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How to estimate wind-turbine infeed with incomplete stock data: A general framework with an application to turbine-specific market values in Germany

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ABSTRACT

This paper analyses market values of wind energy converters at the individual turbine level on a very large scale. Such an analysis is usually precluded by the lack of detailed public data on the stock of wind turbines. We therefore present a general method to estimate incomplete turbine stock data and generate hourly yields of individual turbines based on completed turbine stock data and highly disaggregated hourly wind speed data. On this basis, we calculate hourly infeed and annual market values of up to 25,700 wind turbines in Germany from 2005 to 2015. We show the spread in market values on turbine level, quantify regional differences and discuss the effect of turbine age on market values. We show that turbines in central Germany have, on average, lower market values than turbines in the north, south or far west of Germany. Furthermore, we show that modern turbines reach higher market values than older turbines. We also analyse the drivers of market values, differentiating between infeed-price correlation and standard deviation.

JEL-Classification: D49, Q21, Q42

Index Terms: *renewable energy sources, wind energy, bottom-up modeling, cost minimization, market value, power curves*

Highlights:

- We present a method to estimate unknown stock data on installed wind turbines.
- Reanalysis data and a cost-scaling model are used to determine LCOE-minimal turbines.
- We calculate the hourly infeed of 25,700 German wind turbines for years 2005–2015.
- Market values of turbines are found to differ by region and turbine age.
- We analyse and illustrate the drivers of performance on the individual turbine level.

1 INTRODUCTION

Electricity generation from wind energy has grown rapidly worldwide in the last two decades (IEA 2016). This growth will likely continue owing to technological progress and the increase in demand for environmentally friendly electricity. Hence, the influence of wind energy on the electricity system — and the effect on wholesale electricity prices in particular, described as the *merit order effect* (Sensfuss et al., 2008) — is a topic of interest for researchers worldwide.

However, as wind shares rise, so does the importance of taking the analysis one step further, i.e. to assess how the infeed of a wind energy converter[1] (WEC) influences its own market value, commonly regarded as the wind's marginal value in the day-ahead market. As an intermittent energy source with nearly zero marginal costs is increasingly deployed, its market value drops. This phenomenon triggered research on the extent of this effect and its

[1] We use the terms "WEC" and "turbine" interchangeably.

consequences for electricity systems. Following the seminal paper of Lamont (2008), several authors have assessed reductions in market value and the parameters influencing this phenomenon (Hirth, 2013; Joskow, 2011; Mills and Wiser, 2014; Obersteiner and Saguan, 2010; Winkler et al., 2016). A decrease in market values also influences the competitiveness of renewables (Green and Léautier, 2015; Hirth, 2015; Reichelstein and Sahoo, 2015) and a possible need for prolonged subsidisation (Kopp et al., 2012).

Most of these studies only analyse a fleet's average market value (see Ortner et al, 2016, for a literature overview).[2] The question remains, to what extent is the fleet's value representative of an individual turbine? In other words, how much does an individual turbine's market value vary around the fleet's average? This lack of research is surprising since Lamont's (2008) main insight was that market value is a function of the covariance of an energy source's infeed and electricity prices. However, especially in larger markets, wind conditions within the market — and thus individual infeeds — are not identical but highly variable. Due to varying weather conditions individual values differ by location. Schmidt et al. (2013) proved this for a relatively small country like Austria. For Germany, Grothe and Müsgens (2013) showed that market values for identical turbines differed significantly across the 37 reference locations and the twelve months of data they analysed.

Furthermore, the infeed at a certain location (and thus a WEC's individual market value) varies depending on the WEC technology used. This is important for two reasons. First, technological progress in the field is significant: WECs did not simply get larger in terms of hub height, rated power and rotor size; they also changed in the relation of rotor to capacity. In Germany and the USA, the growth in rotor size has outpaced capacity growth, since 2011 onwards (Ender and Neddermann, 2015; DeutscheWindGuard, 2016; Wiser and Bolinger, 2016). Second, rotor scaling leads to larger capacity factors and to different infeed structures, with repercussions for electricity systems (Fraunhofer IWES, 2013).

The lack of research on market values on the level of individual turbines may be explained by the unavailability of data on the hourly infeed of individual turbines.[3] To determine a turbine-specific infeed in a market, one needs disaggregated data on wind speed and detailed information on the turbines installed: the start-up date, the deployed power curve (which maps wind speeds to electricity generation), the location and the hub height. As already noted in Becker (2017), complete datasets are quite rare and usually available datasets have large information gaps. For Germany, Europe's largest wind market, there is no public dataset with

[2] Hirth and Müller (2016) quantify the difference in market values of a modern wind fleet to an older one, finding that modern turbines reach higher market values. However, as turbines in a market are neither identically designed nor exposed to identical wind conditions, the question remains to what extent statements on "the" value are meaningful for single turbines.

[3] Hourly generation data for individual turbines is rarely published as it is business-sensible information of investors.

the above mentioned information.[4] The need for an estimation or gap filling method is also present at the European level: although Gonzalez Aparicio et al (2016) used data from a commercial provider in modelling hourly infeed for the EMHIRES dataset, it still required comprehensive processing to fill considerable gaps (essentially hub heights and power curves[5]). Their processing followed a gap-filling approach based on reliable data on existing wind farms. For the German market, Becker (2017) applied more sophisticated statistical methods to complete missing data. We will present an alternative to both approaches.

Partly due to information requirements imposed by subsidisation schemes, at least some data on the wind sector is available in most countries. Usually, installation numbers and aggregated annual infeed data are publicly available. This paper presents an economical approach to estimating WEC-specific hourly infeed based on other available information in a system. This is achieved in two steps: First, the data on a WEC's technical parameters is completed by deriving deployed power curves and hub heights for all capacities installed. Power curves are estimated based on the WEC model and height, which minimizes levelised cost of energy (LCOE) at the WEC's position, with investment costs estimated using a mass-cost model. In a second step, this WEC data is combined with hourly, locational wind speeds at the turbine height to calculate hourly infeed.

We applied this approach to Germany. We then used the completed stock data to calculate hourly yields and individual market values of ~25,700 individual turbines, comparing them to the average market value of all German turbines. Based on this empirical approach, our paper is the first to analyse market values on the level of individual turbines on such a large scale. Our results are available in the online appendix to this paper, along with completed stock data and historical market values. Contributing to the literature on the economics of wind energy, we answer three research questions:

1. Methodology: How can a WEC's hourly infeed be estimated based on incomplete data?
2. Structure: What is the historical development of turbine market values in Germany?
3. Drivers: What influences the difference in market values observed?

The answer to the first question presents a methodological contribution, which can also be applied to other wind markets. The answers to the second and third questions, as well as the data offered in the online appendix, are of interest to international researchers who advise market designers on the drivers of wind energy market value. These findings may also be useful for investors, regulators, wind farm operators and traders in Germany.

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[4] By the end of 2017, a capacity register (Marktstammdatenregister) will come online (see Stratmann, 2016); but since stock capacities are only obliged to register within two years from its start, there will not be a complete dataset before 2019.

[5] 61 % of hub heights needed to be estimated. 28 % of power curves were missing and henceforth either estimated, based on the laws of physics, or assigned the most commonly used turbine in the market. Processes results are not published.

The remainder of the paper is structured as follows. Section 2 presents the methodology we used to complete the information on all turbines in the stock and subsequently calculate the hourly infeed and market values from the complete dataset. Section 3 analyses the model quality. Section 4 answers our research questions. Conclusions and further research are discussed in section 5.

2 METHODOLOGY AND DATASETS

This section first analyses the data necessary to calculate turbine-specific market values. We then describe our methodological approach to determining these values and apply that approach to develop empirical estimates for Germany.

We define the annual market value ($MV_{j,y}$ in €/MWh) of a turbine j in year y as the sum of its hourly yield ($yield_{j,y,h}$, in MWh), multiplied by the hourly wholesale price ($p_{y,h}$, in €/MWh) divided by its annual yield:

$$MV_{j,y} = \frac{\sum_{h=1}^{8760} yield_{j,y,h} \cdot p_{y,h}}{\sum_{h=1}^{8760} yield_{j,y,h}} \tag{1}$$

Consequently, the annual market value of the fleet MV_y^{fleet} (i.e. all wind turbines in the system) is defined as all turbines' volume-weighted average price:

$$MV_y^{fleet} = \frac{\sum_{j=1}^{J} \sum_{h=1}^{8760} yield_{j,y,h} \cdot p_{y,h}}{\sum_{j=1}^{J} \sum_{h=1}^{8760} yield_{j,y,h}} = \frac{\sum_{h=1}^{8760} yield_{y,h}^{fleet} \cdot p_{y,h}}{\sum_{h=1}^{8760} yield_{y,h}^{fleet}}, \tag{2}$$

with $yield_{y,h}^{fleet} = \sum_{j=1}^{J} yield_{j,y,h}$. As we are interested in the market values of single turbines compared to the fleet's value, we introduce *absolute performance,* which is the difference of Eq. (1) and (2):

$$abs\_pf_{j,y} = MV_{j,y} - MV_y^{fleet} \tag{3}$$

Absolute performance is thus positive when a turbine earns payments above the energy-weighted average of all turbines in the system (or an imaginary benchmark turbine). A performance of zero means that a turbine's market value corresponds to the energy-weighted average value of all turbines in the system. If a turbine were to produce the same amount of energy in each hour, its market value would correspond to a baseload technology and thus to the annual average day-ahead price ("base price").

The absolute performance given by Eq. (3) can be rewritten introducing expectations. This assumes that the hourly wholesale electricity price and the corresponding contribution of an intermittent energy source such as wind can be interpreted as random variables. Consequently, the yearly market value is the expected sum of hourly revenues divided by the turbine's expected annual yield (see also Lamont, 2008):

$$abs\_pf_{j,y} = E(yield_{j,y,h} \cdot p_{y,h})/E(yield_{j,y,h}) - E(yield_{y,h}^{fleet} \cdot p_{y,h})/E(yield_{y,h}^{fleet}) \quad (4)$$

Extending Lamont (2008), Eq. (4) can be reformulated (see also Genoese et al., 2016; Jägemann, 2015) according to the following proposition:

$$abs\_pf_{j,y} = \sigma(p_{y,h}) \cdot \left(cor(yield_{j,y,h}, p_{y,h}) \cdot \frac{\sigma(yield_{j,y,h})}{E(yield_{j,y,h})} - cor(yield_{y,h}^{fleet}, p_{y,h}) \cdot \frac{\sigma(yield_{y,h}^{fleet})}{E\left(yield_{y,h}^{fleet}\right)} \right) \quad (5)$$

The proof of this proposition is presented in appendix A. The benefit of Eq. (5) is that it reveals the drivers of absolute performance. In the equation, σ refers to standard deviation and *cor* to correlation between infeed and prices. We refer to standard deviation divided by expected yield as *normalized standard deviation*. It decreases if the technology runs less constantly (see nominator) or achieves higher yields (see denominator).

