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The benefit of long-term high resolution wind data for electricity system analysis

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ABSTRACT

Future energy systems rely increasingly on the wind power supply. Understanding its characteristics is essential for the functioning of future electricity systems. Critical low wind situations may endanger the security of supply. So far, historical observations of wind power production are limited to few recent historical years and may not suffice to quantify the expected overall wind contribution, its variability, and its regional balancing effects for future electricity systems. With a novel long-term high-resolution wind power production dataset (hourly on a 6×6 km grid for 20 years) we derive new insights. First, we find advantages of our high-resolution dataset compared to previous studies. Second, we find a strong variation in annual wind production (variation of up to 14% for Germany). And third, we find a potential benefit from electricity exchange with neighboring countries in low wind conditions (for Germany in 81% of the low wind situations). The results are highly relevant for further investigation on the level of secured capacity or to identify optimal power transmission capacities within energy market modeling.

1. Introduction

Weather dependent renewable energies, in particular wind energy, has recently gained an increasing importance for energy systems all over the world. For instance, the European wind capacity share raised from 6% (41 GW) in 2005 to 16.7% (154 GW) in 2016 [1]. Thus, for understanding future energy systems, the overall wind power contribution, its short- and long-term variability as well as its regional balancing effects are crucial. Especially regarding energy system reliability the unique characteristics of wind power production, such as low wind situations, play an important role.

This encounters at least two major challenges. First, available historical wind power production data is insufficient for future predictions. Due to the rapid expansion of wind employment, extensive long-term observations are scarce. Therefore, simulations of wind power time series using current and expected future wind park fleets are required. However, this is leading to the second issue - the lack of meteorological observations with sufficiently high spatio-temporal resolution at the long-term scale, matching with operation sites to perform such simulations.

Recently a number of studies are making use of wind datasets from various reanalysis products in order to deal with these issues [2–6]. However, most of these studies are limited in the sense of spatial coverage (single countries), coarse spatial resolutions or the level of details concerning the conversion from wind energy to electricity generation. For instance, Staffell and Pfenninger [6] apply NASA's Modern-Era Retrospective Analysis (MERRA) in combination with a country based calibration to European wind parks calculating long-term wind power time series. Although the temporal resolution (hourly) of the MERRA reanalysis is sufficient for most energy related applications, the accuracy of the wind dataset might suffer from its coarse horizontal grid spacing (approximately 50 km in Europe) since important local effects happen at sub-grid scales.

In this article, we face these challenges by applying a novel wind power model to a unique high resolution wind dataset. The hourly and $0.055^\circ \times 0.055^\circ$ (approximately 6×6 km in Germany) resolution dataset is obtained from the brand-new reanalysis product of the Consortium for Small-scale Modeling (COSMO-REA6). In

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combination with a location specific European wind park portfolio of 2014, we generate a high resolution wind power database on an advanced level of details. Since the COSMO reanalysis contains long-term time series of 20 years, we are able to capture the broad range of variations, in particular the long-term variability of wind speed and hence electricity generation. In addition we apply a country based calibration to our model results using bias corrections triggered by historical time series.

We focus on three main insights from this approach. First, we have a closer look at advantages of our higher spatial resolution compared to other previous studies which rely on coarser reanalysis products. Second, by using long-term data we are able to analyze the variability and occurrence frequency of extreme events in the wind power sector. This leads to the question whether it is reasonable to define representative years as it is common in many energy studies. Third, we investigate regional balancing effects induced by wind power generation, on a European scale, as well as on a national scale (Germany). This highlights once more the advantages from extending electricity grids to reap the benefits from balancing effects. The dataset can be applied in further high-detailed energy market models and cost-benefit analyses.

The paper is structured as follows: In Section 2 we develop and apply the model to simulate wind power time series. The modeling results are further analyzed in Section 3 with respect to annual variation and balancing effects. We finally conclude in Section 4.

2. Methodology

In this section, the methodology is presented. Due to the high-resolution in time and space, the model has the potential to outperform existing wind datasets with a coarser resolution. Since wind speeds are highly dependent on regional effects (surface roughness, landmass, etc.) a high resolution is crucial to derive detailed data which is necessary for follow-up analysis in e.g. electricity dispatch and investment models, transmission grid expansions, as well as security of supply analysis.

2.1. A model for high resolution wind power production

We develop a method to accurately estimate spatially and temporally high resolution wind power production time series for given installed wind park capacities in a certain domain. The method is implemented in the Renewable Energy Output Model (REOM). To calculate the power output P_{out} of a single wind turbine at a known location for given instantaneous wind speeds at hub height v_{hub} the following equation, also called power curve, is used:

$$P_{out} = \begin{cases} 0 & v_{hub} < v_{in} \\ \frac{1}{2}\pi R^2 c_p \rho_{hub} \cdot v_{hub}^3 & v_{in} <= v_{hub} < v_r \\ C & v_r <= v_{hub} < v_{out} \\ 0 & v_{hub} => v_{out} \end{cases} \tag{1}$$

The rotor diameter R, efficiency c_p, capacity C, cut-in wind speed v_{in}, cut-out wind speed v_{out} as well as rated wind speed v_r are determined by the specific turbine type. The cut-in wind speed is the speed, where a turbine starts to generate power output. At rated wind speeds it produces at maximum (capacity) level and for wind speeds above the cut-out it stops due to technical limitations and security issues. The wind speed v_{hub} and air density ρ_{hub} from equation (1) need to be known at the turbine's hub height, since both quantities vary substantially with height.

