development Plan 2018 (ENTSO-E (2018)). The starting year of the model is 2015. Existing capacities in 2015 are based on a detailed database developed at the Institute of Energy Economics at the University of Cologne, which is mainly based on the Platts WEPP Database (Platts (2016)) and constantly updated. Based on these start values, the model optimizes the electricity system until the year 2050. The European CO_2 reduction targets are implemented as yearly CO_2 quotas, which impose a reduction of emissions by 95 % in 2050 compared to 1990 levels. Additional reduction targets for the intermediate years are implemented with 21 % reduction in 2020 compared to 2005 and 43 % in 2030 compared to 2005. All values are based on official reduction targets formulated by the European Commission.[22] Investment into nuclear power is only allowed for countries with no existing nuclear phase-out policies. Fuel costs and investment costs for new generation capacities are based on the World Energy Outlook 2017 (International

[20]See Richter (2011) for a detailed description of the model.

[21]Austria (AT), Belgium (BE), Bulgaria (BG), Switzerland (CH), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Great Britain (GB), Greece (GR), Croatia (HR), Hungary (HU), Ireland (IE), Italy (IT), Lithuania (LT), Latvia (LV), Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Sweden (SE), Slovenia (SI), Slovakia (SK)

[22]See https://ec.europa.eu/clima/policies/strategies for detailed explanations.

Energy Agency (2017)). Yearly national electricity consumption is assumed to develop according to the ENTSO-E Ten-Year Network Development Plan 2018 (ENTSO-E (2018)). The detailed numerical assumptions are presented in Appendix C.

The country-specific reliability target in the capacity value framework of the large-scale application is set to an EEU, which corresponds to a loss of load expectation of 3 hours per year in every modeled country. This value is often applied in theory (e.g., Keane et al. (2011)) as well as in practice (e.g., in the capacity markets in Great Britain or by the ISO New England).[23]

4.2. Input data for variable renewable electricity generation and load

In addition to the assumptions described in the previous section, detailed data on weather-dependent renewable energy sources are required in order to assess contributions to security of supply of wind power generation and to generate robust estimates for the capacity value. We apply a novel dataset for wind and solar power generation based on the meteorological weather model COSMO-REA6. The data for wind power generation from existing capacities is based on Henckes et al. (2018b). The wind speed data derived from the weather model is combined with a detailed dataset of European wind parks, which includes location, installed capacity, hub-height and turbine data in order to generate a consistent hourly time series of wind power generation over 20 years (1995-2014).

The same methodology is extended in our application for potential future generation capacities. We assume power curves based on state-of-the-art onshore and offshore wind power plants for new capacity investment.[24] These plants are assumed to be distributed on a 24x24 km grid over whole Europe in order to determine wind generation data for potential new generation investment. Again, a consistent hourly 20 year time series of wind power generation is generated.

Even though solar power generation is not the focus of the present analysis we also use high resolution hourly time series for solar power. The data is generated based on solar irradiance data of COSMO-REA6 for the same 24x24 km grid over Europe as for wind power

[23]In European countries, reliability targets measured in $LOLE$ generally range from 3 to 8 hours per year (Table 6 in European Commission (2016a)). Note that in case of a loss of load event, the system operator typically still has a number of options before finally resorting to selective disconnections, amongst others asking generators to exceed their rated capacity, invoking demand side balancing reserves or reducing voltage levels (Newbery (2016)). We estimate the EEU corresponding to $LOLE = 3$ in each country based on the historical ordered residual load curve in each modeled country. The resulting EEU for all markets are listed as shares of yearly demand in Table C.3 in Appendix C.

[24]The considered wind turbines are Enercon E-126 EP4 for onshore wind and Vestas V164 for offshore wind. Power curves for both turbines were determined based on technical data on the manufacturer websites.

generation. The methodology is described in detail in Frank et al. (2018) and Henckes et al. (2018a).

In order to keep the large-scale investment and dispatch model computationally tractable, the spatial and temporal resolution of wind and solar power generation data has to be reduced. We apply a two-step clustering approach in order to accomplish this. In a first step the spatial resolution is reduced by clustering the high resolution data into representative wind and solar regions. The number of regions for onshore wind and solar is chosen based on the surface area of each country. Additionally one offshore wind region with water depths smaller than 50 m for bottom-fixed offshore wind turbines and one region with water depths between 50 m and 150 m for floating offshore wind turbines are considered. In total the model consists of 54 representative regions both for onshore wind and solar power and 41 representative regions for offshore wind in Europe (see Table C.5 in Appendix C). A detailed description of the spatial clustering methodology is presented in Appendix B.