Differentiating between infeed-price correlations as a first driver of performance and normalized standard deviation as a second, we assert the following. First, the larger a turbine's correlation in comparison to that of the fleet (ceteris paribus) the larger the difference in correlations and thus a single turbine's absolute performance. This holds because all standard deviations and expected yields are positive. Second, the smaller (ceteris paribus) a turbine's normalized standard deviation in comparison to that of the fleet, the larger its absolute performance. This follows whenever the infeed-price correlation of wind energy is negative — which is the case for all turbines in our dataset.

Since annual wholesale electricity prices vary significantly across years, we complement absolute performance with a relative performance measure[6], which makes performance comparable over time:

$$rel\_pf_{j,y} = (MV_{j,y} - MV_y^{fleet})/MV_y^{fleet}$$

$$= \frac{\sigma(p_{y,h}) \cdot \left(cor(yield_{j,y,h}, p_{y,h}) \cdot \frac{\sigma(yield_{j,y,h})}{E(yield_{j,y,h})} - cor(yield_{y,h}^{fleet}, p_{y,h}) \cdot \frac{\sigma(yield_{y,h}^{fleet})}{E(yield_{y,h}^{fleet})} \right)}{E(p_{y,h}) + cor\left(yield_{y,h}^{fleet} \cdot p_{y,h}\right) \cdot \frac{\sigma(yield_{y,h}^{fleet})}{E(yield_{j,y,h})} \cdot \sigma(p_{y,h})} \quad (6)$$

When discussing relative performance empirically (section 4), we focus on this equation and the two components of infeed-price correlations and normalized standard deviations.

Yet, the analysis requires data on hourly wholesale electricity prices and the WECs' hourly infeed in order to parameterize Eq. (1) to (6). Prices are readily available in many systems (e.g. https://www.energidataservice.dk/en for the German, Danish, Swedish and Norwegian system), but hourly generation of individual WECs is hardly published. Hence, we developed an approach to model this based on other, more readily available data. This approach is applied to the German market, but it can also be used in other markets.

6 A relative performance above zero means that both absolute performance and market value are larger than those of the fleet.

The power output of a WEC is based on the laws of physics (see also Gonzalez Aparicio et al.; 2016):

$$power = 1/2 \cdot A \cdot c_p(v) \cdot \rho \cdot v^3 \qquad (7)$$

with A being the rotor area (in m²), c_p the WEC's power coefficient (yielding the ratio of power extracted from the power in the wind), ρ the air density (in kg/m²) at standard atmospheric conditions and v^* (in m/s) the relevant wind speed at a WEC's hub height, which varies across locations and accelerates with height.

In economics and business, a WEC's technical characteristics are usually aggregated in a power curve $PC_j(v^*)$, which describes the relation between wind speed and infeed in standard atmospheric conditions (independent of hub height):

$$yield_{j,y,h} = PC_j(v^*) \cdot l_j \qquad (8)$$

Eq. (8) also includes a loss parameter l_j (without dimension), which corrects for limited availability (outages), wind shadow and electrical losses.[7]

Hence, the empirical calculation of hourly yields of a single WEC requires data on the WEC's power curve, its linking with hourly wind speeds — corrected for air density at the WEC's position[8]—and information on losses. Accordingly, linking all power curves with wind speeds at all WEC positions lets us model hourly yields of a system's entire fleet bottom up. This combination requires the following information:

a) The **number of WECs** deployed in a system.

b) The **power curves of the WECs**. Each WEC has a model name from a WEC manufacturer, and each model name features a distinct power curve given in its technical specifications.

c) The **hub heights of the WECs**. Unlike the power curve, height is not set in the model name as each model is usually available in at least two different heights.

d) The **locations of the WECs** (longitude, latitude).

e) **Hourly wind speeds** at the WEC positions (i.e. locations and hub heights).

Information on a) is usually available in developed markets. If the data in points b) to e) is missing, it can be estimated based on elements of available data. Depending on the amount and type of data, the following approach may need to be adapted, but the general methodology can be applied to other systems.

In the following sections, we first explain how to complete stock data (see 2.1 to 2.1.6 in Figure 1 and note that the numbering in the figure corresponds to the section numbering).

7 Note that the loss parameter could also vary between years y and hours h. We opted for a parameter depending on turbines only based on lack of data for a more precise parametrization (see 2.1.4 and online appendix, table 9).

8 *Position* refers to the three dimensions of longitude, latitude and hub height. *Location* refers to longitude and latitude only.

Second, we show how to link hourly wind speeds with all power curves at WEC positions to arrive at hourly yields and market values (see 2.2 to 2.2.3 in Figure 1).

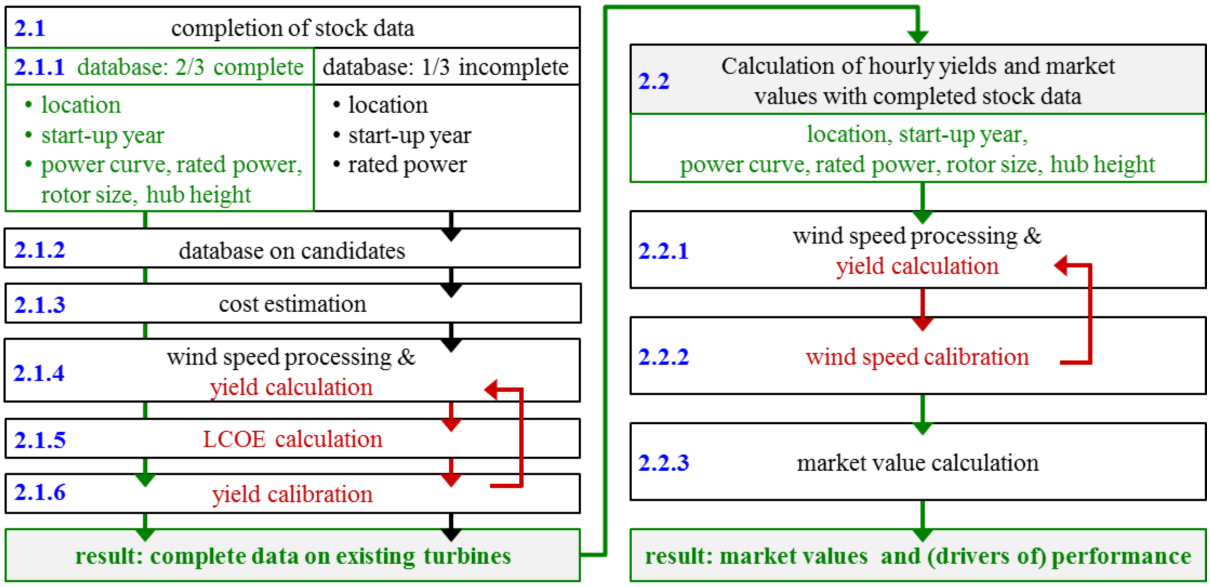

Figure 1: Method to complete stock data and its application to model market values.

To the best of our knowledge, we are the first to apply this economical method and to publish disaggregated results on stock data and market values for a complete set of several thousand WECs in a country. The remainder of section 2 describes the methodology of each step of Figure 1.

2.1 Completion of stock data

We first gathered as much data as possible on the power curves, locations and hub heights of the stock. Second, we built a database of the WECs, which could be used to estimate WECs with unknown power curves and hub heights. Third, we estimated WEC investment costs with a mass-cost model. Fourth, we processed wind speed data and calculated yields of all WECs coming into consideration for yet undetermined WECs[9]. Fifth, we combined costs and yields to calculate the LCOE. We selected WECs with the lowest LCOE to provide the missing information (i.e. power curves and hub heights for the undetermined WECs). Sixth, we compared annual yields of the completed stock with empirical data. A calibration parameter was introduced to match the fleet’s yield with the empirical data and calculations were iterated.

2.1.1 Database of the stock

The starting point for a stock database is thorough research of public data on national regulators, transmission system operators (TSO), statistical offices and other suppliers. In Germany, we found that ~25,700 turbines (43 GW) were installed by the end of 2015. For capacities with start-up years between January 1994 and July 2014, we used public TSO data

[9] We use the term “undetermined” for WECs whose power curves and hub heights could not be looked up.

(Netztransparenz), covering ~23,200 turbines and corrected for gaps and inaccuracies. For each turbine, TSO data contained a unique identity code (linked to support payments under the Renewable Energy Act), rated power of the turbine, its start-up date and the postcode of its grid connection. Exact geo-coordinates were known or could be traced via Google maps for ~10 % of all entries. For the remaining ~90 %, we translated the turbines' postcodes into geo-coordinates using OpenGeoDB, a public database of geo-coordinates of German settlements. We then interpreted these as a turbine's exact location. TSO data revealed neither model names (thus power curves) nor hub heights. Based on this data, we did desktop research to uncover power curves and hub heights of as many turbines as possible.

For turbines commissioned since August 2014, public data from the regulator (Bundesnetzagentur) — covering around 2,500 turbines — was used as investors had to register new turbines (with location, rated power, model name and hub height) after that date to receive subsidies. Combining these collections of data, we identified models and positions (location and hub height) of 67 % (~17,200 turbines) of the stock. For the remaining ~8,500 undetermined turbines, we only knew the location, rated power and start-up date. Hence, we had to derive power curves and hub heights for one-third of the turbines.

