Optimal Siting of Wind Farms in Wind Energy Dominated Power Systems

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Abstract: Electricity from renewable energy (RE) sources gained in significance due to green-friendly governmental initiatives in the form of either direct subsidizes, tax incentives or tradable certificates. Thereby, RE generators are incentivized to maximize energy feed-in or the remuneration from governmental subsidizes, meanwhile neglecting any market interaction. Consequently, wind farms are clustered in windy regions. Along with the governmentally initiated integration of RE generation into power markets, the siting of RE generators will change. In wind power dominated power systems that fully integrate RE generators into power markets, wind farms will compete against each other and try to maximize their market value. Hence, wind speed correlations with other wind farms will become increasingly important when choosing a site in a uniform or zonal pricing system. To quantify the impact of market integration on future wind farm siting, an approach is developed that takes into account the local wind potential of a certain site, wind speed correlations to other sites and their installed capacities. An optimization that minimizes the normalized sum of wind power correlations to all other sites and their respective normalized installed wind power capacity is performed. To achieve a predefined minimum energy output, the average wind yield is considered as an additional constraint. The outcome is an optimal wind farm site in a wind energy dominated system. Running this for a given wind power expansion scenario enables decision makers to foresee the spatial development of wind farm installations. To demonstrate the model's applicability, a case study is performed for Germany. Thereby, wind speed data for four years from the European reanalysis model COSMO-REA6 is used. The results indicate that a full market integration of RE generators will space out more evenly new wind farms. Thereby, wind farms can economically benefit from the non-simultaneity of wind speed.

Keywords: wind energy; wind energy integration; market value; wind farms; correlation; siting; wind speeds

1. Introduction

The success of electricity produced by renewable energy (RE) sources is continuing all over the world. Especially onshore wind power plays an pivotal role in modern power systems due to its low costs. In Germany, the installed capacity of onshore and offshore wind power surpassed 50 GW by the end of 2016 [1]. As in Germany, the success of RE sources is carried by governmental support schemes in many countries. Until now, various different support schemes have emerged. Generally, they can be categorized into three main types, namely fixed feed-in tariffs, feed-in premium and green certificates (combined with RE obligations) [2]. Fixed feed-in tariffs guarantee a fixed compensation in a non-discriminatory manner for each unit of energy produced. This significantly lowers the risk for investors, which explains the success of fixed feed-in tariffs in terms of the deployment of RE sources [3].

Generally, all energy-based support schemes incentivize investors to build energy-maximized wind farms at sites with high wind yields. This results normally in spatially non-diverse wind farm clusters and especially in Germany in the necessity to considerably extend the transmission and distribution grid.

To foster the market integration of generation from RE sources and to incentivize demand-oriented generation, Germany introduced a feed-in premium scheme in 2012 [4], which was further amended in 2014 [5] and lastly in 2017 [6]. Under the current regulation, remuneration comprises a so-called market premium and the revenues from selling electricity on the day-ahead market. The market premium is the difference between the guaranteed fixed remuneration (under the current regulation [6] determined in a technology-specific auction) and the average monthly reference price. Thereby, the reference price is separately determined for each technology group, e.g., wind onshore and solar power. Because the reference price is monthly averaged, there exists a yet little incentive to plan and operate a RE power plant market-driven.

In the near future, it can be expected that more market-oriented schemes will be introduced in Germany and around the world. Further ahead, RE generators might bid with their levelized costs of electricity into power markets. Such system changes are likely to foster the spatial diversification of wind farm sites because wind farm investors will compete for shrinking market values. As discussed and quantified in literature, the market value of wind decreases with an increasing penetration level ([7–9]). This is caused by the simultaneity of wind power production. However, existing approaches, such as [7–9], neglect the spatial dimension of wind power market values. So far, only [10] provides an approach for estimating site-specific wind energy value factors but disregards market interrelationships. In the future, sites that exhibit less average wind speeds might become more attractive for investors when they are negatively correlated with the majority of wind farms. Such wind farms can benefit from high prices while the majority of wind farms faces low wind speeds. This effect will stabilize to some extent the market value of wind power in wind energy dominated systems that have integrated RE generation into power markets.

This paper investigates the impact of a full market integration on the spatial arrangement of wind farms. It is assumed that wind power makes up the larger share of power production and that wind power is thus the major price driver. Instead of modeling the entire power system, the two most influential factors on the wind energy market value in wind power dominated systems are analyzed. This includes the correlation of wind power feed-in to other wind farms and their installed capacities. By minimizing the sum of both, meanwhile considering minimum wind speed requirements, the next eligible site can be identified. To achieve comparable optimization criteria, both measures are unity-based normalized. The applicability of this approach is demonstrated in a case study for Germany. 10 GW of wind power is added to the system that fully integrates RE generation. A comparison with current spatial market values illustrates the applicability of the model. With only two input data sets, namely wind speed time series and wind power installation statistics, meaningful spatial wind power expansion scenarios can be derived.