Based on the spatially reduced data a temporal clustering is performed in order to identify time slices, which allow to reduce the temporal resolution without losing the statistical properties of weather-dependent wind and solar power generation and load. Load data is based on hourly national vertical load[25] data for all considered countries for the years 2011-2015 taken from ENTSO-E (2016). Note that these historical measurements - being the result of a functioning electricity market - may include some price responsiveness of consumers or load shedding. However, historical load represents the best approximation available for the variable electricity demand over time. Additionally, price responsiveness during times of scarcity is low (Lijesen (2007)), which justifies the assumption of inelastic load. The historical load data is normalized and scaled based on the assumptions for total yearly future electricity demand development in order to generate consistent time series.[26] Each of the five years is then combined with the 20 years of renewable energy generation data in order to get a good representation of the joint probability space, resulting in 100 synthetic years of hourly load and renewable energy data. Hereby, we assume stochastic independence between load and wind.

Based on this dataset and the temporal clustering approach presented in Nahmmacher et al. (2016), we generate 16 typical days for the time slices used in the investment and

[25] i.e., national net electricity consumption plus network losses.

[26] Scaling historical load time series implies that the temporal structure of electricity demand does not change in the future. Consequently, possible changes in the demand structure as a result of increasing electrification in the mobility or heating sector are not accounted for.

dispatch model.[27] As depicted in Figure 1, these typical days are used as input data only for the electricity market model while the capacity value calculations are based on the full temporal resolution of the data set.

4.3. Results and discussion

This section presents the model results, which are determined based on the described methodology and assumptions in an application for wind power. Section 4.3.1 presents the resulting contribution of wind power to security of supply. Based on these results Section 4.3.2 discusses differences between the proposed optimization methodology and existing modeling approaches, which do not account for the endogeneity of the capacity value of wind power generation.

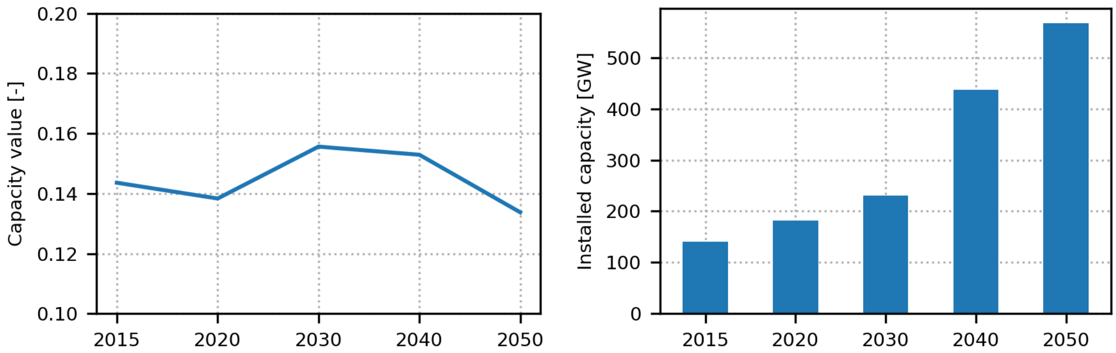
The applied iteration algorithm converges also in the large-scale application after only a few iterations (see Figure A.1 in Appendix A). In order to check the presented results for robustness we ran the model with a wide range of start values for the capacity value. All robustness checks showed quick convergence and merely identical results.

4.3.1. Contribution of wind power to security of supply

The main novelty of the presented methodology is the explicit endogenous representation of the contribution of wind power generation to security of supply in a large-scale model for electricity markets. Figure 3 shows the resulting aggregated average national capacity value of European wind power plants together with total installed wind power capacity in Europe for the simulated years. The presented values can be interpreted as the average share of wind power capacity in Europe that can be considered as firm capacity in the respective year, assuming cooperation with respect to reliability by means of an efficient usage of interconnectors.

The depicted results show that the contribution of wind power to security of supply is above 10 % in all considered model years. In 2015 the capacity value of wind amounts to roughly 14 % on average. Until 2020 this value only slightly decreases despite capacity additions. The reason is that interconnections between European countries are extended according to the Ten-Year Network Development Plan 2018 of ENTSO-E. As a result the decline in average capacity value, which results from additional generation capacities and decreasing returns to scale, is dampened by additional interconnectors. This dampening

[27] Nahmmacher et al. (2016) show in their analysis that, in investment models for electricity markets, even less than 10 typical days are sufficient to obtain similar results to model runs with very high temporal resolution.