Due to the cubic dependency of the power output by the wind speed at hub height in equation (1), it is crucial to have highly accurate wind input data. The wind input data is obtained from reanalysis data on a pre-defined grid. Two steps are necessary to get the wind speed at the specific turbine location and hub height. First of all, wind speeds are horizontally interpolated from adjacent grid points to the exact specific wind park location using the inverse distance weighting method. Second, wind speeds need to be vertically interpolated, respectively extrapolated to the adjacent hub height. Reproducing the vertical wind profile is a challenging task due to the complexity of atmospheric stability conditions [7–9]. In this paper, we use a vertical interpolation between the first six model layers obtained from the reanalysis data by a 3rd order fit.

2.2. Application of REOM: generation of a European long-term dataset

A wind park dataset is necessary to provide information about geographical coordinates, commission dates (production start dates), hub height, rotor diameter as well as the specific power curve characteristics (cut-in, cut-out, rated speed and capacity) for every single wind park in Europe. We use an extract of the worldwide database for wind turbines and power parks from *The Wind Power*[1] [10], last updated in April 2016. In order to be able to compare different years of weather and hence wind power production, we use the European wind power park fleet of the end of 2014 as the basis for our long-term wind power production simulations. After filtering out parks without a detailed location, production status or commission date information, 15 400 European parks contributing to an overall installed capacity of 119.85 GW for 2014 are left. However, some parameters are still lacking to different extents. For instance, for more than half of all parks in Europe the rotor diameter is unknown and for roughly 40% the exact hub height is lacking. In these cases default values are set, obtained by the mean of the particular parameter and country. In the Appendix Figs. A1 and A2 show the distribution of installed capacity in Europe for 2014 and Table A1 summarizes the parameter availability.

Imprecise wind input, due to the cubic dependency in equation (1), results in highly inaccurate wind energy outputs. Since wind speed is highly variable in time and space it is desired to use temporal and spatially high resolution wind input data. Reanalysis products are an approach to solve the lack of high resolution and homogeneously distributed data. They are systematic approaches to generate long-term datasets on a defined homogeneous grid for climate research by combining an assimilation scheme for historical observations with a certain atmospheric circulation model. Several reanalysis datasets are available for different historical periods, spatial domains and resolutions. However most of these products have a coarse horizontal resolution [6], e.g. ERA-Interim with approximately 80 km in Europe, due to their global coverage and computational limits. This might be a problem especially in mountainous regions, where the meteorological model is not able to reproduce the underlying terrain and capture wind speed variations adequately [11]. To reduce these inaccuracies we use the novel high resolution reanalysis dataset COSMO-REA6 from the Climate Monitoring Branch of the Hans Ertel Center for Weather Research (HErZ-TB4) funded by the German Weather Service (DWD). It provides hourly wind data between 1995 and 2014 in Europe on a 0.055° (approximately 6 km) horizontal grid spacing with 40 different vertical layers. For more details about the reanalysis model and dataset see Bollmeyer et al. [12].

Staffell and Pfenninger [6] point out that a key factor for

[1] www.thewindpower.net.

previous wind power production studies using reanalysis products is "the need for calibration, or bias correction, to bring simulated capacity factors in line with reality". They find significantly varying bias correction factors for different European countries showing the site dependency of such corrections. We follow the simple and promising bias correction method of Staffell and Pfenninger [6] by using the bias of the simulated wind power output instead of directly taking reanalysis wind speeds.

To correct our new simulated time series by the capacity factor bias in every country we use the wind power production database from the European Network of Transmission System Operators for Electricity (ENTSO-E) as a basis for comparison. The database contains monthly wind power capacity factors (CF) between 2010 and 2014 for all European countries. Similar to Staffell and Pfenninger [6] the resulting bias factors show significant regional dependencies. Country-wise correction factors can then be applied to calculate new wind speeds at the specific hub heights yielding bias corrected wind power production time series for all European wind power parks. We need to mention here, that specific single wind park sites might face significant errors due to the usage of country averaged production data from ENTSO-E.

With the wind park and reanalysis dataset we are able to calculate hourly time series for all wind turbine locations in 30 countries, including 28 countries of the European Union (EU-28) complemented by Norway and Switzerland (from now on defined as Europe), for a time period of 20 years between 1995 and 2014.

This dataset is very useful in the field of energy meteorology and energy economics because of two distinct characteristics. First, we derive hourly wind production time series for each wind turbine location. Our high-resolution data (hourly time-resolution on 6×6 km) provides superior accuracy compared to classical European-scale wind datasets (e.g. 6-hourly temporal resolution for ERA-Interim and 50×50 km horizontal grid as for MERRA-2). Second, we can gain additional insights on long term energy output of wind turbines over a time span of 20 years that could not have been measured historically. By providing these insights, we can especially contribute to energy systems planning. Here, time series over a time span of 20 years lead to much more robust results and insights compared to the historical measurements.

3. Results

3.1. Evaluation of the underlying reanalysis dataset

First of all we have a closer look at the reanalysis wind speed input dataset. Yet there are only few studies dealing with the performance of the COSMO reanalysis product due to the recency of the dataset. Kaiser-Weiss et al. [11] compare statistical properties of wind speeds observed at 210 meteorological stations over Germany with near-surface fields of the COSMO-REA6, ERA-Interim and ERA-20C reanalysis products for recent years. With respect to monthly correlations, they find for 96% of all stations a correlation coefficient $R \geq 0.8$ and for 80% of the stations $R \geq 0.9$ in the case of COMSO-REA6, in contrast to 82% and 47% for ERA-20C as well as 89% and 66% for ERA-Interim. They state that the improved correlation of COSMO-REA6 is "valid for daily, monthly and seasonal scale" and add that regional reanalysis "improves monthly correlations […] in areas with more complex topography".