2.1.2 Database on candidates

For the undetermined WECs, we built a database of all WECs that could potentially have been built. These WECs are referred to as *candidates*. The input for the database was based on model names of the WECs already determined as well as expert interviews on models deployed in Germany.[10] Though this database of candidates may be partly German-specific, it can be used internationally as many of the candidates were sold worldwide by manufacturers such as Vestas, Siemens or General Electric. However, it can (and most likely should) be adjusted for other countries or regions. A candidate is defined by the following six features:[11]

1) A **power curve,** specified by the model name. Information on power curves is indispensable to calculate yields and can be taken from a model's technical specifications.
2) A distinct **hub height**.
3) Duration of **market availability**, which defines the years in which a candidate was commercially available in a given system. This feature was assumed through a combination of stock analysis, internet research, expert interviews and manufacturer interviews.[12]

[10] Note that this database will also serve to model the hourly yields of the determined turbines (to arrive at the fleet's infeed).

[11] Features 1) to 4) are needed if transferred to another system, whereas features 5) and 6) are due to our case study of Germany.

[12] Market availability may be German-specific, though time spans should not differ largely if transferred to other markets.

4) A distinct **wind class certification**. WECs are certified according to the loads and the average and peak wind speeds expected on site.[13] Hence, WECs cannot be built invariably at every position. For some models, certification differs with hub height, as loads accelerate with height. Internationally, three classifications prevail (I for high-, II for medium- and III for low-wind sites). The classification of a site can be approximated by its long-run prevailing wind speeds. Legal permissibility was assumed if the on-site conditions match a candidate's certification.[14]

   For our empirical case, the approach to wind-class permissibility was slightly adapted. First, as the German wind classifications differ from the international ones (zone IV for high- through zone I for low-wind sites), they were also captured in the candidate's database. Second, to derive permissibility of a candidate at a location of an undetermined WEC, zone classifications of all administrative districts and municipalities — set by the Deutsches Institut für Bautechnik — were converted to postcodes and stored in our stock database. Hence, permissibility of a candidate was detected by comparing the locational classification with the candidate's certificate.

5) **Rotor size**, specified by the model name. This information was used in our case study of Germany to compare a candidate's total height (hub height plus rotor radius) with regional height restrictions.[15] We therefore studied the uncovered stock data and conducted expert interviews on the development of German height limitations, setting up a matrix of 99 postcode boundaries with maximum heights permitted (online appendix, table 1).

6) **Rated power**, specified in TSO data for any capacity installed.

In total, our database comprised 576 candidates (188 models with several hub heights of 32 manufacturers; online appendix, table 2). Based on the features listed above, we were able to assign a set of commercially available and legally permissible candidates to each undetermined WEC[16]. Candidates complying with these criteria were labelled as *qualified candidates* or *q-candidates*, and each undetermined WEC was assigned at least one q-candidate. The q-candidates were given the corresponding geo-coordinates of the undetermined WECs to calculate their positional yields (see 2.1.4) and LCOE (see 2.1.5).

The q-candidate to determine an undetermined WEC was chosen based on the lowest LCOE (2.1.3 to 2.1.5). We derived LCOE for each q-candidate (subscript *qc*) such that

$$LCOE_{j,qc} = \frac{IC_{qc,installation} + \sum OC_{j,qc,y} \cdot yield_{j,qc,y} / (1+i)^y}{\sum yield_{j,qc,y} / (1+i)^y}, \tag{9}$$

[13] Certifications were taken from a model's technical specifications.

[14] WECs certified for higher loads (speeds) can be used at sites with lower loads (speeds), but not vice versa.

[15] This comparison may be omitted for systems without height limitations.

[16] As we know each undetermined turbine's rated power, we can restrict the set to those with the same rated power.

with IC as a q-candidate's investment costs—differentiated by its installation year (subscript y) — OC as operational costs (in €/MWh) and i as the weighted average cost of capital.

2.1.3 Cost estimation

As shown in Eq. (9), calculating LCOE requires data on investment costs. However, detailed information on investment costs for each q-candidate (i.e. differentiated by model, hub height and installation year) is publicly unavailable. Hence, we estimated it with the mass-cost model of Fingersh et al. (2006) and its upgraded version (Maples et al., 2010), both developed at the National Renewable Energy Laboratory (NREL)[17]. NREL's model projects investment costs of turbine configurations up to 10 MW, given rated power, rotor, hub height, c_p, drive train design, maximum rotor speed, maximum tip speed and maximum tip speed ratio. Cost projections are based on 24 mass-cost relations of major turbine components and their composition of raw materials.

This complex model suits our needs well for three reasons. First, the model takes into account differences in rotor size and tower heights of candidates with identical rated power. Second, NREL's model was developed with data from the mid-2000s. In our case, more than 80 % of undetermined turbines were built before 2012, and more than half between 2000 and 2009. Thus the model fits the timespan in focus. Third, the model can be transferred to international markets, whereas most other studies are country specific.

To estimate costs, we first applied specified inflation indices of the US Bureau of Labor Statistics (2015) to single components of the mass-cost model. We then converted these figures from USD to EUR (online appendix, table 3). In accordance with McKenna et al. (2014), we incorporated a market factor into this US model to account for higher absolute turbine and equipment prices in Germany. However, as our database contained more candidates and periods, we opted for yearly market factors for different turbine classes. The factors were chosen to fit historical cost characteristics described in German market studies (Deutsches Windenergie Institut, 1999, 2002; Deutsche WindGuard, 2013, 2015) (online appendix, table 4). This way, absolute costs were adjusted while relative differences due to turbine design were conserved, as assumed by NREL.[18] Our approach to select the best-fitting q-candidate focuses primarily on the relative differences between candidates.

Concerning operational costs (increasing over lifetime), the average cost of capital (depending on full load hours) and the depreciation period (20 years), we followed Deutsche WindGuard (2013, 2015) (online appendix, table 5).

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[17] The 2010 version partially upgraded the 2006 version; we call the upgraded version the "NREL model" throughout. Perkin et al. (2015) refer to NREL's 2006 version as "the most robust, publically available cost-scaling model".

[18] Investment costs of all candidates and a comparison with published list prices of 86 candidates in 2001 and 2004 are offered in the online appendix, tables 6-7.

2.1.4 Wind speed processing and yield calculation

As shown in Eq. (9), calculating LCOE requires data on yields. A q-candidate's yield is determined by its power curve and the wind speeds at its position. Yields were ascertained in three steps. First, we determined the wind speeds at a q-candidate's location. Second, we estimated the wind conditions at a q-candidate's specific hub height. Third, we used this processed wind-speed data to calculate annual yields at the q-candidate's position.

We used reanalysis wind speed data at 80 and 140 metres hub height above ground at a spatial resolution of 10 by 10 km at hourly time resolution for years 1994 to 2015, provided by anemos.[19] Without access to anemos data, CFSR (NCAR), ERA-interim (Dee et al., 2011), ERA5 (ECMWF) or MERRA-2 (NASA) data could be used as alternative, though at lower spatial and temporal granularity. For a discussion on appropriateness and differences in quality, see Brower et al. (2013), Carvalho et al. (2014), Jimenez et al. (2012), Kubik et al. (2013a), Liléo and Petrik (2011).

Calculation of LCOE is based on long-run wind-speed data of 10 to 25 years (Brower et al., 2013; Jimenez et al., 2012; Liléo and Petrik, 2011). In accordance with McKenna et al. (2015) and Ritter et al. (2015), we use 20 years (from 1994 to 2013) as a basis for each q-candidate.

Dividing the German landmass into a 10 by 10 km raster yields around 3,500 raster nodes. As q-candidates were never positioned exactly at a node, we horizontally interpolated wind speeds at the desired location. Here, we followed Ritter et al. (2015) by applying inverse distance weighting. To this end, each q-candidate's distance to its four nearest nodes was measured. New hourly series at hub heights of 80 and 140 metres, $v_{y,h,loc}^{80}$ and $v_{y,h,loc}^{140}$, were calculated as the horizontal distance-weighted means of the speeds of each q-candidate's four nearest nodes. Since several q-candidates feature the same postcode, this led to 5,934 new hourly wind speed series at the two heights.

The most exact next step would be to continue with these hourly wind speed series. However, this would require extraordinarily large computational resources to complete based on 20-year data in hourly resolution with several q-candidates to be considered for ~8,500 undetermined turbines. Furthermore, this is not mandatory for LCOE calculations (see Eq. (9)): computation of annual yields can also be based on distributional parameters of the wind-speed series. Using distributions instead of hourly data massively reduces computational time.

Calculating annual yields based on distributions required three processing steps. First, the two series $v_{y,h,loc}^{80}$ and $v_{y,h,loc}^{140}$ had to be corrected for air density as power curves describe the relation of wind speeds to output in standard atmospheric conditions only (see Eq. (7)). The correction is shown in appendix B. Second, we had to derive the shape (a) and scale (b) parameters of the Weibull distribution at both heights of the corrected series, giving parameters $a_{y,loc}^{80}$, $a_{y,loc}^{140}$, $b_{y,loc}^{80}$ and $b_{y,loc}^{140}$. With these, it would have been possible to

[19] anemos processed original NCEP data from NCAR to receive a spatial resolution of 5 by 5 km at 30-minute intervals. Aggregating it to 10 by 10 km at 60-minute intervals comprised around 28 gigabytes. The processing described in this section increased it to more than 100 gigabytes.

calculate annual yields of a q-candidate at exactly 80- and 140-metre hub heights, but not at other heights. Hence, the third step was to vertically adapt the air density corrected wind speeds to other hub heights z. If we had used hourly wind-speed series, the power law (see 2.2.1) could have been applied. Yet, since we use distributions, new distributional parameters (a) and (b) were inter- and extrapolated for vertical correction, as shown for shape parameter a:

$$a_{y,loc}^{z} = \left(a_{y,loc}^{140} - a_{y,loc}^{80}\right)/(140-80) \cdot (z-80) + a_{y,loc}^{80} \tag{10}$$

Annual yields of a q-candidate qc to be considered for an undetermined turbine j were then estimated by inserting a q-candidate's Weibull probability density function, $wpdf$, as in Eq. (11)[20], into the subsequent Eq. (12) (Schallenberg-Rodriguez, 2013):

$$wpdf_{j,qc,y}\,(v^{z}) = b_{y,loc}^{z}/a_{y,loc}^{z} \cdot \left(v^{z}/a_{y,loc}^{z}\right)^{b_{y,loc}^{z}-1} \cdot e^{-\left(v^{z}/a_{y,loc}^{z}\right)^{b_{y,loc}^{z}}} \tag{11}$$

$$annual\_yield_{j,qc,y} = 8760 \cdot l_j \cdot x_{j,y}^{yield} \int_0^{\infty} wpdf_{j,qc,y}(v^{z}) \cdot PC_{qc}(v^{z})\, dv^{z} \tag{12}$$

We quantified the loss parameter l_j, including wind shadow as a function of farm size[21], availability loss as a function of installation year, and electric and other losses (online appendix, table 8).[22] Parameter $x_{j,y}^{yield}$ is set to 1 at this stage. It will be modified (and explained in detail) in section 2.1.6. We thus achieved 20 annual yields for all q-candidates to be considered for an undetermined turbine.