The remainder of this paper is organized as follows. The methodology is presented in Section 2. First, an algorithm that models the current wind yield optimal approach is introduced. Second, the spatial dimension of wind energy value factors is discussed and, third, the main approach to model an optimal siting of wind farms in wind energy dominated power systems is described. Section 3 contains a case study for Germany and discusses the main findings. The results are compared with current spatial wind energy value factors in Germany. The paper concludes in Section 4.

2. Methodology

Depending on the RE support scheme or level of market integration, different criteria influence the choice of location for a new wind farm. Wind yield optimal siting is addressed in Section 2.1. Site-specific wind energy value factors and their impact on the site selection in future power markets are discussed in Section 2.2. Section 2.3 introduces an algorithm that enables modeling spatial wind expansion scenarios in such markets using merely wind speed time series and wind power installation statistics.

2.1. Wind Yield Optimal Wind Farm Siting

In many nowadays support schemes, the income of wind farm operators is purely based on the energy produced disregarding electricity wholesale prices, time of feed-in and location of the power plant (in uniform pricing schemes). Hence, wind farm operators have a clear incentive to maximize the wind farm's energy output over a predefined funding period and investors will pick a site that exhibits the highest wind yield. In the paper at hand, this behavior is modeled by choosing an optimal site s_{opt} within a set of available sites $\mathcal{S} = \{1, \ldots, S\}$ that maximizes the average expected wind yield. Thereby, the average expected wind yield is a naive forecast using historical wind speed measurements of several years at a site, i.e., $\bar{v}_s$. Given that information for S sites, the next eligible site s_{opt} is defined by $\operatorname*{argmax}_{s \in \mathcal{S}} \{\bar{v}_s\}$. At this site, a predefined wind farm with an installed capacity of ΔP is added to the system. To account for space limitations, the maximum regional wind power density $\rho_r^{\max}$ in MW/km^2 is introduced. In addition, $P_c^{\max}$ represents the maximum additional admissible capacity within a country. This allows for a consideration of national expansion plans and scenarios, respectively. Multiple sites can be within a region, i.e., $f : \mathcal{S} \twoheadrightarrow \mathcal{R}$, with $\mathcal{R} = \{1, \ldots, R\}$. Algorithm 1 determines the additional capacity for each site and region within a country. Thereby, the maximum additional capacity $P_c^{\max}$ needs to be set beforehand. Once a site is chosen as the optimal site s_{opt}, this site is considered to be fully developed and, hence, removed from the set of available sites, i.e., $\mathcal{S} \leftarrow \mathcal{S} \setminus s_{\text{opt}}$. If the maximum capacity density of a region $\rho_r^{\max}$ is surpassed, all sites within this region are disregarded from any further expansion activities, i.e., $\mathcal{S} \leftarrow \mathcal{S} \setminus \mathcal{S}_{\mathcal{R}(s_{\text{opt}})}$.

Algorithm 1: Wind yield optimal wind farm siting.

1: $\mathcal{S} \leftarrow 1, \ldots, S$
2: $\mathcal{R} \leftarrow 1, \ldots, R$
3: $P_s \leftarrow 0, \ \forall s \in \mathcal{S}$
4: $P_r \leftarrow 0, \ \forall r \in \mathcal{R}$
5: $P_c \leftarrow 0$
6: **while** $P_c < P_c^{\max}$ **do**
7: 　　$s_{\text{opt}} \leftarrow \operatorname*{argmax}_{s \in \mathcal{S}} \{\bar{v}_s\}$
8: 　　$P_{s_{\text{opt}}} \leftarrow P_{s_{\text{opt}}} + \Delta P$
9: 　　$P_{\mathcal{R}(s_{\text{opt}})} \leftarrow P_{\mathcal{R}(s_{\text{opt}})} + \Delta P$
10: 　　$P_c \leftarrow P_c + \Delta P$
11: 　　$\mathcal{S} \leftarrow \mathcal{S} \setminus s_{\text{opt}}$
12: 　　**if** $\rho_{\mathcal{R}(s_{\text{opt}})} \geq \rho_{\mathcal{R}(s_{\text{opt}})}^{\max}$ **then**
13: 　　　　$\mathcal{S} \leftarrow \mathcal{S} \setminus \mathcal{S}_{\mathcal{R}(s_{\text{opt}})}$
14: 　　**end if**
15: **end while**

