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A new approach to assess wind energy potential

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Abstract

To meet the increasing global demand for renewable energy, such as wind energy, an increasing number of wind parks are being constructed worldwide. Finding a suitable location requires a detailed and often costly analysis of local wind conditions. Plain average wind speed maps cannot provide a precise forecast of wind power because of the non-linear relationship between wind speed and production. We suggest a novel, globally feasible approach to assess the local wind energy potential: First, meteorological reanalysis data are applied to obtain long-term low-scale wind speed data at specific turbine locations and hub heights. Second, the relation between wind data and energy production is for the first time determined via a five parameter logistic function using actual high-frequency energy production data. The resulting wind energy index allows for a turbine-specific estimation of the expected wind power at an unobserved location. A map of the wind power potential for Germany exemplifies our approach.

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Keywords: Wind power, energy production, renewable energy, onshore wind, MERRA

1. Introduction

Because of increasing energy demand worldwide and the willingness to reduce greenhouse gas emissions, renewable energies, such as wind energy, are rapidly growing: The global cumulative installed capacity of wind energy increased from 6 GW in 1996 to 318 GW in 2013 and is expected to reach 596 GW in 2018 [1].

Planning a new wind farm begins with the search for a suitable location. Besides suitable surface conditions and legal aspects, geographical wind conditions and timing are also important. There are many studies which pertain to deriving detailed long-term wind speed maps for individual countries (e.g., U.S. [2] and Germany [3]). These maps of long-term average wind speeds are a rough indicator for average local wind conditions, but they are inadequate for deriving the expected wind energy production because of the non-linear relationship between wind speed and production. To overcome this problem, a long record of high-frequency wind speed at the turbine location and hub height is required. Then, the wind

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power production can be estimated by transforming the high-frequency wind speed to wind power production via a wind power curve (e.g., [4]). For example, Dahmouni et al. [5] estimate the net energy output at one location in Tunisia by measuring the wind every 10 minutes in different heights and combining it with the power curve provided by the turbine producer. The wind power curve given by the turbine producer requires high-frequency mast wind speed to derive production. However, from the perspective of installing a turbine at a new location, long-term high-frequency measurements of wind speed at various locations and heights are very time-consuming and costly and can hardly be conducted.

As an alternative to the power curve, the wind power density (WPD) is often applied, which is the amount of energy that can be extracted out of the wind from a physical viewpoint. For example, Karsli and Geçit [6] derive the wind power potential of one location in Turkey from hourly wind measurements via the WPD. This approach is also applied in [7] using the Weibull analysis and in [8] and [9] using meteorological reanalysis data. Gunturu and Schlosser [8] criticize, however, that the WPD overestimates the real on-site production and should be used only as an illustrative point. Hence, the linkage between wind speed at a higher scale (e.g., hourly averages) and true production deserves further investigation, and the expected energy production at potential locations has to be derived using different tools.

In this paper, we propose a new way to estimate the long-term wind energy potential of a new location by applying a wind energy index, which mainly consists of two steps: First, we derive lower scale wind speed data at the turbine location at hub height by processing meteorological reanalysis data. These data are available throughout the world at low spatial and temporal scales, so our approach is feasible globally. Second, we estimate an analytic production function based on real production data, which converts the meteorological reanalysis data into production data. Based on local wind speed data derived for an unobserved location, this production function provides an estimate of the turbine's low-scale energy production. By aggregating the estimated production to a larger time scale and long-term historical data, the proposed wind energy index is able to assess the long-term wind energy potential for any location.

2. Methods

2.1. Framework

To measure the potential of wind power production at a specific location, we develop a quantitative and objective wind energy index that represents the actual wind energy production of a certain turbine type. To obtain such an index, there are several necessary steps.

First, the type of database to calculate the wind energy index has to be chosen. Whereas production data are difficultly available and not always reliable, wind speed are easily to obtain. An innovative wind speed dataset that has been recommended in the wind power analysis is reanalysis data, such as the Modern-Era Retrospective Analysis for Research and Applications (MERRA) data provided by NASA [10]. MERRA reanalysis data reconstruct the atmospheric state by integrating data from different sources, such as conventional and satellite data [8,11]. They offer a complete worldwide grid of wind data at a spatial resolution of 1/2° latitude and 2/3° longitude (about 45 km × 54 km in Germany) and an hourly temporal resolution since 1979. The wind data consist of a northward and an eastward wind component at three different heights (2 m, 10 m and 50 m above ground).