2.1.5 LCOE calculation

Costs (see 2.1.3) and yields (see 2.1.4) could then be inserted into Eq. (9) to calculate the LCOE of all q-candidates. For each undetermined turbine j, the cost-minimal q-candidate was chosen. This approach assumes that investors chose turbines that minimized LCOE subject to local wind conditions.

2.1.6 Yield calibration

As discussed in Staffel and Pfenninger (2016), though reanalysis data reproduces the infeed's structure well, bias on the overall level of output must be corrected. Hence, hourly yields of all WECs were aggregated as annual yields on the country and state levels. Aggregates were then compared to empirical yields (online appendix, table 9) of the country (in line with Staffel and Pfenninger, 2016). As of 2008, data for smaller geographic entities, namely German states, has been available and thus used in this paper. Yields were mostly overestimated, which is in line with Staffel and Pfenninger (2016) and Decker et al. (2012), who also find overestimation by modelling infeed with reanalysis wind speed data. Leaving

[20] Note that a q-candidate qc for turbine j is distinctly linked to the location of j and the hub height of qc. This is why script and superscript are omitted in the probability density function.

[21] To correct for losses due to wind shadow, we integrated into our stock database the number of turbines that were erected together—and hence make up a farm—by installation year and postcode.

[22] To give an indication of the order of magnitude, a farm of four WECs has a total loss of 15 % on gross yield.

such a mismatch uncorrected may lead to choosing “wrong” q-candidates. Thus for any WEC, we incorporated an annual yield correction parameter $x_{j,y}^{yield}$ at the end of Eq. (12), which was found by building the ratio of empirical to calculated yields.[23] Hence, we assumed that all WECs within the same geographic entity (country or state) experience the same bias. $x_{j,y}^{yield}$ adjusts a WEC’s annual yield, thus changing the LCOE. Hence, yield calculations of all q-candidates (step 2.1.4) – according to Eq. (12), LCOE calculations (step 2.1.5) and yield calibration (step 2.1.6) – were repeated until the choice of q-candidates was stable. At the end of this iterative process, every undetermined WEC had exactly one LCOE-minimal q-candidate, which provided all missing data. This completed stock data is available in the online appendix, table 10.

2.2 Calculation of hourly yields and market values with completed stock data

At this point, we have complete stock data (especially power curves and hub heights), hourly wind speed data at each turbine’s location at 80 and 140 metres above ground and wind speed distributions at each turbine’s position. To derive hourly infeed and market values, we did not use the distributional parameters of section 2.1.4. Instead, we vertically corrected the hourly wind speed series $v_{y,h,loc}^{80}$ and $v_{y,h,loc}^{140}$ to each turbine’s hub height. We chose this approach for two reasons. First, since the stock was already determined, we had just one specific turbine at a position instead of several q-candidates, making it now less computationally intensive to work with long time series. Second, drawing from distributions to derive hourly values would not match historical wind speeds and thus hourly wholesale electricity prices, which are influenced by wind speeds. Further statistical processing would be required (Schmidt et al., 2013). Hence, we chose to use the hourly time series already at hand.

2.2.1 Wind speed processing and yield calculation

An established way to vertically interpolate hourly wind speeds from one height to another is the application of the “power law” (Gonzalez Aparicio et al., 2016; Kubik et al., 2011; Schallenberger-Rodriguez, 2013). The procedure is shown in Eq. (13), in which $v_{y,h,loc}^{80}$ is the locational wind speed at an 80-metre hub height, z the hub height required, $v_{y,h,loc}^{z}$ the locational speed at z and $s_{y,h}$ the shear coefficient or power exponent:

$$v_{y,h,loc}^{z} = v_{y,h,loc}^{80}(z/80)^{s_{y,h}} \tag{13}$$

The shear coefficient measures the vertical change in wind speeds. As speed data in two different heights was available[24], it was derived as follows:

---

[23] For LCOE calculations, yield data suffices on annual level.

[24] If only one height is given, the logarithmic law can be applied. This law, however, requires information on the roughness length (Kubik et al., 2011, McKenna et al., 2014), a constant in the law’s equation that depends on the surface roughness. Roughness length guidelines for different grounds in Europe are given in Silva et al. (2007).

$$s_{y,h} = ln(v_{y,h,loc}^{140}) - ln(v_{y,h,loc}^{80})/ln(140) - ln(80) \quad (14)$$

Based on $s_{y,h,loc}$ (with subscript loc referring to the WEC's location), hourly wind speeds were converted from 80 metres to the specific hub height z by applying Eq. (13). Additionally, the series was corrected for air density, as explained in appendix B, giving $v_{y,h,loc}^{z,corr}$. The turbine's hourly yield at its position was then derived according to Eq. (8), with the relevant wind speed v^* being $v_{y,h,loc}^{z,corr}$.

2.2.2 Wind speed calibration

Like in 2.1.6, we compared the yields of all turbines in the same geographic entity with corresponding empirical yields, incorporating a calibration parameter. As only annual data of historical yields were available, we aggregated our hourly estimates accordingly. However, we could not simply use the annual calibration parameter derived in 14 owing to the non-linear relation between wind speed and power output (see Eq. (7)). WECs usually produce electricity at wind speeds between 3 and 25 metres per second only, with the slope of output depending on the specific WEC design (i.e. power curve). Therefore, an optimal estimation of hourly yields requires correcting wind speeds (see Staffel and Pfenninger, 2016) instead of adjusting yields (as sufficient for estimating annual yields). The correction parameter $x_{j,y}^{speed}$ was found by raising the ratio of empirical to calculated yields to the power of one-third. Hourly yields were calculated with Eq. (8), with $v_{y,h,loc}^{z,corr} \cdot x_{j,y}^{speed}$ being the relevant wind speed v^*. Yield calculations and calibrations were then repeated until observed and calculated yields matched.

2.2.3 Market value calculation

As a final step, hourly yields of all turbines were combined with hourly wholesale prices[25] to calculate market values, relative performance, infeed-price correlations and normalized standard deviations, according to Eq. (1) through (6).

3 MODEL QUALITY

To validate the quality of our approach, we analysed the WECs chosen (steps 2.1 to 2.1.6) as well as the reproduction of market values (performance) (steps 2.2 to 2.2.3) on the level of single turbines and the whole fleet. Additionally, as we are interested in explaining the drivers of performance, we will present how well infeed-price correlations and normalized standard deviations can be reproduced.

[25] We used data from the German EPEX-spot day-ahead auction as wholesale prices for reasons of liquidity and transparency. Note that prediction errors in the day-ahead wind forecast may change market values or lead to balancing costs, which are not considered in this paper.

3.1 Quality of chosen WEC-model

We evaluated the model choice of a q-candidate by repeating steps 2.1 to 2.2.3 for the turbines that were already determined by research. In other words, the model choices could be checked against known stock data. We concentrated the analysis on hub heights and rotor diameters. Concerning hub height (Figure 2), the model's error interval was below 10 metres in 58 % of cases. In 90 % of cases (red bars), it was below 25 metres. Concerning rotor diameter (Figure 3), the error interval was within ± 4 metres in 59 % of cases. In 90 % of cases (red bars), it was between -8 and $+12$ metres.

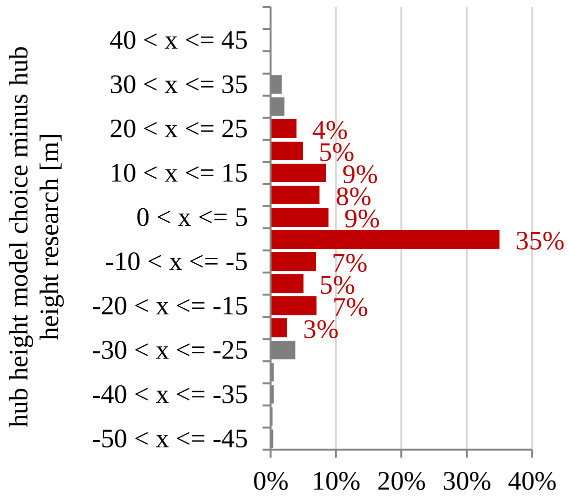


Figure 2: Model quality: hub height deviation.

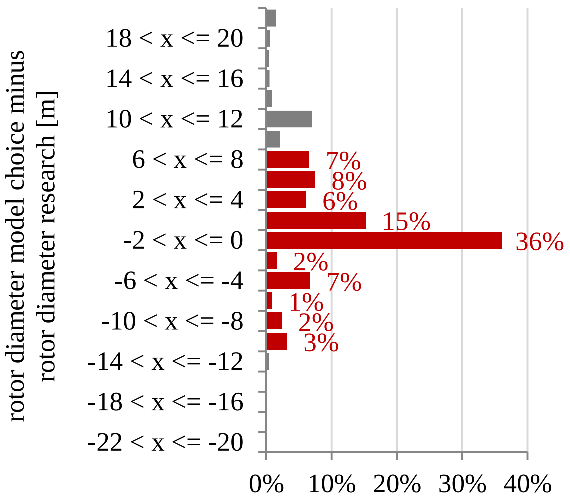


Figure 3: Model quality: rotor deviation.

3.2 Quality of performance and drivers on WEC level

To test the reproduction of performance and drivers on the individual turbine level, data on existing turbines was needed. We had access to 200 historical infeed curves of 122 real, regionally dispersed turbines from the years 2008 and 2012–2015. Each curve covered at least one legal year. This information let us calculate hourly yields, market values and performance and benchmark these against the modelled output of identical power curves and positions.