(a) Aggregated average capacity value of wind power in Europe

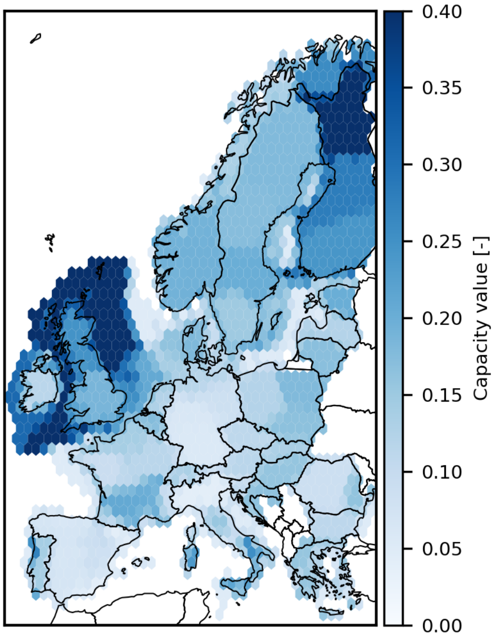
(b) Aggregated installed wind capacity in Europe

Figure 3: Average contribution of wind power to security of supply in Europe

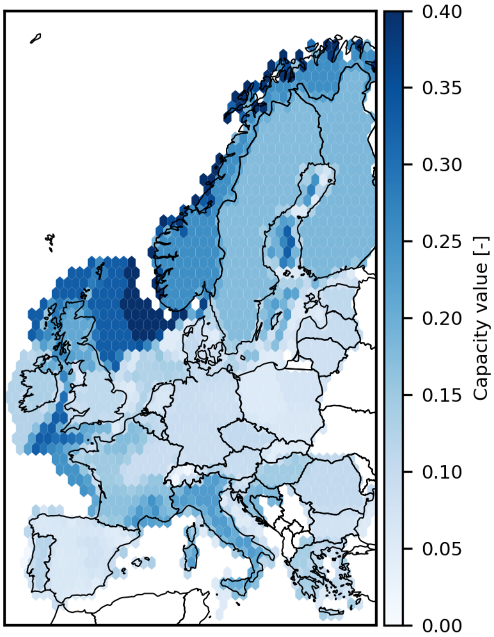
effect emerges because we calculate the capacity value based on the ability of wind power to provide secure capacity given the availability of interconnections to neighboring countries. Consequently, as interconnector capacities increase, the ability of wind power to provide secure capacity in combination with interconnectors also increases.

Remarkably, between 2020 and 2030 the average capacity value of European wind power increases despite continued capacity additions. This effect can be explained by technological innovation as a large share of the existing wind power plants reach the end of their technical lifetime during this time span. Consequently, many old wind power plants with relatively low rated capacities and hub heights are substituted by state-of-the-art wind turbines, which enable more stable and reliable wind power generation on average. As a result the capacity value increasing effect of technological innovation in combination with continued increased market integration outweighs the decreasing effect of decreasing returns to scale. After 2030, the two increasing effects are less pronounced because the wind power plant fleet is already to a large part renewed and the extension of interconnectors is less pronounced. Additionally total installed wind power capacity more than doubles from roughly 230 GW in 2030 to over 560 GW in 2050. Accordingly, the average capacity value of wind power decreases between 2030 and 2050.

In addition to the described average effects in Europe, the model results show a strong heterogeneity across different regions. To illustrate this, Figure 4 shows the regional capacity value in 2030 and 2050, based on color-coded maps. It is shown that the capacity credit varies between 1 % and 40 % across countries and declines in most regions between 2030 and 2050. Interestingly this is not the case for all regions, for example in some regions in France and Italy as well as some offshore regions in France and Norway, the capacity value remains constant or even increases. In all mentioned regions, this can be explained by small installed wind power capacities in 2030 and no or relatively small capacity additions between 2030 and 2050. Thus, no decreasing return to scale effect arises, which would reduce the capacity value. At the same time, the temporal structure of residual load in neighboring regions changes due to wind and solar capacity additions, increasing the value of the temporal wind structure in the mentioned regions. It can be concluded that the differing temporal patterns of wind power generation as well as the differing total installed capacities, technology mixes and interconnection capacities lead to heterogeneous contributions of wind power to security of supply across countries.