The wind speed data have to be horizontally interpolated to the turbine location and vertically extrapolated to the turbine height. The wind speeds at the four nearest MERRA grid points are interpolated to the turbine's location weighted by their horizontal distance (inverse distance weighting). The vertical extrapolation is performed using the log wind profile (e.g., [8]):

$$V_z = \left(\frac{u_*}{\kappa}\right)\log\left[\frac{(z-d)}{z_0}\right] \tag{1}$$

where V_z denotes the wind speed at height z, u_* the friction velocity, κ the von Kármán constant (~0.41), d the displacement height, and z_0 the surface roughness. The three unknown parameters u_*, d, and z_0 can be calculated by solving the three dimensional equation system for the wind speeds at 2 m, 10 m and 50 m. By plugging in the turbine height for z, the wind speed at turbine height z, can be obtained.

The most crucial step is to transform local wind speed data into a wind energy index that reflects actual wind energy production. We examine the relation between observed wind speed and the resulting production from a statistical perspective and estimate the underlying function. A function type capturing the boundedness and the typical 'S' shape of the production function is the class of logistic functions. A special type also allowing for asymmetry is the five parameter logistic (5PL) function [12]:

$$f(x;a,b,c,d,g) = d + \frac{a-d}{\left(1+\left(x/c\right)^b\right)^g} \tag{2}$$

with $a,b,d \in \Re$ and $c,g \in \Re^+$. The parameters d and a describe the lower and upper bounds, respectively, and are set to the minimal and maximal production. The parameters b,c and g determine the slope of the function, where g particularly controls the asymmetry (symmetric for $g=1$). When the function is fitted to the available production data, it can be used to estimate the production at a new location where only wind speed data are available.

2.2. Wind energy index

The index we suggest to estimate the production potential at a certain location translates the derived wind speed at this location into expected wind energy and is defined as follows:

$$I(\tau_1,\tau_2) = \sum_{t=\tau_1}^{\tau_2} f_{\mathrm{5PL}}\left(V_z(t)\right) \tag{3}$$

where: $V_z(t)$ indicates the hourly wind speed at the turbine location and turbine height; $f_{\mathrm{5PL}}(\cdot)$ is the 5PL function; and τ_1 and τ_2 denote the start and end date of the index accumulation. The estimated hourly production can be summed up for different time horizons, such as daily, monthly, or yearly, depending on the aim and the availability of data.

To evaluate the performance of our models, we compare the simulated production from Eq. (3) with the true production on different aggregation levels, i.e., hourly, daily, or monthly. First, we calculate Pearson's correlation coefficient to examine their dependency. Second, we measure the estimation accuracy by the root-mean-square error (RMSE). When the production function for a certain turbine type is estimated based on all available data, we assume that it is valid for all locations with the same turbine type in Germany. To test if this assumption holds true, we perform a leave-one-out cross validation: Instead of using all n locations for fitting the production function, we use $n-1$ locations. The left-out location then simulates a new, unobserved location and is used to test the estimated function. This procedure is repeated n times so that each location is left-out once.

3. Empirical Analysis

3.1. Data

We use data for wind energy production at seven wind parks A–G situated in Germany (see Fig. 2). They consist of a different number of turbines (33 in total), which are all of the same type and capacity, namely 2.3 MW. The data are reported in an interval of 10 minutes and last a minimum of 1.5 years. We cleaned the data according to the error code provided by each turbine. By this procedure, we manage to estimate the true relation between wind speed and production regardless of technical issues. Because the number of turbines varies from 1 to 8 among the wind parks and the turbines influence one another's wind conditions and efficiency, we average the production of all turbines in a wind park to obtain a time series that is representative for the whole park.

The MERRA data used in this study come from the "MERRA IAU 2d atmospheric single level diagnostics (AT1NXSLV)" and are available at times 12:30 a.m., 1:30 a.m., 2:30 a.m., … , 11:30 p.m. for each day since 1979 [13]. We use the variables U2M, V2M, U10M, V10M, U50M, and V50M, which indicate the eastward and northward wind speeds measured in m/s at heights of 2 m, 10 m and 50 m above the ground surface. To cover all of Germany, grid points with a latitude between 5.33° E and 16° E and a longitude between 47° N and 56° N are used. These grid points are depicted in Fig. 2.