2.2. Site-Specific Wind Energy Value Factors

In wind energy dominated power systems that fully integrate production from RE sources into the power market, wind farm investors will select a site that optimizes the expected revenues that can be earned on the spot market. Thereby, the wind value factor of the very site plays an important role. According to [7], the wind energy value factor can be defined as:

$$\nu^w = \frac{\bar{p}^w}{\bar{p}}, \tag{1}$$

In which $\bar{p}^w$ is the wind-energy-weighted spot price and $\bar{p}$ the average spot price. As discussed in [10], wind energy value factors are site-specific and hub-height-specific due to varying wind speed

conditions. In the paper at hand, the site-specific and hub-height-specific wind energy value factor is denoted as v_s^w. Thereby, $\bar{p}^w$ is replaced by a site-specific average revenue for each unit of energy, so that:

$$v_s^w = \frac{\bar{p}_s^w}{\bar{p}} \tag{2}$$

Thereby, $\bar{p}_s^w$ is computed as follows:

$$\bar{p}_s^w = \frac{\sum_{t=1}^{T} p_t^{\text{spot}} \cdot I_{s,t}}{\sum_{t=1}^{T} I_{s,t}}, \tag{3}$$

In which p_t^{spot} is the spot price in t and $I_{s,t}$ is the energy feed-in in t at site s. To assess the wind energy value factor of a single wind farm compared to the entire fleet of wind farms within a market zone, the relative wind energy value factor $v_{rel,s}^w$ is introduced:

$$v_{rel,s}^w = \frac{v_s^w}{v^w} = \frac{\bar{p}_s^w}{\bar{p}^w} \tag{4}$$

$v_{rel,s}^w$ can be used to rate the quality of wind farm sites. In systems that exhibit a high share of wind power, wind power is the main price driver. Hence, with an increasing share of wind power, v^w will converge towards 1 but will never become equal unless wind power is the sole generation technology.

When choosing a new site, the site-specific wind energy value relative to the market v_s^w or relative to the market-wide fleet of wind farms $v_{rel,s}^w$ should be optimized for the wind farm's life time. Yet, certain sites can have high market value factors while being characterized by low average wind speeds and, thus, possibly insufficient revenues. Hence, market value factors and expected wind yields should be considered simultaneously.

As in [7], estimating future market value factors ideally requires a detailed unit commitment model that endogenously accounts for investments into new technologies. The paper at hand introduces an alternative approach for identifying an optimal site in wind energy dominated systems while taking into account the market interaction with existing wind farms.

2.3. Spot Market Optimal Wind Farm Siting

If wind power production is the major price driver within a market zone, the correlation with existing wind farms becomes crucial. Due to the merit-order effect ([11–13]), spot prices are lower when wind power production is high, i.e., when there is a oversupply of (wind) energy in the market. Vice versa, prices are high when the overall wind power production is low. Hence, if the potential production at a specific site is negatively correlated with the market-wide wind power production, the site-specific wind energy value factor is higher than for positively correlated sites. Modeling site-specific wind energy production with a high spatial resolution, ideally on wind farm level, requires inter alia detailed information about all wind farms in the system. That is why we consider a standardized wind to power curve (normalized with the rated power) for all sites instead. The normalized power feed-in $I \in [0, 1]$ is computed as follows:

$$I(v) = \begin{cases} 0 & \text{if } v < v_{\min} \\ \frac{v^3 - v_{\min}^3}{v_r^3 - v_{\min}^3} & \text{if } v_{\min} \leq v \leq v_r \\ 1 & \text{if } v > v_r \\ 0 & \text{if } v > v_{\max} \end{cases} \tag{5}$$

Thereby, v_r is the rated wind speed, i.e., the wind speed at which the wind power plant reaches its rated power. $v_{\min}$ is the cut-in wind speed and $v_{\max}$ the cut-out wind speed.

The correlation matrix that describes the correlation between the wind power feed-in *I* at all potential sites $\mathcal{S}$ is denoted as $\mathbf{R}_{\mathcal{SS}}$. Thereby, Pearson's correlation coefficient is applied to compute the pairwise correlations in $\mathbf{R}_{\mathcal{SS}}$. Hence, all elements in $\mathbf{R}_{\mathcal{SS}}$ lay in the interval $[-1, 1]$. Ideally, a site should be preferred if the sum of correlations to all other sites, i.e., $\mathbf{r}_i = \sum_{i \in \mathcal{S}} \mathbf{R}_{\mathcal{S}i}, \forall i \in \mathcal{S}$, is minimal. However, if a certain region has a high installed capacity already, sites in that region should be rated as less favorable and vise versa. That is why, we propose to simultaneously consider the correlation and the ratio of the installed capacity in the site's region to the installed capacity in the market area or country, i.e., $\frac{P_{\mathcal{R}(s)}^{inst}}{P_c^{inst}}$. For all sites, the respective capacity share is given by the vector $\mathbf{c}_{\mathcal{S}}$. To achieve equivalent optimization criteria, a unity-based normalization or feature scaling is performed for the sum of correlations and the share of installed capacities. The unity-based normalized sum of correlations is $\mathbf{r}_{\mathcal{S}}^{\star}$ and each element is computed as follows:

$$\mathbf{r}_i^{\star} = \frac{\mathbf{r}_i - \min\{\mathbf{r}_{\mathcal{S}}\}}{\max\{\mathbf{r}_{\mathcal{S}}\} - \min\{\mathbf{r}_{\mathcal{S}}\}}, \ \forall i \in \mathcal{S} \tag{6}$$

Theoretically, $\mathbf{r}_i$ can be in the interval $[-|\mathcal{S}|, |\mathcal{S}|]$, in which $|\mathcal{S}|$ is the cardinality of the set $\mathcal{S}$. After the normalization, $\mathbf{r}_i^{\star} \in [0, 1]$. The vector containing all unity-based normalized capacity shares for all sites is denoted as $\mathbf{c}_{\mathcal{S}}^{\star}$. Algorithm 2 shows the algorithm that selects the optimal site based on $\mathbf{r}_{\mathcal{S}}^{\star}$ and $\mathbf{c}_{\mathcal{S}}^{\star}$. The basis structure of Algorithm 2 is equal to Algorithm 1. Yet, the optimization of s_{opt} is not purely based on the wind yield. To not fully neglect the expected wind yield, a minimum wind yield limit $\bar{v}_s^{\min}$ is defined. By doing so, wind farm operators can anticipate average full load hours. Before the optimization, all sites that do not fulfill this minimum wind speed requirement are removed from the set of possible sites, i.e., $\mathcal{S} \leftarrow \mathcal{S} \setminus \mathcal{S}_{\bar{v}_s < \bar{v}^{\min}}$. Another possibility would be to consider the wind yield as an optimization criterion as well. However, setting this minimum wind yield constraint exogenously, enables building different scenarios what is expected to yield further insight. In addition, the required wind yield to maximize revenues depends strongly on future back-up technologies that set spot market prices in phases with low winds.

Algorithm 2: Spot market optimal wind farm siting.

1: $\mathcal{S} \leftarrow 1, \ldots, S$
2: $\mathcal{S} \leftarrow \mathcal{S} \setminus \mathcal{S}_{\bar{v} < \bar{v}_s^{\min}}$
3: $\mathcal{R} \leftarrow 1, \ldots, R$
4: $P_s \leftarrow 0, \forall s \in \mathcal{S}$
5: $P_r \leftarrow 0, \forall r \in \mathcal{R}$
6: $P_c \leftarrow 0$
7: **while** $P_c < P_c^{\max}$ **do**

8: $\quad s_{\text{opt}} \leftarrow \underset{s \in \mathcal{S}}{\arg\min} \{\mathbf{r}_s^{\star} + \mathbf{c}_s^{\star}\}$
9: $\quad P_{s_{\text{opt}}} \leftarrow P_{s_{\text{opt}}} + \Delta P$
10: $\quad P_{\mathcal{R}(s_{\text{opt}})} \leftarrow P_{\mathcal{R}(s_{\text{opt}})} + \Delta P$
11: $\quad P_c \leftarrow P_c + \Delta P$
12: $\quad \mathcal{S} \leftarrow \mathcal{S} \setminus s_{\text{opt}}$
13: $\quad$ **if** $\rho_{\mathcal{R}(s_{\text{opt}})} \geq \rho_{\mathcal{R}(s_{\text{opt}})}^{\max}$ **then**

14: $\quad\quad \mathcal{S} \leftarrow \mathcal{S} \setminus \mathcal{S}_{\mathcal{R}(s_{\text{opt}})}$
15: $\quad$ **end if**
16: **end while**

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3. Application and Results

Assessing wind power expansion scenarios using Algorithms 1 or 2 requires reliable wind speed data with high spatial and temporal resolution. This data, wind farm data and their combination is introduced in Section 3.1. Section 3.2 presents a case study for Germany that is carried out to demonstrate the model's merit. Moreover, main results are presented and discussed in Section 3.3. Section 3.4 contains a comparison with currently observable market value factors in Germany.