To further assess the wind speed quality of data produced by reanalysis we compare COSMO-REA6 (6 km grid), ERA-Interim (80 km grid) and MERRA-2 (50 km grid) wind speeds to observations. The data used here are the synoptical observations (SYNOP) provided by the DWD with a temporal resolution of 10 min (averages). In order to compare only with independent observations, SYNOP stations lower than 100 m above sea surface are omitted since these observations are used for the COSMO assimilation procedure. The observations are compared to the nearest grid point of the respective reanalysis. As the observations are compared to 10 m wind reanalysis data only observations with measurement height between 8 and 12 m are taken into account. The DWD provides for every SYNOP observation site a spatial representativeness value. To avoid comparisons with observations influenced by local obstacles, sites with representative values greater than 500 m are considered only. Thus, 59 different SYNOP stations remain with 10 min observations. Table 1 shows the bias, standard deviation and Pearson correlation coefficient of COSMO-REA6, MERRA-2 and ERA-Interim compared to SYNOP observations. The time period of investigation are hourly values in the year 2014. COSMO-REA6 represents the mean absolute wind speeds best with a slight underestimation of $-0.14\ ms^{-1}$. The other two reanalysis slightly overestimate the wind speeds. In addition to the smallest systematic error, COSMO-REA6 shows the lowest standard deviation and highest linear correlation coefficient. Thus, COSMO-REA6 performs best in representing absolute values of observations.

There are various processes on different spatiotemporal scales determining the atmospheric wind field. To get an insight on how well the processes at the different temporal scales are simulated (and therefore produce realistic spatial wind variability) a method suggested by Cannon et al. [13] is used. We compare the observed (OBS) and reanalyzed (R) wind speed differences (δv) between different observation sites i, j:

$$\delta v_R = v_{R,i} - v_{R,j} \tag{2}$$

$$\delta v_{OBS} = v_{OBS,i} - v_{OBS,j} \tag{3}$$

Fig. 1 shows the linear correlation coefficients between the observed and synthetic wind speed differences for COSMO-REA6, MERRA-2 and ERA-Interim. The correlations increase from small to large distances, because large scale processes are in general better represented than small scale processes. COSMO-REA6 shows significant higher correlations to observations, followed by MERRA-2 and ERA-Interim. As COSMO-REA6 shows highest correlations for all distances, COSMO-REA6 outperforms the other two reanalysis not only in representing small scales processes but also large scales processes.

3.2. Evaluation of the REOM model

As a next step we compare the ENTSO-E time series on a monthly basis to bias corrected control data containing REOM wind power simulations between 2010 and 2014. To estimate the performance of the REOM model only countries with reliable installed capacity data in the considered time span are taken into account, leaving 21 European countries. The average European CF of 22.85% in ENTSO-E is slightly underestimated by our model (22.01%), yielding a difference of 3.6%. The good fit throughout the time period can be seen in Fig. 2a. However, it is evident that the spreads between the 10 and 90% percentiles vary significantly between REOM and ENTSO-E due to over- and underestimations in certain

Table 1
Bias, standard deviation (STD) and Pearson correlation coefficient (R) of COSMO-REA6, MERRA-2 and ERA-Interim compared to 59 SYNOP observation sites in Germany for 2014.

	Bias [ms^{-1}]	STD [ms^{-1}]	R
REA6	−0.14	1.44	0.74
MERRA	0.53	1.76	0.67
ERA-I	0.17	1.65	0.67

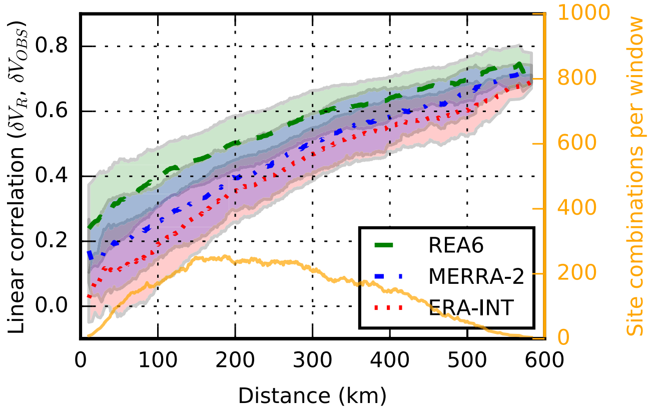

Fig. 1. Linear correlation of observed wind speed differences (site to site) and reanalyzed wind speed differences as a function of site distance. Solid lines show the moving average in a window of ±25 km. The standard deviation of the moving average is shadowed.

countries. The same can be observed on an intra-annual scale - the monthly averaged CF across Europe are showing very good agreement in spring and summer months but also some bias in autumn and winter (cf. Fig. 2b).

Considering output reductions of 5% in all ENTSO-E data due to transmission and distribution losses, as suggested by Staffell and Pfenninger [6], would result in an even closer match. The simulations show high correlations for almost all countries in Europe. They range between 0.98 for Germany and 0.71 for Bulgaria leading to an average correlation coefficient of 0.88 for entire Europe. As an example, Fig. 2b illustrates the German CF between 2010 and 2014 for the historical data, the bias corrected and uncorrected REOM data. It is evident that the model is able to capture the general trends. The bias correction shifts the data towards the ENTSO-E values, yielding comparable capacity factors. Looking at errors, the model shows root mean square errors between 1.45% (Germany) and 6.78% (Bulgaria), while 3.97% are estimated in average for Europe.