(a) Capacity value of wind power in 2030



(b) Capacity value of wind power in 2050

Figure 4: Regional capacity values of wind power in the European electricity system

Based on the market-specific capacity values the equivalent firm capacity of wind power can be calculated. The results for all considered countries in 2050 are shown in Figure 5. It differentiates between firm capacity that is provided by wind power plants within the respective country and firm capacity that is provided cross-border via interconnections to neighboring markets, given they cooperate with respect to reliability. Again it is apparent that the contribution of wind power to security of supply varies substantially between countries depending on the capacity value and the installed capacities. In comparatively large

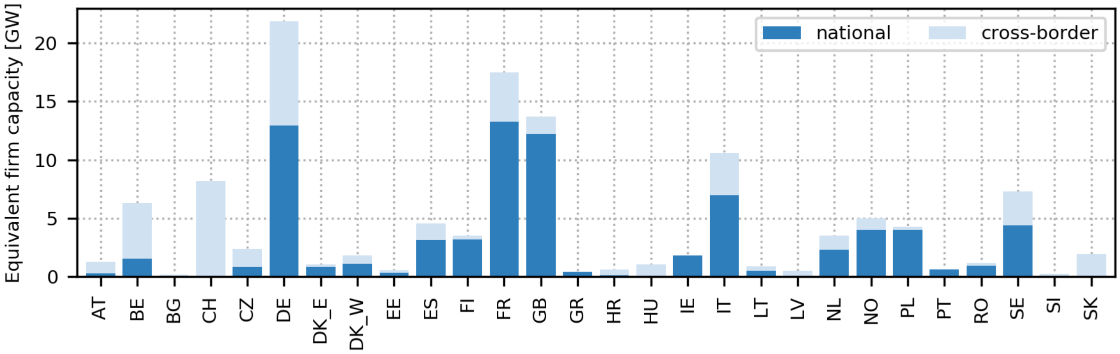


Figure 5: National and cross-border equivalent firm capacity provision of wind power in European countries in 2050

countries such as Germany, France or Great Britain the national equivalent firm capacity of wind power amounts to more than 10 GW. Additionally, it is shown that substantial cross-border contributions are present in many countries. In Switzerland, for example, the equivalent firm capacity provided by wind in neighboring countries amounts to more than 5 GW. This is a result of increasing Swiss market integration and large installed wind power capacities in neighboring countries, especially Germany and France.

4.3.2. Implications on electricity system configuration

As shown in the previous section, the contribution of wind power capacities to security of supply can be substantial. Additionally the results show that the capacity value of wind power is heterogeneous across countries and varies over time depending on the installed capacity of wind power, the available transmission capacities between countries and technological innovations. In practice however, long-term scenarios of the electricity system are typically based on the assumption of a fixed exogenous capacity value (e.g. 5 % in Jägemann et al. (2013)). Because of these modeling practices we analyze in this section how the results of our proposed methodology differ from existing modeling approaches with fixed capacity values for wind power. We thereby compare our model results to equivalent model runs with fixed capacity values for wind ranging from 0 % to 20 %.

Figure 6 shows the difference in firm capacity requirements for European countries in 2050 for simulations applying exogenous wind power capacity values compared to simulations applying endogenous capacity values, which account for their temporal and spatial heterogeneity. Positive values imply additional firm capacity requirements with exogenous capacity values. Applying fixed exogenous wind capacity values results in inefficient amounts of firm capacity provision, with an overestimation of firm capacity requirements when applying wind capacity values below 10 % for most countries. In addition, the heterogeneity of the capacity value across different countries implies that country- or even region-specific evaluations of the capacity value are necessary in order to correctly estimate the required dispatchable firm capacity.