3.1. Data

3.1.1. Wind Speed Data

A reanalysis data set was used to perform this case study. Reanalysis systems reintegrate historical weather observations or assimilation data with state-of-the-art numerical weather models. This enables a consistent and comprehensive long-term weather monitoring. Here, the COSMO-REA6 reanalysis data set based on the COSMO model is used [14]. A comparison with actual wind speed mast measurements at relevant heights that demonstrates the suitability for the case study in this paper can be found in [15]. Moreover, daily and monthly average wind speeds are compared with wind mast measurements in [16] and general improvements to present reanalysis models, namely ERA-Interim and ERA-20C, are found. The spatial resolution is $0.055°$ or 6 km and the temporal resolution of the model output is one hour or a quarter of an hour. COSMO-REA6 covers the whole of Europe but it was cropped to Germany for this case study. The remainder comprises 9525 points within Germany, which represent the set of possible sites $\mathcal{S}$. Wind speeds of the six lowest model levels were extracted. The wind profile power law was implemented to vertically interpolate wind speeds. Thereby, the exponent α was computed separately for each hour using wind speeds of two neighboring model levels to account for changing atmospheric conditions. Overall, a four-year-long data set was used, which consists of hourly wind speeds from the beginning of 2011 to the end of 2014. For all sites, hub heights were set to 120 m. Figure 1a shows the average wind yield over all considered years at a hub height of 120 m for 9525 different points in Germany. A hub height of 120 m was chosen because it roughly represents current industry standards. In general, correlations are expected to remain similar for higher hub heights. In Figure 1a, it can be seen that wind resources are more favorable in Northern Germany. On the contrary, mountainous regions in the south exhibit average wind yields of 3 m/s and less. That is one reason why most wind farms have been erected in the north and northeast of Germany. A transformation of hourly wind speed time series through the standardized wind-to-power curve according to (5) is shown in Figure 1b. This corresponds to the share of full load hours. e.g., $\bar{p}_s = 0.4$ equals 3504 ($8760 \cdot 0.4$) full load hours.
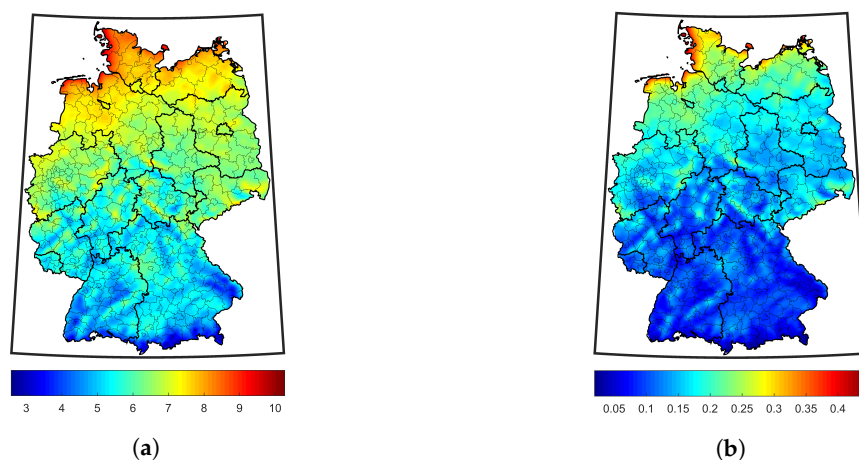

(**a**)   (**b**)

Figure 1. Average wind in m/s at a hub height of 120 m and corresponding average normalized energy yield during 2011–2014. (**a**) Hourly average wind yield $\bar{v}_s$; (**b**) Average normalized energy yield $\bar{p}_s$.

3.1.2. Wind Farm Data

Both algorithms introduced in Section 2 take into account the scarcity of land by limiting the power density per square kilometer. Hence, the currently installed capacity in each region needs to be known. Here, the classification of territorial units for statistics (NUTS), in particular NUTS 3, was applied. In Germany, NUTS 3 corresponds to 402 unique regions, i.e., $R = 402$. The area of each region is based on areal data from the German Federal Agency for Cartography and Geodesy [17]. Distribution and transmission system operators in Germany are obliged to publish information on RE power plants. An edited version of this master data set provided by [18] was used for this case study. The status of the installations was 2015. Given that geographical identifiers of each RE power plant include inter alia the postal code, German postal codes had to be assigned to NUTS 3. This assignment is based on correspondence tables from Eurostat [19]. A more detailed wind farm data set, which could be used for future studies, and different approaches for fixing incomplete wind farm data sets are described in [20].