To evaluate the performance of the REOM model in combination with the COSMO-REA6 dataset on an hourly basis, the modeled wind production is compared to published hourly means of wind production data by EEX for the reference years between 2010 and 2014 in Germany. The hourly time series are as well highly correlated ($R = 0.97$) and the German average CF is underestimated by 3.9%, with 17.08% CF for REOM and 17.88% CF for EEX. An investigation of the diurnal cycle averaged over the 5 years shows that REOM is in good agreement with EEX and only slightly underestimates the CF during night times and vice versa during midday (cf. Fig. A3). The occurrence frequencies of capacity factors (cf. Fig. A4) show that the REOM underestimates the lowest range of CF ($< 10\%$) and slightly overestimates CF between 10 and 30% compared to EEX.

Besides these minor differences between our simulation results, ENTSO-E and EEX our model performs well on annual, seasonal, daily as well as hourly time scales. It is able to reproduce the general trend in wind power generation as well as its magnitude on the European and country based scale. However a country based bias correction is applied to our simulations, the performance quality still differs between countries significantly.

3.3. Long-term variability of wind power production

By making use of 20 historical weather years, we are able to simulate the wind power production over a comparably long time span with high resolution. We model the wind power generation in Europe for the installed capacities that existed in 2014. With this approach we are able to analyze the variation of wind power generation over a long time span which enables us to compare the characteristics of different weather years regarding annual average generation, high and low wind conditions. Note that the research focus is on the analysis of the wind variability and its characteristics. We explicitly do not perform a cost-benefit analysis of wind production sites nor an economic viability analysis. Thus, economic characteristics as renewable subsidies, electricity demand and supply, or market values are not relevant for this investigation. However, the underlying high resolution dataset can be applied to improve existing research as for instance applied in the high resolution market value estimation of Obermüller [14].

The distribution of hourly simulated wind generation over the time span of 20 years is plotted for Europe and Germany in Fig. 3a and b. In Europe, the capacity factor takes on values between 0% and 68%. For Germany, higher CF can also be observed that take on

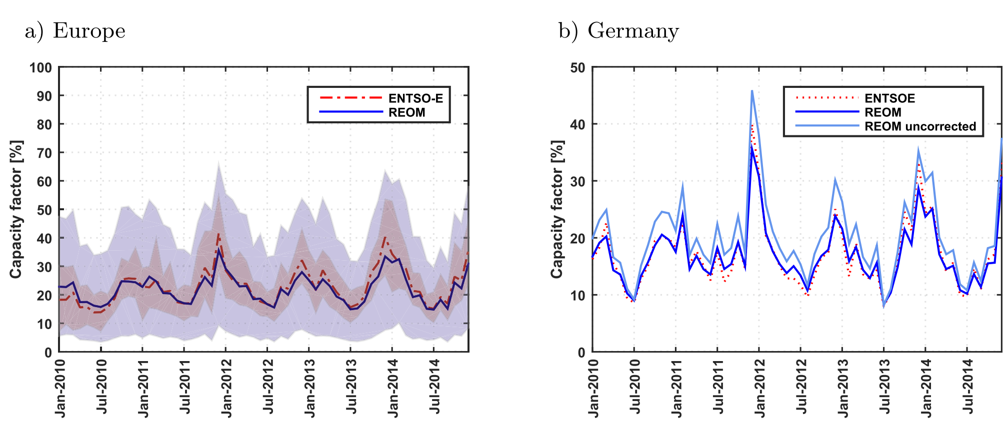

Fig. 2. Monthly means of capacity factors between 2010 and 2014. In a) for REOM (blue, solid) and ENTSO-E (red, dashed) averaged over all European countries. In addition the 10 and 90% percentiles are shaded. In b) only for Germany. In addition the uncorrected REOM (blue, dashed) is shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