Figure 4 shows the correlation of modelled versus empirical relative performance according to Eq. (6). The modelled performance gave the correct algebraic sign 90 % of the time and thus correctly identified under- and over-performers. Building on the difference between relative performance, we found that in 90 % of cases the deviation was within ± 2 percentage points. This matters for reading our performance atlases, presented in section 4.

To show the quality of drivers of performance, Figure 5 first depicts the normalized standard deviations of modelled versus empirical yields. The error interval was in the range of ± 1.5 % in 90 % of cases. Second, Figure 6 depicts infeed-price correlations of modelled versus empirical yield. Here, the error interval was in the range of ± 0.035 in 90 % of cases.

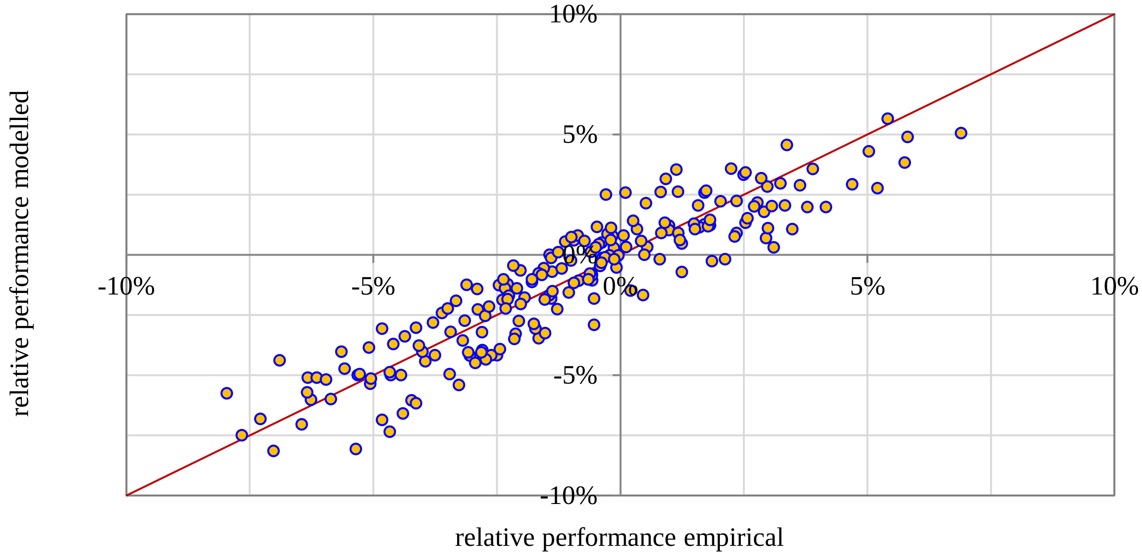


Figure 4: Empirical vs. modelled relative performance.

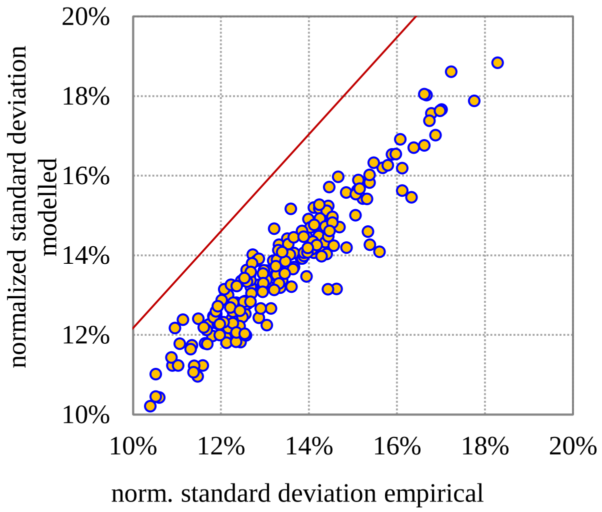


Figure 5: Empirical vs. modelled standard deviations.

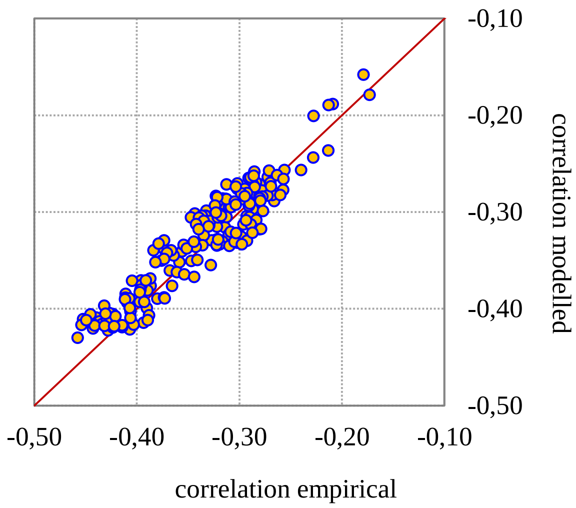


Figure 6: Empirical vs. modelled infeed-price-correlations.

3.3 Quality of performance and drivers on fleet level

To test the reproduction of market values and drivers on the fleet level, the fleet's hourly infeed curve from years 2006 to 2015, as published by TSO, was benchmarked against our model output.

Based on the differences in market values, the absolute mean error of the ten cases was -0.14 percentage points. Concerning the absolute differences in infeed-price correlations and normalized standard deviations, the mean error was -1.8 and -0.7 percentage points, respectively (see appendix C).

Comparing the fleet's empirical infeed to our model is distorted, however, since TSO data lacks up to 12 % of the annual yields reported in state statistics, and thus of the yields on which our model was calibrated.[26] We assume our used statistics to be accurate as subsidies are based on it. Despite this gap, appendix D shows our representative results of commonly used quality measures (correlation, distribution, match of energy step change) to judge the quality of our fleet's hourly infeed curve as compared to empirical samples for exemplary year 2014.

4 RESULTS

This section analyses market values in Germany derived with the methodology described in section 2. We calculated the WEC-specific infeed for eleven years (from 01/01/2005 to 31/12/2015) for up to 25,700 WECs in hourly resolution and derived relative performance and drivers. Here, we answer questions two (structure) and three (drivers) from the introduction.

4.1 Numerical variation

Figure 7 presents the turbines' relative performance according to Eq. (6)**.** It shows the median, six levels of percentiles and the fleet's performance, which is zero by definition. A complete dataset for up to 25,700 turbines in available in the online appendix, table 11. Our results confirm that the fleet was no monolithic block. Market values of single turbines, even aggregated on the annual level, could exceed the average by 5 % or more, while market values of other turbines were more than 7 % below average. Hence, in extreme cases, the difference between two turbines could exceed 12 %. Furthermore, 25 % of turbines exceeded the fleet's market value by more than 1 % (2 % of turbines by more than 4 %) on average from 2005 to 2015. During this same period, the lowest 25 % of turbines undercut the fleet's average by 1.6 % (2 % of turbines by ~4 %). Results that are less aggregated (e.g. in monthly resolution) show higher deviations, which is particularly relevant in systems — like in Germany — where turbines can switch monthly between different subsidy schemes (Grothe and Müsgens, 2013). Hence, our results show that assessing individual turbines based on calculations of the fleet's market value can be misleading.

Two additional results are noteworthy: First, the median is negative in nine of the eleven years, meaning that more than 50 % of WECs have negative relative performance. As the fleet's performance is the energy-weighted sum of deviations and sums up to zero, it follows that WECs that perform above the median have higher yields than the median WEC. Thus, the market is made up of relatively few over-performers, which also have higher yields and market values. Second, relative performance fluctuated little in years 2010 and 2011. During both years, wind speeds were relatively low within most German regions (IWR). The resulting low full-load hours (a low ratio of annual yield to rated power) presumably reduced the "self-cannibalization" of WECs, which in turn may have reduced differences in relative performance between WECs.

[26] Gonzalez Aparicio et al. (2016) also observe "mismatches for most of the [European] countries between the total annual production reported and the sum of the hourly reported values", for the year 2015.

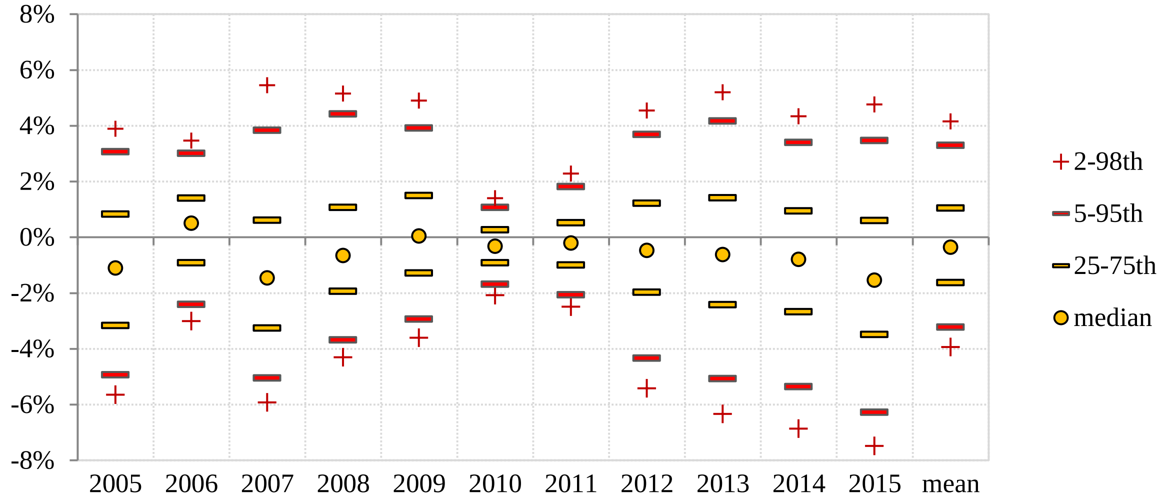


Figure 7: Percentiles of relative performance, years 2005–2015 and mean of all years.

Dividing (absolute) market values as of Eq. (1) and (2) by the base price (which varied between 32 and 66 €/MWh), we get a percentage value, which shows the wind's relative market value in the electricity market (see Figure 8 for percentiles). In contrast to Figure 7, Figure 8 emphasizes the downward trend in wind's relative market value for the fleet (red line) and for individual WECs.