3.1.3. Combination of Wind Speed and Wind Farm Data

By combining wind speed and wind farm data, the most relevant drivers for wind farm siting decisions in a competitive environment, namely wind power correlations and installed capacities, can be derived. Figure 2 depicts both measures and their combination. Figure 2a shows the normalized capacity at each site $\mathbf{c}^\star_{\mathcal{S}}$, which was derived from the installed capacity in each region r (NUTS 3). As expected, the north and northeast of Germany contain the major share of wind farms, whereas some regions in the south contain none. The normalized sum of wind power correlations $\mathbf{r}^\star_{\mathcal{S}}$ is plotted in Figure 2b. It becomes obvious that wind speeds at sites in the center of Germany are positively correlated with many other sites. Sites at the border, especially in Southern and Northern Germany, are only positively correlated with neighboring sites, which explains their relatively low sum of normalized correlations. As can be seen in Figure 2c, sites in Southern Germany and generally at the border of Germany are more preferential in terms of the two used optimization criteria. However, especially sites in the south are characterized by low average wind speeds. To account for low average wind yields, Algorithm 2 allows to only develop sites which are characterized by a minimum wind yield $\bar{v}^{\min}$. In addition, all sites that are within a region with a population density of 450 people per km^2 or above were removed from the set of eligible sites. Finally, Figure 3 shows all sites with the optimization criterion $\mathbf{r}^\star_{\mathcal{S}} + \mathbf{c}^\star_{\mathcal{S}}$ excluding non-eligible sites, which are marked as black dots. The lower the value, the better the site. It can be seen that large cities within Germany are not considered given that they are not suited for wind farm installations.
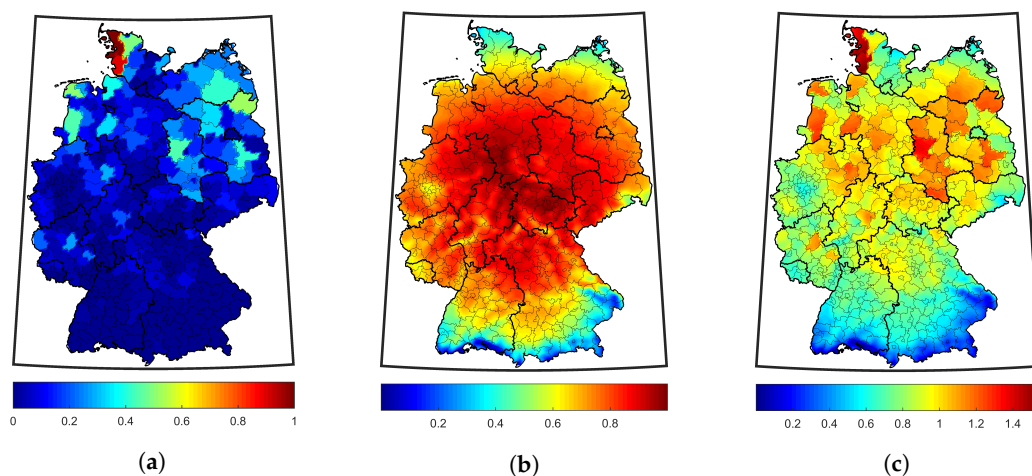

Figure 2. Normalized installed capacitiy $\mathbf{c}^\star_{\mathcal{S}}$, normalized sum of correlations $\mathbf{r}^\star_{\mathcal{S}}$ and their sum for each site $s \in \mathcal{S}$. (**a**) $\mathbf{c}^\star_{\mathcal{S}}$; (**b**) $\mathbf{r}^\star_{\mathcal{S}}$; (**c**) $\mathbf{r}^\star_{\mathcal{S}} + \mathbf{c}^\star_{\mathcal{S}}$.

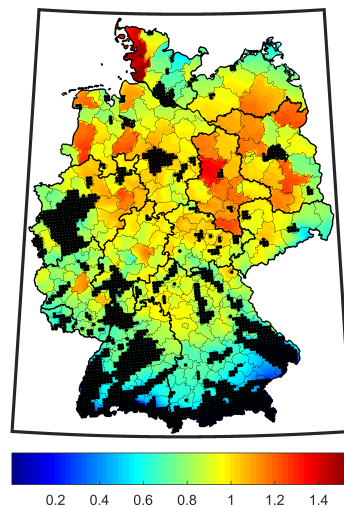**Figure 3.** $\mathbf{r}_{\mathcal{S}}^{\star} + \mathbf{c}_{\mathcal{S}}^{\star}$ for eligible sites with $\bar{v}^{\min} = 5\frac{m}{s}$.

3.2. Case Study

To investigate the impact of different farm siting criteria, a case study was conducted. The wind power installations were assumed to remain at the level of 2015. Then, 10 GW of wind power was added to the system. Each wind farm comprised 10 MW. The maximum wind power density $\rho_{\mathcal{R}(s_{\text{opt}})}$ was set to 5 MW/km^2 for this case study. Overall, three different minimum wind speeds were tested, namely 5, 6 and 7 m/s, to gain further insight. These minimum wind speeds represent typical low and medium average wind speeds in Germany (cf. Figure 1a). Table 1 summarizes all case study parameters.