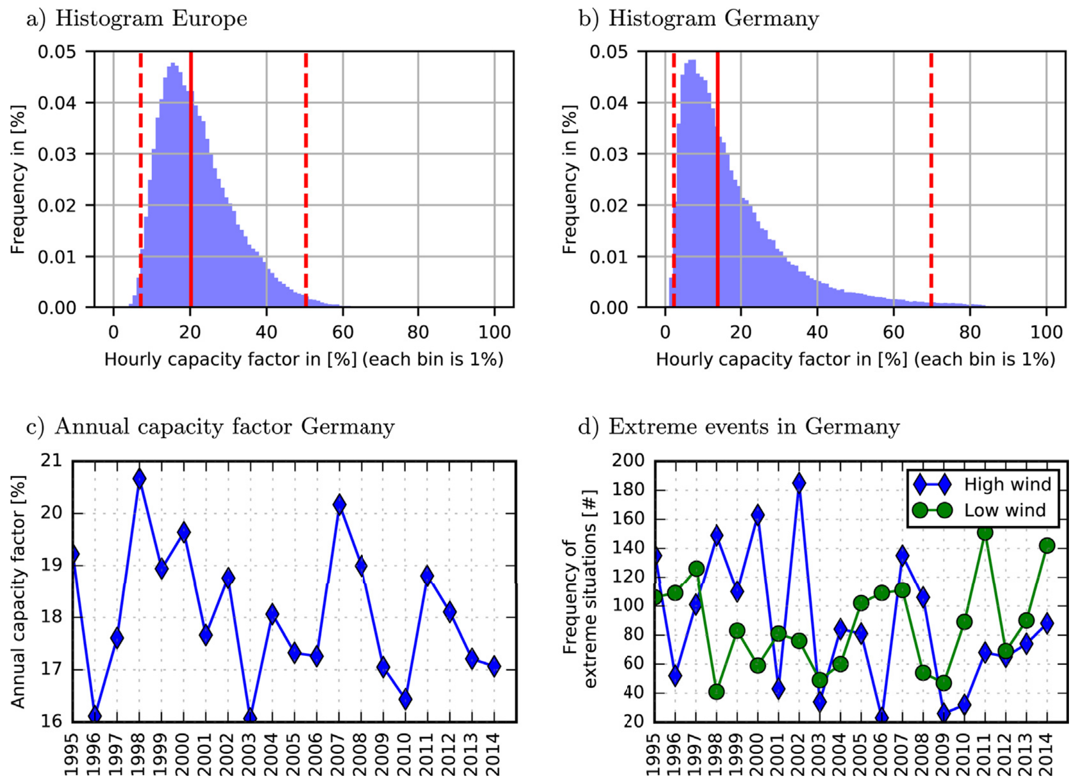

Fig. 3. Distribution of the hourly capacity factors in Europe (a) and Germany (b) between 1995 and 2014, red dashed lines illustrate the 1% and 99% percentiles and red solid lines the median. The annual moving average (c) and occurrence of extreme events (d) in Germany are shown for the same period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

values as high as 88%. Generally, we find that the German distribution of CF inhibits more extreme conditions with high or low capacity factors. In Europe as a whole these extreme low and high values cannot be observed because there are balancing effects between countries.

This leads on the one hand to a low probability of very low CF and on the other hand to a very low probability of very high CF. In this paper, we define low wind situations as situations below the 1% percentile threshold of the wind production distributions and, vice versa, high wind situations above the 99% percentile of the wind production distributions (exemplary plotted for Europe and Germany in Fig. 3a and b as red dotted lines). These are relative thresholds with respect to the different capacity and production levels. This means the absolute threshold for a German low wind condition is different from the European absolute threshold. The absolute threshold for the German low wind situations is at a CF of 2.27% or a production level of 0.8 GWh, whereas the European threshold is a CF of 7.13% or 8.54 GWh (high wind in Germany 69.83% or 24.57 GWh, Europe 50.31% or 60.29 GWh).

Table 2
Statistics of the simulated annual capacity factors for Germany between 1995 and 2014.

	Capacity Factor [%]	Deviation to mean [%]
min	16.1	−11.0
25%	17.2	−4.9
mean	18.1	–
75%	19.0	5.0
max	20.7	14.4

Fig. 3c and d shows the average annual CF for Germany and the occurrences of low and high wind situations for the whole time period. We see that the average CF can have huge variations between different historical years. For example between 1996 and 1998 the difference amounts to 4.6%-points in CF which means that in 1998 wind was able to generate 14.04 TWh more compared to 1996. In relative terms, the wind power production in 1996 would have been only 78% of the wind power production in 1998. The maximum deviation to the 20-year-average annual CF is 14.4% (see Table 2). One relevant point is wind degradation, i. e. the wind power adjustment process which could occur due to climate change. By Fig. 3c no annual degradation process is obvious. A corresponding OLS estimation shows no significant trend in annual wind capacity factor degradation. Small-scale regional effects could occur but have limited relevance for our national-level investigation focus.

The variation between different years is not only large in average terms but also with respect to the extreme high and low wind conditions. In Fig. 3d we can see that there is a large variation in the occurrence of low and high wind conditions in Germany. Based on the observations there is no clear link between the frequency of extreme wind conditions and the annual wind power production. For instance, 2011 was an average year in terms of annual wind power production with an exceptionally high number of low wind conditions and a comparably low number of high wind conditions. It is therefore not sufficient to define a representative year which covers characteristics of the whole time horizon that can, for example, be used for energy system modeling purposes. Especially in order to capture extreme events that may determine the reliability of future electricity systems, it is essential to consider observations from a long historical time span.

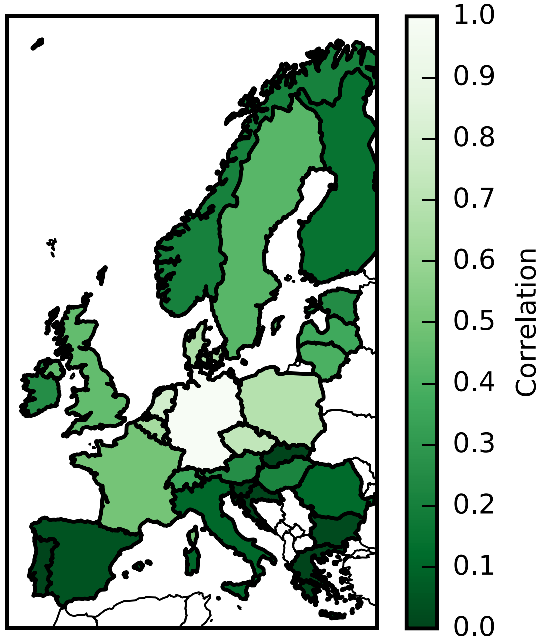

Fig. 4. Correlation of German and European wind power production between 1995 and 2014.

3.4. Balancing potentials in Europe and Germany

Balancing effects between different European countries can occur as long as there is enough transmission capacity available between countries. In this paper we will abstract from the limitations of transmission capacity and shed light on the theoretical potential of balancing effects assuming sufficient availability of transmission capacity. We are aware of the fact, that the underlying data by itself has limited potential to quantify the correct amount of transmission extensions. To quantify this, a dynamic energy dispatch and investment model would be necessary which accounts for physical power flows. However, the underlying data can serve as high-detailed input for further investigations in energy market models (e.g. Bertsch et al. [15]) and is thus highly relevant. The work of Hagspiel et al. [16] applies our wind dataset to evaluate the regional cooperation benefits on firm capacity under security of supply aspects.