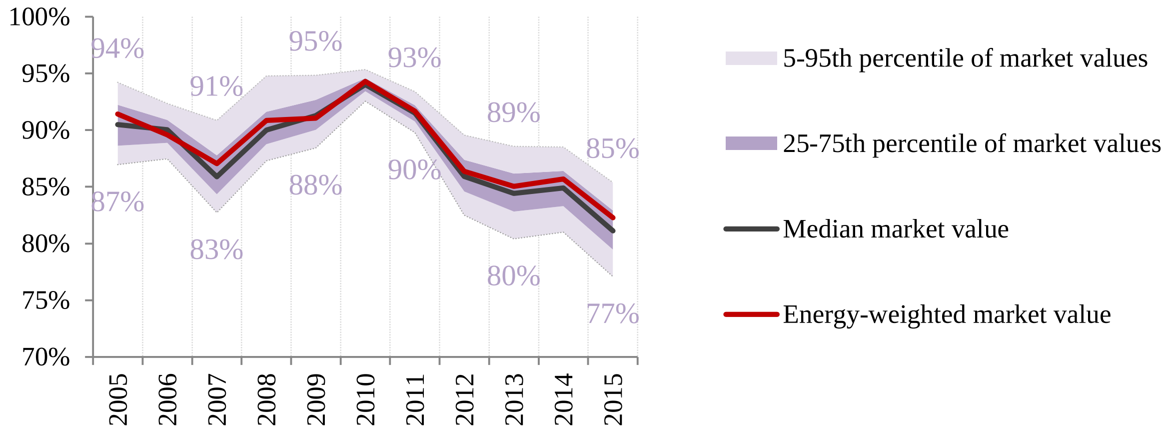


Figure 8: Percentiles of market value in percent of average wholesale prices.

Test Eqation (6) explains a turbine's relative performance based on two core components: normalized standard deviation of both turbine and fleet and the correlation of their respective infeed with wholesale prices. In the following, we show empirical results for both.

Analysing infeed-price correlations (Figure 9), we see a decrease over time for both the fleet and the depicted percentiles, meaning that wind's infeed came increasingly in line with low prices in the day-ahead market. This result can be explained by increasing wind capacity in Germany, which led to higher "self-cannibalization". The fleet's infeed-price correlation was more negative than that of individual WECs. The lower result for the fleet may be explained by its high effect on day-ahead prices compared to single turbines. Remember that a higher correlation (in this case less negative) increases relative performance as it means that high infeed comes in line with high prices.

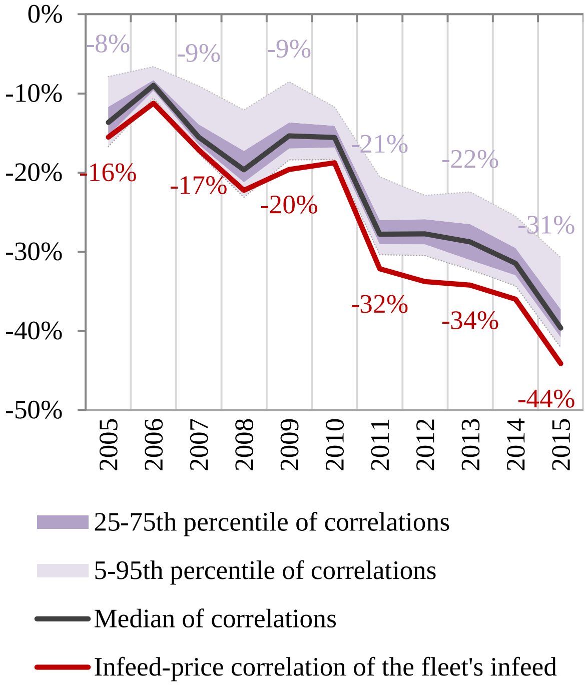


Figure 9: Percentiles of infeed-price correlations.

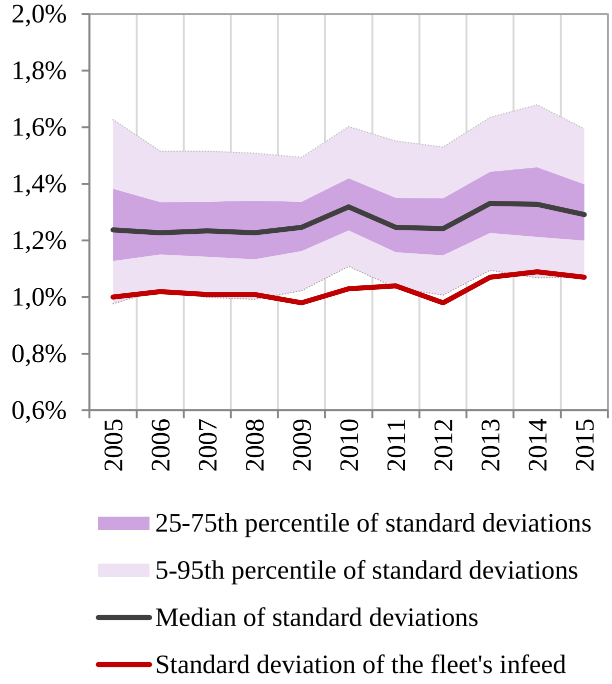


Figure 10: Percentiles of normalized standard deviations.

Concerning normalized standard deviations (Figure 10), we find that both the fleet's as well as the median turbine's normalized standard deviations are fairly constant over time. Furthermore, the figure shows that the fleet's normalized standard deviation is smaller than the standard deviation of at least 95 % of individual turbines. Remember that a low normalized standard deviation increases relative performance as long as infeed-price correlations are negative.

Taking into account Figure 8 – Figure 10, we deduce that the drop of the fleet's market value follows from a decline in correlation and not from an increase in normalized standard deviation.

4.2 Regional variation

Figure 11 illustrates the regional variation of annual relative performance in Germany. Performance in a 10 by 10 km^2 area is calculated as the average of all WECs located in it. Our results show that performance can be clustered in at least four sub-regions within Germany, three of them over- and one under-performing: WECs in coastal regions, the far west and the south performed above average, while those in the centre of Germany performed below average.

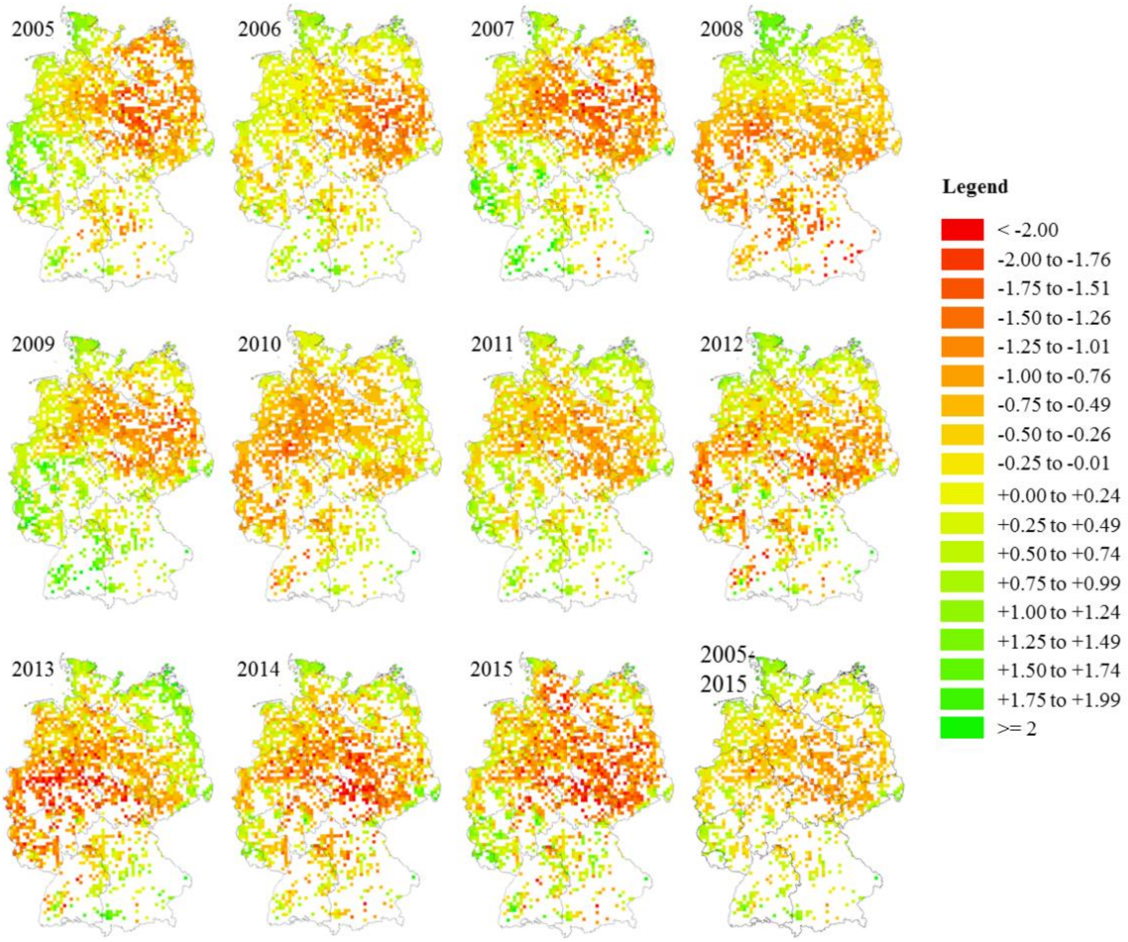


Figure 11: Regional variation of relative performance.

To quantify these regional differences, we defined coastal areas as within 30 kilometres of the coastline, western Germany as within 30 kilometres of the western border and southern Germany as the two southern states of Baden-Wuerttemberg and Bavaria. Central Germany comprised all other WECs.