Table 1. Case study parameters.

Parameter	Value
$\rho_{\mathcal{R}(s_{\text{opt}})}$	5 MW/km^2
ΔP	10 MW
$P_c^{\max}$	10 GW
$v_{\min}$	5/6/7 m/s

3.3. Wind Farm Siting Results

The spatial wind expansion based on Algorithm 2 for three different minimum wind speeds is shown in Figure 4. Figure 4a depicts the spatial distribution of 10 GW when the minimum wind speed is set to 5 m/s. It becomes obvious that the majority of new wind farms was placed in the south of Germany. This is due to the low correlation with the majority of wind farms in Northern Germany. Sites that are located in the borderland are advantageous as well. When comparing Figure 4a–c, it can be seen that new installations shift further north when the minimum wind speed requirement increases. However, new wind farms are rather build close to the border of Germany, which corresponds to the border of the price zone. Furthermore, there are certain sites that were developed in all scenarios. e.g., a few sites in the southeastern corner of Germany exhibit relatively high average wind yields and are at the same time almost uncorrelated with the majority of wind farms in the market. For comparison, a wind yield optimal distribution according to Algorithm 1 is depicted in Figure 5. In Figure 5, all windy sites in the north are further developed and just a few sites in the middle of Germany that exhibit relatively high average wind yields.
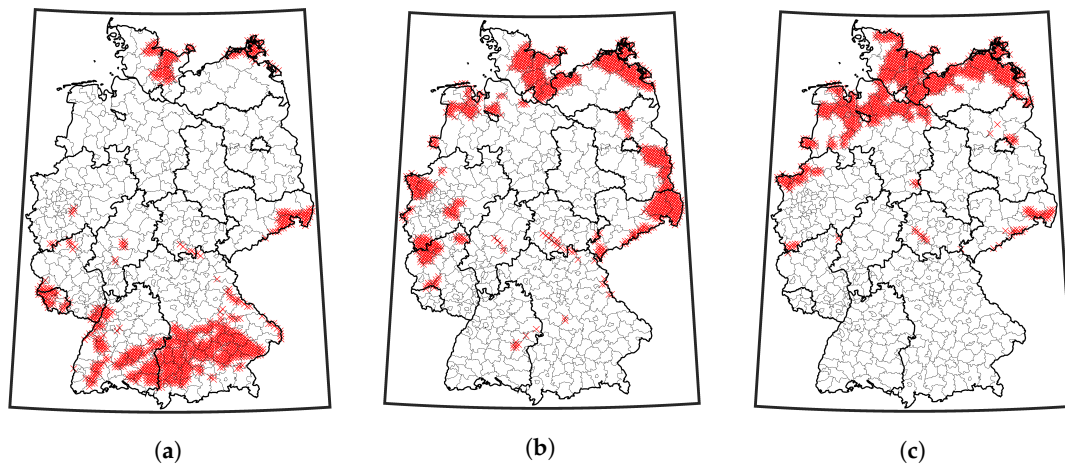
Figure 4. Spatial wind expansion based on Algorithm 2. (**a**) $v_{\min} = 5$ m/s; (**b**) $v_{\min} = 6$ m/s; (**c**) $v_{\min} = 7$ m/s.
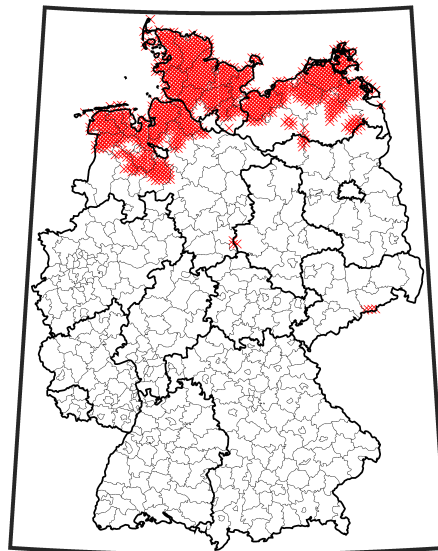

Figure 5. Spatial wind expansion based on Algorithm 1.