For the analysis of balancing effects we distinguish two situations that are relevant with respect to the electricity system. First, balancing effects are beneficial when electricity generation of two locations are uncorrelated. We will refer to this case as average balancing effects. In this case both countries can benefit from the exchange of electricity because generation may be higher in one country when generation is low in the other. Second, we will analyze the case of balancing effects during low wind conditions in Germany. For both balancing effects, average and low wind, we will focus on Germany within the European electricity system.

Fig. 4 shows the correlation of wind power production for each country to the German power production over the whole time span from 1995 to 2014. All countries are positively correlated with the German wind power production and as expected more distant countries are less correlated by trend. This is in line with the results of Monforti et al. [17], although they focus on the correlation compared to Europe instead of Germany (based on a time span 1961–2050 in daily resolution from a data ensemble of 12 regional climate models). For Germany, it is beneficial to be connected to countries with low correlations with their national wind power supply. This may for example be the case for Norway or Austria, which are close by but rather uncorrelated in terms of wind power production. Whereas Germany has already very high transmission capacity to Austria, the connection towards Norway is so far only able via Denmark and a direct connection is currently being built (NORD.LINK). By trading electricity with countries of low correlation, Germany and the respective counter party are both able to benefit during average conditions. When we take a closer look at low wind conditions, this may not necessarily be the case.

During low wind conditions, balancing effects may be lifted when there is still power production available within Europe and especially in neighboring countries. As previously defined, we use a threshold of 2.27% CF which identifies the lower 1% percentile. Fig. 5 shows the histogram of the production in Europe and neighboring countries, when Germany is experiencing low wind conditions. In most cases, the production in Europe and the neighboring countries are also low compared to their 20-year median production (cf. Fig. 3). Nevertheless, the power production is only in some cases a critically low wind situation as to the 1%-percentile threshold for the CF. Within Europe, the capacity factor in 9% of the cases is also below the 1% percentile. For neighboring countries, this probability increases to 19%, which would occur with a joint probability of 0.19%. In all other low wind cases we can expect balancing between countries to take place. This means not all countries are experiencing extreme low wind conditions at the same time.

3.5. Balancing potentials within Germany

Balancing effects can also occur on geographical scopes within countries. Due to the high spatial data resolution of our dataset, the above methodology can easily be extended to analyze inner-country effects. The subsequent focus is Germany. High Northern (i.e. coastal) wind speeds and a corresponding subsidy scheme have caused higher installed wind capacities to be located in the Northern regions. The North German plain is located in this area, which shows low surface roughness enhancing the occurrence of strong winds in near-surface layers. South-German topography consists of mid- and highlands with a higher surface roughness. This leads to significant differences in regional wind locations within the country.

Fig. 6 shows the distribution of capacities (6a), average CF (6b) and correlations of CF time series to the total German wind production time series (6c) in Germany.

The value of each hexagon is obtained by an aggregation of the individual wind turbine values in that area. The capacity is the sum over all capacities within the area. The CF is defined as the average total wind production divided by the total capacity. The correlation is calculated based on the production in each hexagon compared to the total German wind power production. Darker colors point to higher capacities, capacity factors or correlation values.

Wind power capacities are mainly located in the northern part of Germany. The highest concentration of capacities can be found in the north-eastern part. Higher CF are located at the Northern coast. The main reasons are higher wind speeds which evolve over the sea and the North German plain due to more northwest wind situations in central Europe.

The highest correlations of wind power production can be found in the North German plain. Here, high installed wind capacities lead to an implicit weighting of the correlation time series. The aggregated correlations of the hexagons are up to 0.9 in this area compared to the total German wind production. Wind locations (i.e. the corresponding aggregated values per hexagon) in the Southern regions can be weakly correlated as 0.3. This difference is driven by

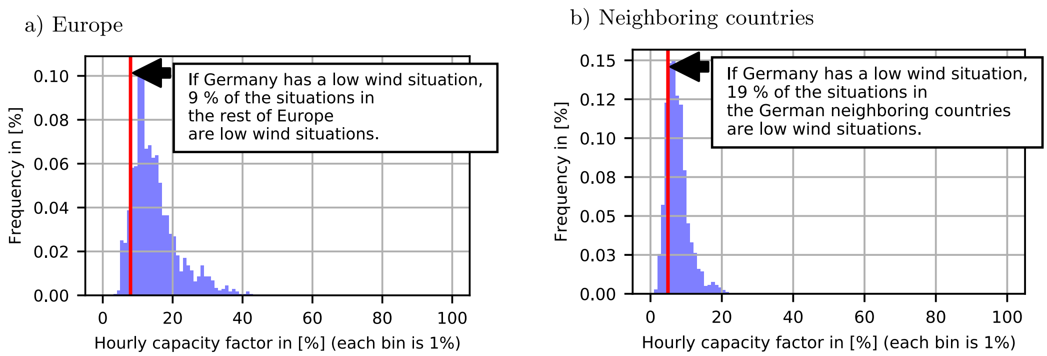

Fig. 5. Hourly capacity factor distribution for Europe (a) and neighboring countries (b) during low wind conditions in Germany between 1995 and 2014.

different wind speeds (e.g. due to the alps and the country-side) as well as less installed wind capacities.