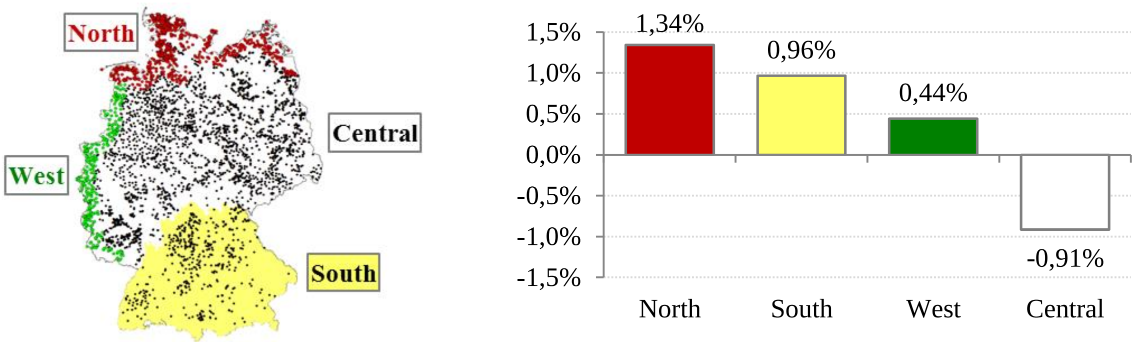


Figure 12: Left: illustration of regional clusters. Right: average relative performance in regional clusters.

Quantitative analysis confirmed that relative performance was above average in the first three sub-regions (see Figure 12). On average in years 2005 to 2015, WECs in the coastal region reached a relative performance of 1.34 %, followed by the south with 0.96 % and the west with 0.44 %. WECs in the centre were at -0.91 %, i.e. below the fleet's market value during the eleven-year timespan.

Analysing the drivers of this development based on Eq. (5), Figure 13 shows the regional differences of the turbines' infeed-price correlations and normalized standard deviations, again referring to the average in years 2005 to 2015. As shown by Eq. (5), high relative performance is reached by the combination of a comparatively high infeed-price correlation and a low normalized standard deviation in a single turbine.

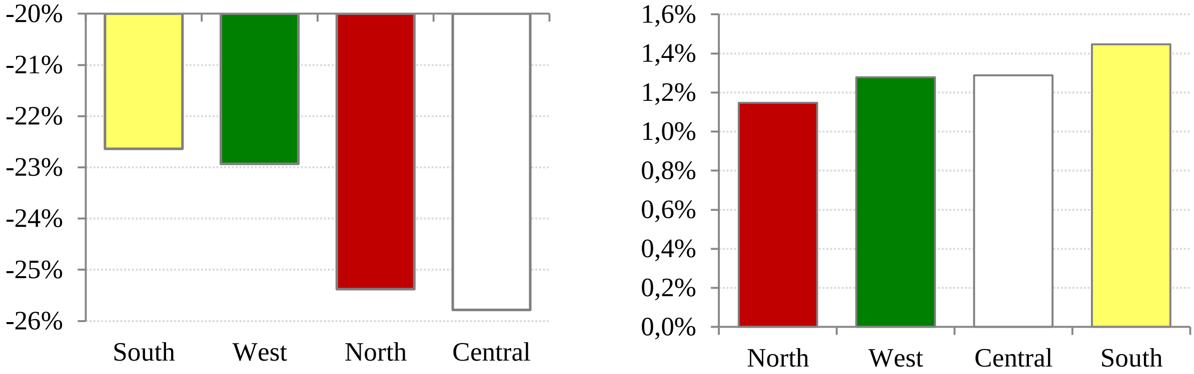


Figure 13: Left: average infeed-price correlation. Right: normalized standard deviation.

Looking at the WECs' regional average infeed-price correlations first, we found that both southern and western WECs had relatively high infeed-price correlations. This most likely means that they earned revenues in times when other WECs were not (yet) producing, and thus wholesale prices were less impacted by wind power. For the south, our findings are in line with Mono and Glasstetter (2012), who found a 64 percent probability that above-average wind speeds in the southwest coincide with below-average wind speeds in the north, whereas this coincidental probability is only 10 % for the centre. For the west, relatively high infeed-price correlations may be explained by the fact that wind in Germany mostly comes from the west. Hence, WECs in western Germany begin producing before other WECs, and thus prices are still relatively high. On the other hand, northern and centrally located WECs feature the lowest infeed-price correlations. We can explain their rank by the fact that the bulk of German wind energy is produced in these regions: nearly a quarter of capacities are located in the north. Furthermore, this region has the highest wind speeds, leading to a strong influence on the total infeed. Though wind speeds are significantly lower in the centre, more than 60 % of capacities are located there. This region thus also strongly influences the overall German infeed. The centre's rank as last may be because high wind speeds in the centre coincide with high speeds in the north (Mono and Glasstetter, 2012), but not vice versa.

Analysing normalized standard deviations, we observed that WECs located in the north have the lowest relative normalized standard deviation, which means that they either profit from steadier wind conditions (enlarging the nominator) or from above average yields (enlarging the denominator), or both. Southern locations, on the contrary, suffer from comparatively high normalized standard deviations, whereas the west and the central region are in between.

Taking both drivers together, as suggested by Eq. (5), we conclude that northern WECs rank first in relative performance (Figure 12) owing to their low normalized standard deviations. The southern WECs rank second mainly due to their atypical infeed behaviour, giving the highest infeed-price correlation. The central region's WECs rank last because they are both highly negatively correlated with wholesale prices and mediocre in terms of normalized standard deviation.

4.3 Turbine design

The last sections have shown that the location of a turbine influences its relative performance. This section analyses how turbine design influences relative performance.

In recent decades, wind energy markets all over the world have seen significant improvements in turbine design (Cheng and Zhu, 2014). Technical development in manufacturing has led to a steady market penetration of turbines with higher hub heights and larger rotor-to-generator ratios. Whereas 20 years ago hub heights of 60 metres were common, today's heights reach up to 120 metres on coastal sites and 140 metres inland. Since wind speeds accelerate at higher heights, the infeed and capacity factor increase with the hub height of the turbine.

Further, increased rotor-to-generator ratios have led to power curves with a steeper increase of output at lower wind speeds. Hence, these turbines produce more electricity at lower wind speeds (May, 2017). This technological progress (in combination with associated reductions in investment costs) is referred to as a "silent revolution" (Chabot, 2013, 2015; Hirth and Müller, 2016). The availability of such "low wind speed turbines" has given additional choices for investors and enabled sites with low wind speeds to be developed economically.[27]

While it is clear that yields increase as heights and rotor sizes increase, the question of how modern turbine design affects performance is a relatively new research topic. Hirth and Müller (2016) as well as Johannson et al. (2017), for a future green-field scenario, find that modern turbine design can reduce reduction of market values following increased wind penetration. We extend the analysis in the following and assess the empirical influence of modern turbine design based on our data of heterogeneous turbines in Germany. We use wind speed and wholesale price data from 2014 and 2015, analysing the performance of turbines built between 1994 and 2013. Unlike aforementioned studies, we also focus on the drivers.

Starting with Figure 14 — which shows the median relative performance in years 2014 and 2015, according to the turbines' installation year—we found that new turbines perform better than old ones. Except for the two oldest generations[28], there is a distinct relation: the newer the turbine, the higher its relative performance. Only turbines built from 2010 on have positive median performance. For WECs installed between 1996 and 2003, 75 % or more are below the fleet's average.

[27] Wiser and Bolinger (2015) report that turbines in the USA originally designed for lower-quality wind sites are more and more in use at sites with high wind speeds, too.

[28] This may be explained by these turbines being located at pioneering and thus excellent wind sites.

Again, we use Eq. (6) to gain additional insight into the reasons for the increased relative performance of newer turbines. Figure 15 shows the median of the WEC generations' infeed-price correlations (brown dots) and normalized standard deviations (blue dots). Especially normalized standard deviations showed an improving trend over time (again, except in the two oldest generations).

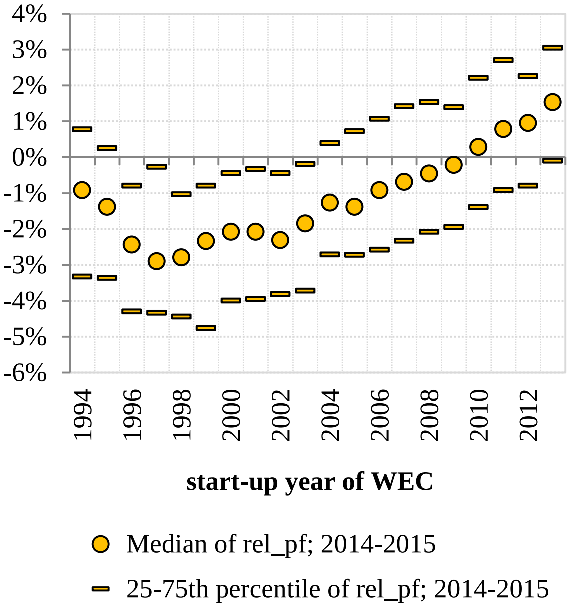


Figure 14: Relative performance by WEC generations.

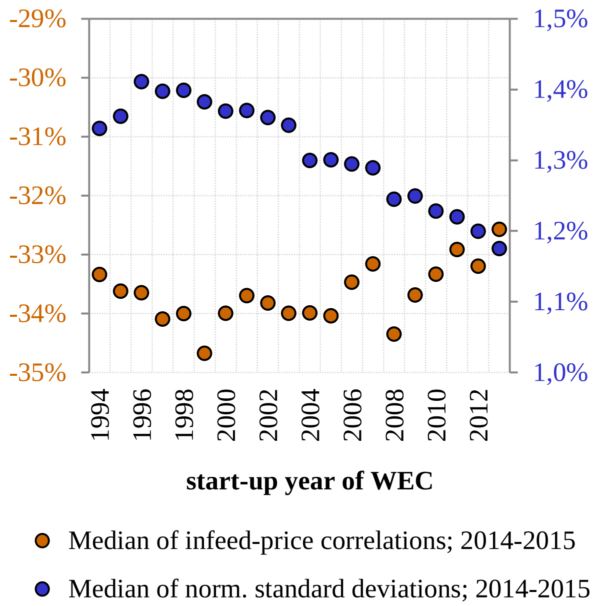


Figure 15: Drivers of performance by WEC generations.

5 CONCLUSION

This paper presents a methodology to estimate missing data on technical parameters of wind turbines, in particular power curves and hub heights. This is achieved by adapting NREL's mass-cost model to determine investment costs and choosing the best fit for an unknown turbine based on minimum LCOE. This general approach, which can be used to complete information for unspecified turbines in different systems, was applied to Germany to complete a dataset of ~25,700 turbines. About two-thirds of these could be determined by desktop research, while the remaining third was determined based on our modelling approach.