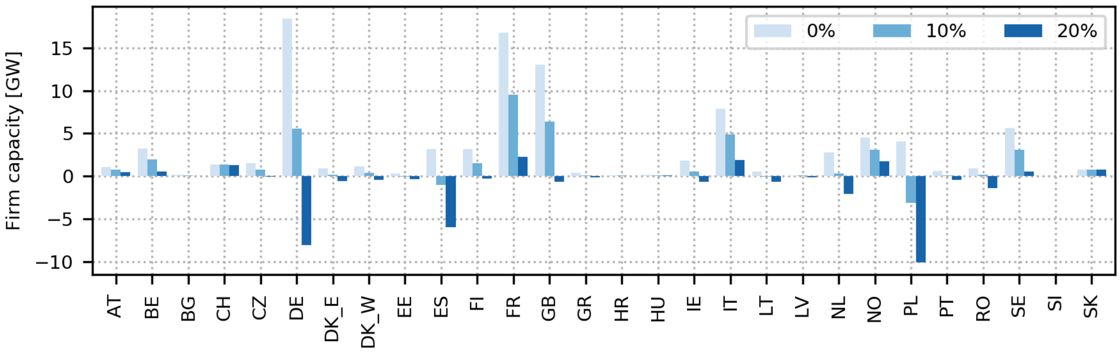
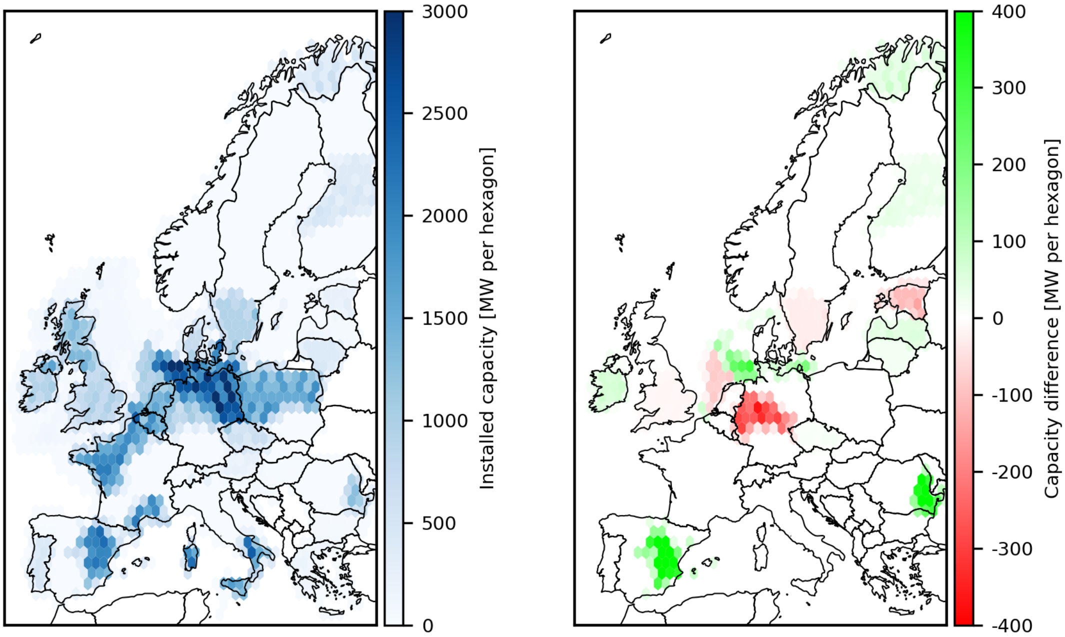


Figure 6: Difference in firm capacity requirements in 2050: Endogenous wind power capacity values vs. exogenous capacity values

The requirement for additional firm capacity translates into additional yearly costs for its provision, i.e. annuitized investment costs as well as fixed operation and maintenance costs. Typically, such additional dispatchable back-up capacity is provided by low-cost open-cycle gas turbines. The additional yearly costs for firm capacity provision when applying exogenous fixed wind power capacity values of 5 % compared to endogenous capacity values amount to 1.5 and 3.8 bn EUR in 2030 and 2050, respectively, which represents additional costs of 3 % and 7 %.

In addition to cost differences the results of our modeling approach also differ in comparison to existing approaches with respect to the geographical distribution of the installed wind power capacity. This is a result of the marginal local contribution of wind power to security of supply, which is reflected in our modeling approach and is often neglected in existing methodologies. To analyze the impact of this effect, Figure 7(a) shows the geographically differentiated installed wind capacities in 2050 based on endogenous capacity value calculations. Figure 7(b) displays the regional differences in installed capacities compared to an equivalent model run with fixed wind power capacity values of 5 %. Green areas on the map in Figure 7(b) indicate that more wind power capacities are installed when endogenously calculating the contribution to reliability, red areas on the other hand indicate that less wind power capacities are installed in the respective area.

The results illustrate that there are substantial regional differences between a model run with a constant capacity value of 5 % and our methodology. The reason for the regional shifts in wind power capacity is that when the contribution to security of supply is accounted for, it can be cost optimal to prefer locations with relatively lower total wind power generation, which instead have a higher capacity value. Consequently there is a trade-off between electricity generation and contribution to security of supply of one unit of wind power capacity. Because of the weather dependency of wind power generation this trade-off depends on the wind conditions in a specific region and the correlations with demand and wind power generation at other sites.