With the same motivation as of the European analysis, which stated that favorable wind locations should have high capacity factors but should be less correlated, we find the following: to achieve highest wind production per installed MW wind capacity, wind locations are favorable in Northern windy areas. However, due to the high correlation in the North German plain, coastal regions would be more favorable compared to areas in the center of the North German plain. Lowest correlation values can be achieved in the Southern regions, i.e. close to the Alps. In this region, however, capacity factors are very low.

4. Conclusions and implications

In this paper, we present a temporal (hourly) and spatial (wind park level) high-resolution wind production model. We apply the model to the 20-year high resolution COSMO-REA6 reanalysis dataset for the EU-28 region (plus Norway and Switzerland). The focus is on the characteristics and the variability of wind power production over 20 years. This dataset and the corresponding analysis allow us to contribute to existing research in three aspects.

First, we show that our wind input dataset, the COSMO reanalysis product, outperforms the widely used ERA-Interim and MERRA time series. Taking this as a basis, we create a novel time series dataset for wind production with our new model and the unique COSMO-REA6 wind speed data. It covers a time span from 1995 to 2014 with an hourly resolution for each European wind park. Our model can easily account for higher temporal or spatial resolution and is only restricted by available input data.

Secondly, we identify the annual variability as well as the frequency of high and low wind situations in Germany for the 20 years of simulation. This analysis indicates that there is no single representative wind year which inhibits characteristics of average production as well as extreme situations. Thus, input weather years need to be carefully chosen and a longer time span could lead to more robust results in energy system modeling.

Thirdly, we find that Germany and European countries have significant balancing effects and can benefit from electricity transmission. On the one hand, we find evidence for average balancing effects based on correlation values. On the other hand, we identify that only a share of low wind situations in Germany are facing low wind situations in neighboring countries or in entire Europe at the same time.

Finally, the scalable REOM as well as the derived new wind production dataset allow further detailed analyses due to their high resolution applicability. The results should be considered in transmission extension analyses as this is strongly dependent on statistical balancing effects of wind production. Our 20-year time-horizon can be assumed to incorporate all relevant occurrences of wind situations. The general investigation can be extended to analyze local balancing effects which has a high relevance for countries with strong regional concentration of wind parks at

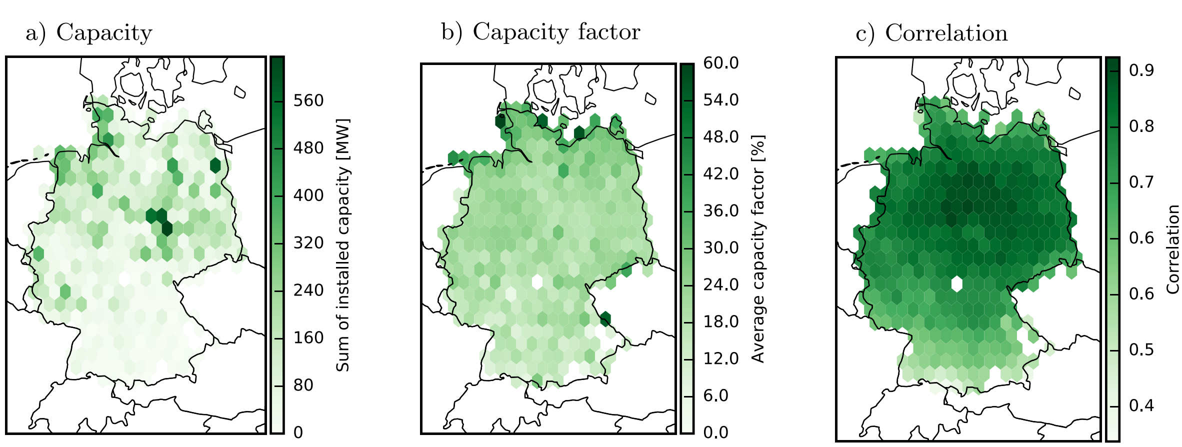

Fig. 6. Wind production in Germany a) sum of installed capacity within each hexagon, b) average capacity factor of wind turbines in each hexagon, and c) correlation of energy production in each hexagon with the total German wind energy production.

windy locations, e. g. Germany. The high resolution wind production dataset can increase the accuracy of electricity system modeling to evaluate security of supply under balancing effects as well as the regional market value of wind in a nodal pricing model. Further improvements of the input wind park dataset would contribute to a higher accuracy of the wind energy model.

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Appendices

A. Distribution of installed wind capacity

The underlying wind park dataset (i.e. installed capacities) varies across Europe. The regional distribution is shown in Fig. A1, which indicates an accumulation at coastal areas: Northern Germany, coasts of Spain as well as Italy. The absolute installed capacity of wind power per country (cf. Fig. A2), which is used for simulations, shows highest installed capacities in Germany, Spain and Great Britain, followed by France and Italy. The installed capacity (in combination with the regional wind speeds) has influence on the correlation, capacity factors as well as balancing effects.

B. Completeness of the wind park dataset

The underlying wind park dataset contains relevant information for the technical characteristics of the installed European wind parks. However, not all information are contained for each wind park or turbine. Table A1 provides statistics as to the completeness of each technical characteristic as well as the used default parameter, in the case of missing values.

C. Evaluation

Subsequently, we evaluate the modeled wind production data and data provided by the EEX transparency platform. The model is not calibrated to this data since the EEX data is an approximation itself. In addition, the EEX dataset only covers Germany and similar informations are scarce concerning all European countries.