3.2. Relation between MERRA wind and production

In-sample estimation. The fitted 5PL function which describes best the relation between the derived MERRA wind speed and the hourly production is depicted in Fig. 1(a) exemplarily for wind park A. Plugging in MERRA wind speeds into the fitted 5PL function leads to estimated values for hourly production ('MERRA production'). When comparing the hourly, daily, and monthly scales, the fit becomes better for higher scales, which is confirmed by increases in the correlations, from 0.82 (hourly), to 0.92 (daily), and 0.98 (monthly) for wind park A. This can be explained by an averaging effect of estimation errors. The RMSE increases from 0.39 (hourly), to 5.2 (daily), and 38.5 (monthly), but this increase results from different magnitudes of production on different time scales: They correspond to 57%, 31%, and 8% of the total average production in these periods. The good fit of the monthly scale is also visible from Fig. 1(b), where the monthly true and MERRA productions are depicted for wind park A. The average ratio of the RMSE to the monthly production for all wind parks lies around 10%.

Out-of-sample estimation. We also evaluate the performance of our approach in estimating wind production at an unobserved location (out-of-sample) by conducting a leave-one-out cross validation (see Section 2.2). As expected, the RMSE for the out-of sample estimation increases compared to that for the in-sample estimation (Table 1), the average error is 20% of the total production. The correlation, however, remains almost equal compared to that in the in-sample estimation.

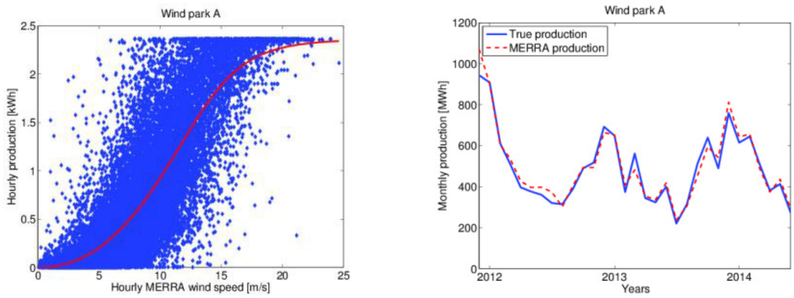

Fig. 1: (a) Fitting hourly production with hourly MERRA wind speed using the 5PL function; (b) temporal development of monthly MERRA production and true monthly production

Table 1: Results of out-of-sample estimation

	Hourly			Daily			Monthly		
	Mean	Corr.	RMSE	Mean	Corr.	RMSE	Mean	Corr.	RMSE
A	0.57	0.82	0.41	13.71	0.92	5.88	416.63	0.98	83.51
B	0.50	0.87	0.26	12.03	0.95	4.15	359.47	0.98	92.99
C	0.63	0.84	0.32	15.10	0.94	4.00	458.16	0.97	48.23
D	0.55	0.81	0.33	13.11	0.93	4.18	397.91	0.95	58.08
E	0.50	0.83	0.34	11.98	0.94	4.57	367.40	0.97	45.10
F	0.38	0.81	0.39	9.09	0.89	7.22	275.85	0.94	116.98
G	0.52	0.84	0.29	12.47	0.94	4.12	383.24	0.96	74.66

3.3. Wind energy potential in Germany

The main advantage of MERRA data is the availability of long-term wind speed data on a global grid. With these data and the aforementioned approach, we can estimate the wind energy potential for every location in Germany by averaging the yearly wind energy index based on historical wind speed data. To balance large fluctuations and to not have bias from structural breaks in wind speed data due to climate change or reanalysis data developments, we choose a time horizon of 20 years, i.e., 1994–2013. Rather stationary wind conditions can be anticipated for this period: The estimated yearly production shows a significant trend for only 30% of the grid points at the 5% significance level, according to the Mann-Kendall test. When assessing the potential of a specific location, however, it has to be investigated if a trend needs to be considered.