(a) Installed wind power capacity in 2050 based on endogenous capacity value calculations

(b) Difference in optimal wind power capacity in 2050: Endogenous capacity values vs exogenous capacity values of 5%

Figure 7: Allocational effects of endogenizing the capacity value of wind power in investment and dispatch models for the European electricity market

It can be seen from Figure 7 that there is for example a shift of offshore wind power capacity from the Netherlands to German and Belgian offshore wind regions if the contribution to security of supply is endogenously accounted for. Additionally, the results show that there is less onshore wind power capacity installed in central Germany. Instead more capacity is installed for example in Spain, Romania, Finland and Norway. Consequently, the results suggest that wind power generation is shifted from Germany to other countries in order to spread wind power plants over a wider area, and take advantage of differing wind conditions on a wider geographical scope.

More generally it can be concluded that there are regional as well as technological differences regarding offshore and onshore wind power plants between our methodological approach and existing modeling approaches. Hence, our results suggest that the contribution to security of supply should be considered in studies that analyze optimal locations of wind power generation in electricity systems based on long-term investment models.

5. Conclusion

This article analyzes the contribution of wind power generation to security of supply in electricity systems and develops a new methodology to endogenously determine the capacity value of generation capacities based on variable renewable energy sources in large-scale optimization models. Our novel framework allows to account for the non-linear dependency of the capacity value of wind power on the amount and spatial distribution of installed wind capacity, considering cross-border cooperation via interconnectors. Building on that, we quantify differences in system costs and wind power capacity allocation in comparison to existing modeling approaches, which typically assign fixed exogenous capacity values for wind power.

We find, based on a large-scale application of the proposed methodology, that wind power substantially contributes to security of supply in a decarbonized European electricity system with capacity values between 1 % and 40 %. The regional capacity value of wind power depends on the region-specific wind conditions, its correlation to other regions, as well as on the installed wind power capacity and the capacity of interconnections to neighboring markets. Assigning fixed and invariable capacity values therefore results in inefficient levels of required back-up capacities in electricity systems with high shares of variable renewable energy. We find that, for the European electricity system, the additional yearly costs for firm capacity provision when applying exogenous fixed wind power capacity values of 5 % compared to endogenous capacity values amount to 1.5 and 3.8 bn EUR in 2030 and 2050, respectively, which represents additional costs of 3 % and 7 %.

Our results imply that long-term scenarios for electricity systems should account for the contribution of variable renewable energy sources to security of supply. Additionally our results suggest that capacity mechanisms, which are being implemented in many countries should allow for participation of generation capacities based on variable renewable energy sources as well as cross-border contributions. However, the assigned capacity values should be determined based on careful assessments of the statistical properties of the variable renewable energy generation and need to be regularly updated in order to account for changes in the system configuration. Finally, our results show that market integration by increasing interconnections between different countries increases the potential of variable renewable energy sources to contribute to security of supply.

In future work our developed methodological approach could be extended to account for the electrical properties of transmission lines by integrating a load flow model. Thereby, internal transmission constraints could be accounted for. Additionally, other metrics for reliability of supply could be integrated in our model. Finally, an application of our approach to solar power generation would be a substantial contribution to the understanding of security of supply in electricity systems with high shares of generation based on variable renewable energy sources.

Appendix A. Convergence

Figure A.1 shows total system costs for each step of the iteration for different start values for the capacity value. It can be seen that total system costs converge quickly to very similar values independently of the start value. It is also apparent that changes in total system costs are negligible after the third iteration. We abort the iteration after the tenth step. The relative change in total system costs between the ninth and the tenth iteration is less than 0.1 %. The results for other start values within the depicted range were merely identical and are therefore omitted in Figure A.1.