Fig. A3 compares the diurnal cycle of both time series. Our simulations show only slight differences with higher values during daytime and lower values in the night.

Fig. A4 shows the high correlation of the modeled CF to the calculated factor based on the EEX data. For very low CF, our simulations are higher than for EEX while this behavior turns around for CF ranging between 10% and 30%.

Table A1
Parameter availability for all wind parks in Europe for the database of *The Wind Power* and their default value averaged over all countries.

Parameter	Availability (%)	Default value
Location	100	–
Commission date	100	–
Number of turbines	100	–
Hub height	60.6	90 *m*
Rotor diameter	37.5	66.7 *m*
Cut-in	66.8	3.5 ms^{-1}
Cut-out	66.8	25 ms^{-1}
Rated speed	66.8	12 ms^{-1}

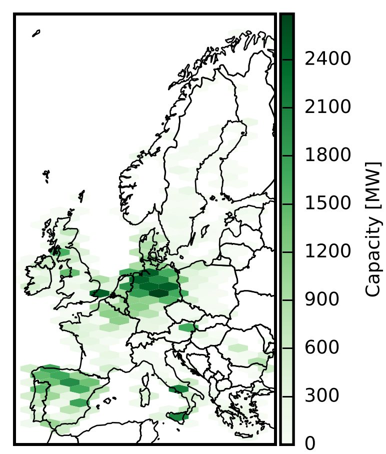

Fig. A1. Distribution of the regional wind capacity [MW] within Europe (aggregated to local hexagons).

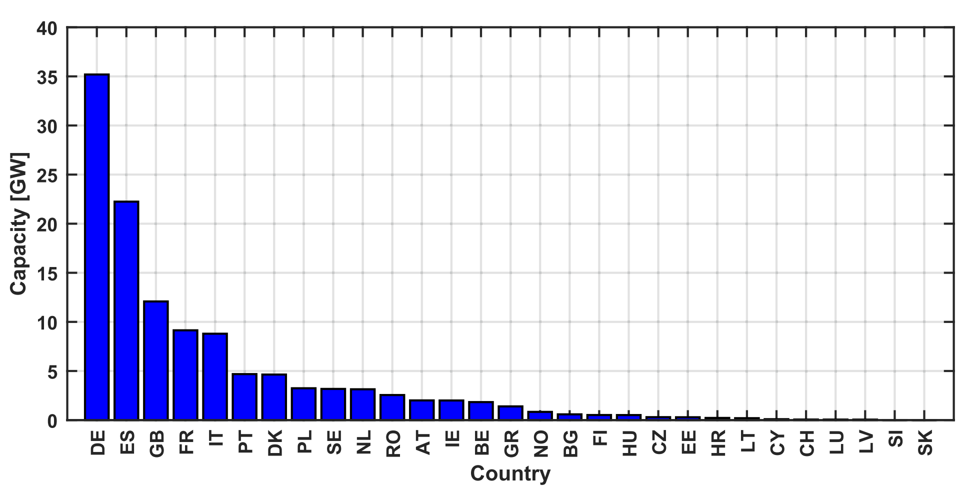

Fig. A2. Installed wind power capacities [GW] in European countries.

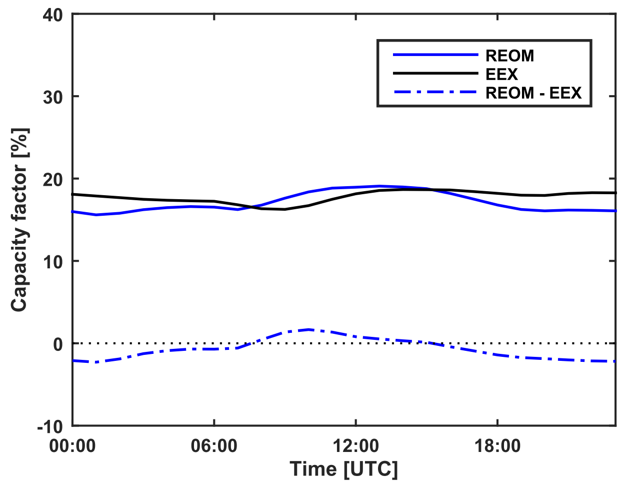

Fig. A3. Moving average of the diurnal cycle of capacity factors between 2010 and 2014 in Germany for REOM (blue, solid), EEX (black, solid) and their residual (blue, dashed). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

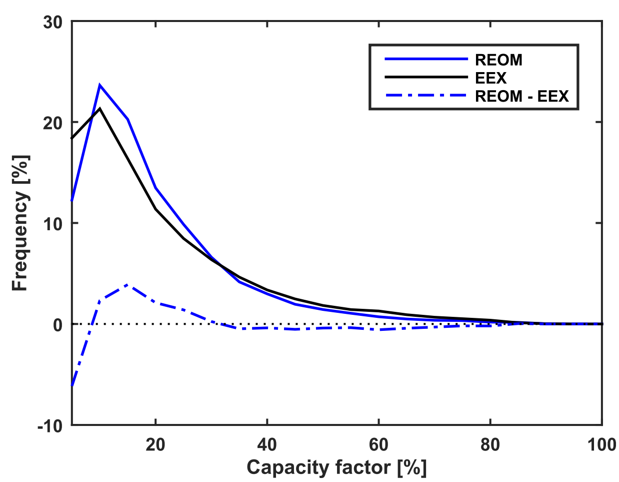

Fig. A4. Occurrence frequency of hourly capacity factors for REOM (blue, solid), EEX (black, solid) and their residual (blue, dashed) in Germany between 2010 and 2014. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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