3.4. Comparison with Observed Market Value Factors

Given that the onshore wind energy's share of gross electricity consumption is already relatively high in Germany, namely 11.9% in 2015 [21], a spatial deviation in wind energy value factors should be observable. Figure 6 illustrates average relative wind energy value factors according to (4) based on price and wind power data from the period 2012–2014. Thereby, day-ahead prices from the EPEX [22] were used. Hourly onshore wind power generation according to [23] was taken to determine the wind energy value factor v^w. Offshore wind power was neglected because of its still low impact. All site-specific value factors were computed for an ENERCON E-101 with a rated power of 3.05 MW using the wind speed data presented in Section 3.1. Thereby, at all sites, the hub height was set to 120 m. In Figure 6, the highest market values could be achieved in Northern and Southern Germany. In general, market values are higher in the borderland of Germany. The low values in the Alps might be explained by low correlations between wind mast measurements and reanalysis model results due to the complex topography as discussed in [16]. Hence, real market factors could be higher in the Alps. However, due to low average wind speeds and the complex terrain, wind power installations are unlikely there.

When comparing Figure 6 and Figure 2b, it can be seen that wind speed correlations to other sites have a high impact on relative wind energy value factors. Hence, the normalized sum of correlations is a key determinant of the relative wind energy value factor. By adding the wind power capacity as a determinant, as depicted in Figure 2c, the similarities increase except of Northern Germany. As in the period from 2012 to 2014, Northern Germany was frequently experiencing rare winds that drove the relative market value upwards. Yet, this advantage will vanish when more capacity is added in Northern Germany, which will be inevitably under the current support scheme.
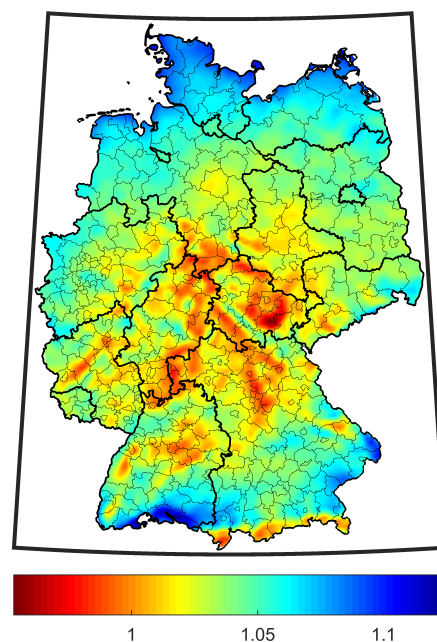

Figure 6. Relative wind energy value factors $v_{rel,s}^w$ during 2012–2014.

4. Conclusions

Feed-in tariffs and other energy-based support schemes have led to a successful deployment of RE sources in many countries. At the moment, there are ongoing debates on the modification of support schemes and even the market design to facilitate the market integration of renewable generation. There is a consensus that the next step will include a further integration of RE into power markets to allow for more competition among them. This will inevitably lead to a different spatial dispersion of wind farms compared to the current situation due to different wind resources in different locations.

To investigate the impact of market integration on the future siting of wind farms, a new model is presented in the paper at hand. We assume that this future system is dominated by wind power, meaning that the larger share of energy is generated by wind power plants, and that these wind farms compete against each other. In such a competitive environment, the correlation of wind power with the remaining wind farms becomes the key siting parameter. Given that high prices occur if the majority of wind farms has no or little wind speeds, investors will opt for sites that exhibit a low correlation with these wind farms. Thus, wind power correlations, average wind yields and wind power installations constitute the three model inputs. Then, it is assumed that investors will pick a site that minimizes the normalized sum of wind power correlations and the normalized installed capacity at these sites meanwhile fulfilling a minimum wind yield. The normalization guarantees that both optimization criteria are in the range $[0, 1]$. By running this algorithm repeatedly, spatial wind expansion scenarios can be generated.

To demonstrate the applicability of this model, a case study for Germany is introduced. 10 GW of wind power are added to the system under the aforementioned assumptions of a full market integration. Results indicate that more competition among wind power producers leads to a spatial

smoothing of wind farm installations. Correlations with the majority of wind farms is especially low at the border of price zones, which results in additional installations there. In addition, a comparison with a wind yield optimal expansion scenario shows that many sites that do not exhibit high wind yields are developed. Hence, more wind farms are required to achieve the same wind energy targets, which might limit the citizen acceptance. However, more wind power installations in the south and close to the border certainly limit the necessity of grid expansion. This could result in lower overall wind power integration costs. Furthermore, wind power production is also more diversified in terms of diurnal feed-in patterns, which facilitates system integration.

The presented approach can only be seen as a first step towards regarding spatial aspects of wind power market values. Its main advantage is its simplicity and its low data requirement. However, the inherent simplifications do not allow for a determination of market value factors. An important issue to resolve for future studies is the integration of multiple input variables. Questions concerning the influence of other generation technologies, such as solar power, and the role of demand need to be answered. Moreover, future work could focus on enhancing the input data set in terms of longer and, hence, more stable times series. Generally, we believe that spatial aspects and the role of correlations should be considered in future debates about market values of RE.

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