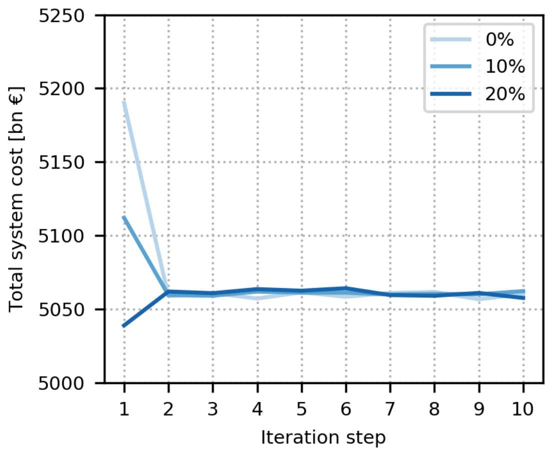


Figure A.1: Convergence of total system costs in large-scale application for different starting values

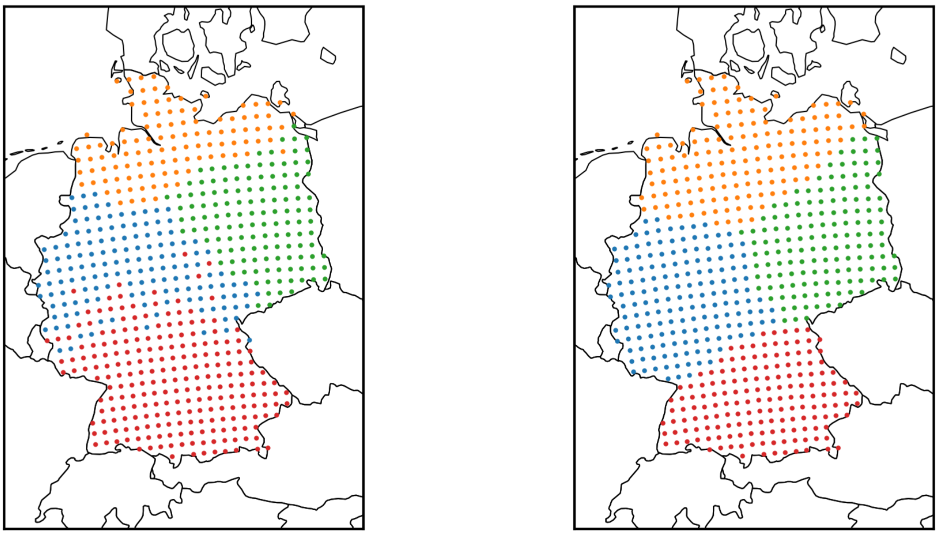
Appendix B. Spatial clustering methodology

The input data for wind and solar power generation is derived from the meteorological reanalyis dataset COSMO-REA6. The data has a high spatial resolution with data points on a 24x24 km grid over whole Europe. In order to keep the electricity market model computationally tractable the spatial resolution has to be reduced. We apply a spatial clustering methodology in order to construct representative regions, which optimally reduce the spatial resolution. Our methodology consists of three basic steps:

1. Derive number of clusters per market and energy source
2. Apply the clustering algorithm
3. Determine regional potential for wind and solar power capacities

In the first step we choose the number of clusters. We use a simple heuristic approach based on the surface area of a country to determine the number of clusters for onshore wind and solar power. The total surface are of each market is divided by 100'000 km^2 and the resulting number is rounded to determine the number of clusters. For offshore wind we choose only one region per market for water depths below 50 m and one region for water depths between 50 m and 150 m. The results are presented in Table C.5.

In the second step we apply a k-means clustering algorithm in order to cluster the data points into the number of chosen regions. Wind power and solar power are clustered independently in order to capture the spatial properties of both energy sources. Based on the clustered data points the energy output of one representative region is calculated by averaging over all data points in a cluster. Figure B.2 shows exemplary the clustering results for onshore wind and solar power in Germany. Each data point is represented by a dot, while the color coding differentiates the resulting clusters.



(a) Wind onshore

(b) Solar

Figure B.2: Exemplary results of spatial clustering for onshore wind power (a) and solar power (b) in Germany

In the third step the potential for installed capacity in each region is calculated for wind and solar power. The calculation is based on the country-level area potentials in Schmidt et al. (2016). Based on the total area potentials we calculate the regional area potentials with the ratio between the number of data points per region and the total data points in the corresponding country, assuming an equal distribution.