Fig. 2(a) shows a map of the average yearly index, i.e., the expected yearly production, for each MERRA grid point and their interpolation. It depicts a rather low potential in southern Germany, but a high potential near the sea. Of course, this map only describes production potential depending on the wind speed. The geographical and structural situation, such as the existence of cities or lakes must also be considered for actual planning. Moreover, the map is turbine-specific. Hence, we assume the same technology used in the wind parks under consideration. Opposite to classical wind maps, it provides the estimated amount of energy that can be produced under local wind conditions.

Fig. 2(b) depicts the coefficient of variation, i.e., the standard deviation of each location normalized by the location's mean. This value is an important indicator for the (model) risk involved in installing a new wind park. It follows that the risk is much lower near the coast with fluctuations around 5% compared to the south which has fluctuations around 10%.

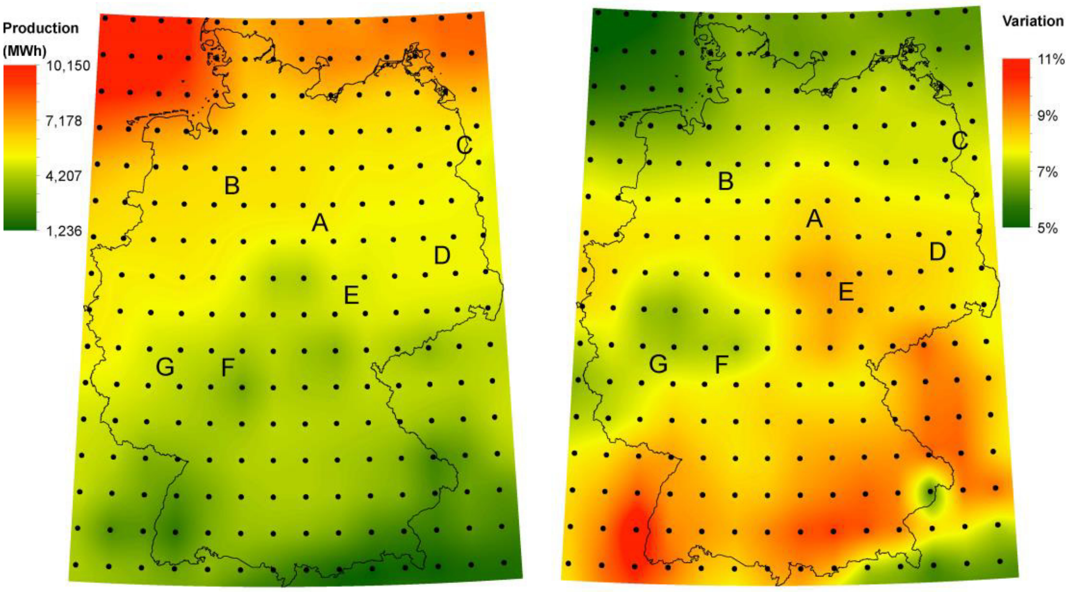

Fig. 2: Map of (a) estimated yearly production and (b) coefficient of variation over 1994–2013; dots indicate MERRA grid

4. Discussion and conclusion

In this paper, we provide a novel and transparent approach to estimate the long-term wind energy potential at an unobserved location by applying a newly developed wind energy index. The production data available for a certain turbine type is used to estimate a general production function which can then be applied to wind data at any new location. The wind energy index provides the expected long-term energy production for this location and a certain turbine type. The resulting wind energy production map for Germany is useful for governments, practitioners, and investors involved in the value chain of a wind farm investment.

Therefore, our approach could meet several needs. First, it allows for a pre-assessment of the suitability of a potential wind farm location at no costs before analyzing the production potential in greater detail by means of site-specific wind measurements. Second, it could fill the gap of missing standards of assessing the wind energy potential from a legal perspective. Third, it could assist in creating a transparent approach for the valuation of wind production derivatives.

However, to achieve any of these aforementioned potentials, this approach has to be adapted to other turbine types. This is possible as long as real production data for different turbine types are available for at least one location. Moreover, the approach can be transferred to other regions in the world since MERRA data are globally available.

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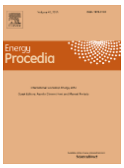

Biography

Matthias Ritter is a research assistant at the Department of Agricultural Economics at Humboldt-Universität zu Berlin, Germany. He graduated in Mathematics and holds a PhD in Economics. His research focuses on weather risk modeling and pricing of weather derivatives.