Appendix C. Numerical assumptions

Technology	2015	2020	2030	2040	2050
Wind onshore	1656	1602	1548	1512	1476
Wind offshore (bottom-fixed, $<$50 m depth)	3493	3168	2473	2236	2061
Wind offshore (floating, $>$50 m depth)	3749	3460	2581	2300	2099
Photovoltaics (roof)	1440	1152	972	882	792
Photovoltaics (ground)	1188	936	774	702	630
Biomass (solid)	3298	3297	3295	3293	3287
Biomass (gas)	2826	2826	2826	2826	2826
Geothermal	12752	10504	9500	9035	9026
Hydro (river)	5000	5000	5000	5000	5000
Compressed air storage	1100	1100	1100	1100	1100
Pump storage	2336	1237	1237	1237	1237
Battery	1000	1000	750	650	550
Nuclear	6253	5684	4832	4263	4263
OCGT	464	464	464	464	464
CCGT	1063	928	928	928	928
IGCC	2350	2350	2350	2300	2300
Coal	1957	1957	1957	1957	1957
Coal (advanced)	2152	2152	2152	2152	2152
Lignite	1596	1596	1596	1596	1596

Table C.1: Assumptions on generation technology investment costs (EUR/kW)

Technology	FOM costs (EUR/kW/a)	Net efficiency (-)	Technical lifetime (a)
Wind onshore	13	1	25
Wind offshore (bottom-fixed, <50 m depth)	93	1	25
Wind offshore (floating, >50 m depth)	93	1	25
Photovoltaics (roof)	17	1	25
Photovoltaics (ground)	15	1	25
Biomass (solid)	120	0.30	30
Biomass (gas)	165	0.40	30
Geothermal	300	0.23	30
Hydro (river)	12	1	60
Compressed air storage	9	0.70	40
Pump storage	12	0.76	60
Battery	10	0.90	20
Nuclear	101-156	0.33	60
OCGT	19	0.28-0.40	25
CCGT	24-29	0.39-0.60	30
IGCC	44-80	0.46-0.50	30
Coal	44-60	0.37-0.46	45
Coal (advanced)	64	0.49	45
Lignite	46-53	0.32-0.46	45

Table C.2: Assumptions on techno-economic parameters of electricity generators

Country	**2015**	**2020**	**2030**	**2040**	**2050**	*EEU* (‰)
AT	70	73	77	80	80	0,005
BE	85	87	89	90	90	0,008
BG	33	41	42	44	44	0,011
CH	63	62	58	56	56	0,006
CZ	63	69	71	74	74	0,007
DE	521	565	547	552	552	0,007
DK_E	13	15	17	18	18	0,014
DK_W	20	26	30	32	32	0,014
EE	8	9	10	11	11	0,015
ES	263	268	282	283	283	0,010
FI	82	90	94	96	96	0,007
FR	475	481	467	447	447	0,013
GB	333	328	322	313	313	0,010
GR	51	57	63	70	70	0,013
HR	17	19	22	24	24	0,010
HU	41	43	47	52	52	0,002
IE	27	31	36	38	38	0,010
IT	314	326	362	400	400	0,007
LT	11	12	13	15	15	0,006
LV	7	8	8	9	9	0,008
NL	113	115	119	122	122	0,006
NO	128	136	150	143	143	0,019
PL	151	163	207	253	253	0,006
PT	49	51	53	56	56	0,009
RO	55	58	64	70	70	0,007
SE	136	142	143	142	142	0,008
SI	14	13	17	20	20	0,007
SK	27	29	33	36	36	0,004

Table C.3: Assumptions on the future development of net electricity demand including network losses (TWh) and the reliability target expected energy unserved *EEU* as share of yearly demand (‰)

Fuel type	**2015**	**2020**	**2030**	**2040**	**2050**
Nuclear	3	3	3	3	3
Lignite	2	3	3	3	3
Coal	9	10	11	11	11
Oil	22	33	49	58	58
Natural gas	15	19	25	28	28

Table C.4: Assumptions on gross fuel prices ($\mathrm{EUR/MWh_{th}}$)

	Number of clusters			
Country	**Wind onshore**	**Wind offshore (<50 m depth)**	**Wind offshore (>50 m depth)**	**Solar**
AT	1	0	0	1
BE	1	1	0	1
BG	1	1	1	1
CH	1	0	0	1
CZ	1	0	0	1
DE	4	1	0	4
DK_E	1	1	1	1
DK_W	1	1	1	1
EE	1	1	1	1
ES	5	1	1	5
FI	3	1	1	3
FR	6	1	1	6
GB	2	1	1	2
GR	1	1	1	1
HR	1	1	1	1
HU	1	0	0	1
IE	1	1	1	1
IT	3	1	1	3
LT	1	1	1	1
LV	1	1	1	1
NL	1	1	0	1
NO	4	1	1	4
PL	3	1	1	3
PT	1	1	1	1
RO	2	1	1	2
SE	4	1	1	4
SI	1	0	0	1
SK	1	0	0	1

Table C.5: Number of spatial clusters for VRE per country

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