With the dataset on WECs completed, we calculated hourly infeed for each individual WEC for the period of 2005–2015. We could then analyse the relative performance of all individual WECs. We found that, even aggregated on an annual level, differences in relative performance between individual WECs varied by 10 percentage points or more. These results contribute to an evaluation of the individual WECs' value under direct marketing, but also to investment decisions and policy planning of optimal wind capacity additions. Furthermore, we found that declining infeed-price correlations for the whole fleet of WECs, most likely due to increased self-cannibalization from increased wind capacity, caused a decline in performance for the fleet of WECs while the fleet's normalized standard deviations remained relatively constant over time.

Furthermore, we analysed regional differences and found that turbines in the centre of Germany show, on average, lower market values than turbines in the north, far west and south. Further analysis revealed that this can be explained by different factors: turbines in the west and south profit from favourable infeed-price correlations, and turbines in the north have favourable normalized standard deviations. Turbines in the centre have both below-average infeed-price correlations as well as unfavourable normalized standard deviations.

Last but not least, our results show that more modern WECs have better relative performance: the more recently a WEC was built, the better — on average — its relative performance. We attribute this mostly to better normalized standard deviations for modern wind turbines, which supports the hypothesis that modern WECs profit from their higher hub heights and increased rotor-to-generator ratios—both of which improve normalized standard deviation.

It seems likely that wind power generation in Germany and other markets will continue to grow. As a consequence, market values for the fleet are likely to decrease further. From a technical standpoint, the stock of wind turbines will be even more heterogeneous as modern turbines will enter the market while (at least some) older ones will still be in operation. As more and more advanced turbines enter the market, we expect relative performance of older turbine generations to drop further. At the same time, the comparative advantage of newly built turbines over the fleet's market value will probably decrease since beating the fleet will become more ambitious.

As a consequence, we believe the type of analysis presented in this paper will be become increasingly important. We suggest further research into how both regional distribution and the speed of technical development change the diverse picture of wind turbines' market values.

We leave the adaption of this paper's methodology to systems outside of Germany for further research. It might also be interesting to study how a massive expansion of offshore wind capacities – in Germany as well as in other systems - will affect relative performance onshore.

ACKNOWLEDGEMENTS

We are thankful for the quality-enhancing discussions with Valerie Blankenhorn and Konstantin Badelt on the geo-works related to this article. Further, we would like to thank Heinz-Theo Mengelkamp of anemos GmbH for providing the wind speed data used in this article.

APPENDIX A: PROOF OF PROPOSITION

Covariance, cov, and correlation, cor, are defined as presented in Eq. (A.1) and (A.2):

$$cov\ (yield, p) = E(yield \cdot p) - E(yield) \cdot E(p), \tag{A.1}$$

$$cor\ (yield, p) = \frac{cov\ (yield, p)}{\sigma_{yield} \cdot \sigma_p} \Rightarrow cov\ (yield, p) = cor(yield, p) \cdot \sigma_{yield} \cdot \sigma_p \tag{A.2}$$

with σ being standard deviation. Inserting Eq. (A.1) and (A.2) into Eq. (4) leads to:

$$\begin{aligned} abs\_pf_{j,y} &= \left(\frac{E(yield_{j,y,h}) \cdot E(p_{y,h})}{E(yield_{j,y,h})} + \frac{cov(yield_{j,y,h} \cdot p_{y,h})}{E(yield_{j,y,h})}\right) \\ &- \left(\frac{E(yield^{fleet}_{y,h}) \cdot E(p_{y,h})}{E\left(yield^{fleet}_{y,h}\right)} + \frac{cov(yield^{fleet}_{y,h} \cdot p_{y,h})}{E\left(yield^{fleet}_{y,h}\right)}\right) \\ &= \left(E(p_{y,h}) + cor(yield_{j,y,h}, p_{y,h}) \cdot \frac{\sigma(yield_{j,y,h})}{E(yield_{j,y,h})} \cdot \sigma(p_{y,h})\right) \\ &- \left(E(p_{y,h}) + cor(yield^{fleet}_{y,h} \cdot p_{y,h}) \cdot \frac{\sigma(yield^{fleet}_{y,h})}{E(yield_{j,y,h})} \cdot \sigma(p_{y,h})\right) \\ &= \sigma(p_{y,h}) \cdot \left(cor(yield_{j,y,h}, p_{y,h}) \cdot \frac{\sigma(yield_{j,y,h})}{E\left(yield_{j,y,h}\right)}\right. \\ &\left. - cor(yield^{fleet}_{y,h}, p_{y,h}) \cdot \frac{\sigma(yield^{fleet}_{y,h})}{E\left(yield^{fleet}_{y,h}\right)}\right) \end{aligned} \tag{A.3}$$

□

APPENDIX B

Hourly wind speed series were corrected for differing monthly air densities ρ_m, according to:

$$v_{y,h,loc}^{z,corr} = v_{y,h,loc}^{z}(\rho_m/\rho_0)^{1/3}, \tag{B.1}$$

whereas $v_{y,h,loc}^{z}$ is the wind speed series at height z, ρ_0 air density at standard atmospheric conditions, and $v_{y,h,loc}^{z,corr}$, the air density corrected wind speed series at height z.

Eq. (B.1) builds on the procedure described in IEC[29] (2013). Correction is necessary as power curves describe the relation of transforming speeds to output at standard atmospheric pressure, see Eq. (7), but pressure and thus air density vary with height and temperature. ρ_m was derived according to:

$$\rho_m = p_0\left(1+\frac{\alpha \cdot h}{T_0}\right)^{-\frac{g}{R_S * \alpha}} \Big/ R_s \cdot \left(T_{ref} + \alpha\left(h - h_{ref}\right)\right), \tag{B.2}$$

whereas p_0 is standard atmospheric pressure (1013,25 hPa), $\boldsymbol{\alpha}$ temperature gradient (−0,0065 K/m), T_0 temperature at sea level (288,15 K), g gravitational acceleration (9.80665 m/s^2), R_s universal gas constant for air (287 J/(kg K)), T_{ref} temperature at the closest weather station at height h_{ref} and h, the sum of the required hub height and the location's specific height above sea level. For our case, monthly temperature averages of 338 weather stations operated by the German Weather Service served as input. Locational heights (online appendix, table 10) were identified with ArcGIS.

Consequently, yearly Weibull shape and scale parameters were calculated with $v_{y,h,loc}^{80,corr}$ and $v_{y,h,loc}^{140,corr}$.

[29] In its original form, ten-minute data on wind speeds and air densities should be used. Eq (B.1) holds true for WEC with active power control (pitch-, not stall-regulated). The vast majority of turbines were active controlled. Stall-regulation is a concept of very old WEC and no longer used.

APPENDIX C

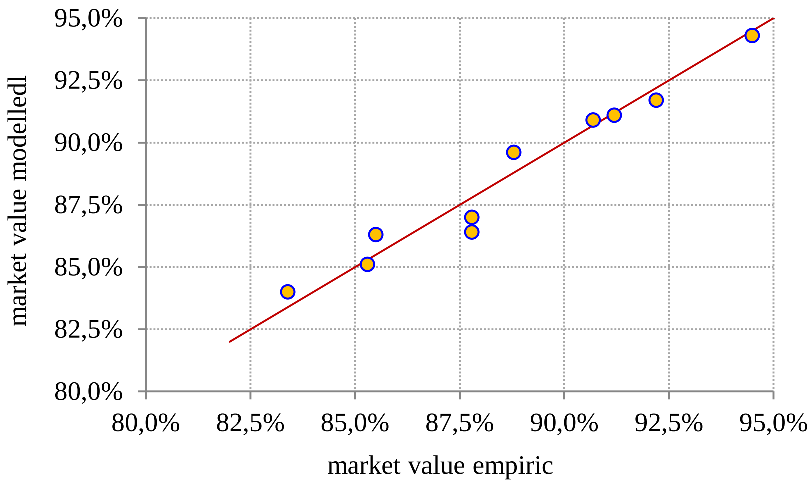
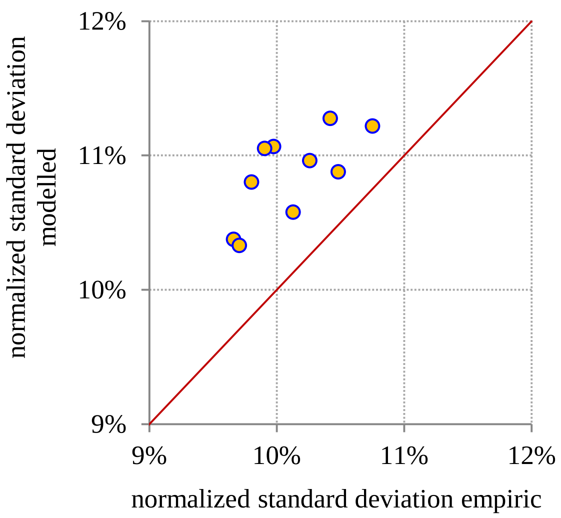


Fig. C1: Empirical (x-axis) vs modelled (y-axis) market value of the fleet [% of base price].



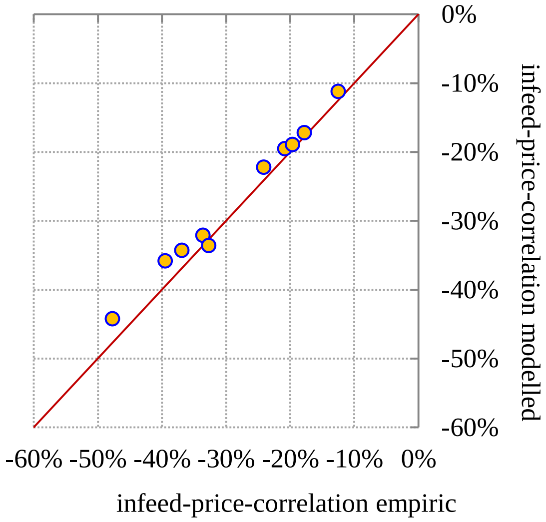


Fig. C2: Empirical (x-axis) vs modelled (y-axis) normalized standard deviation of the fleet.

Fig. C3: Empirical (x-axis) vs modelled (y-axis) correlation of infeed and price.

APPENDIX D

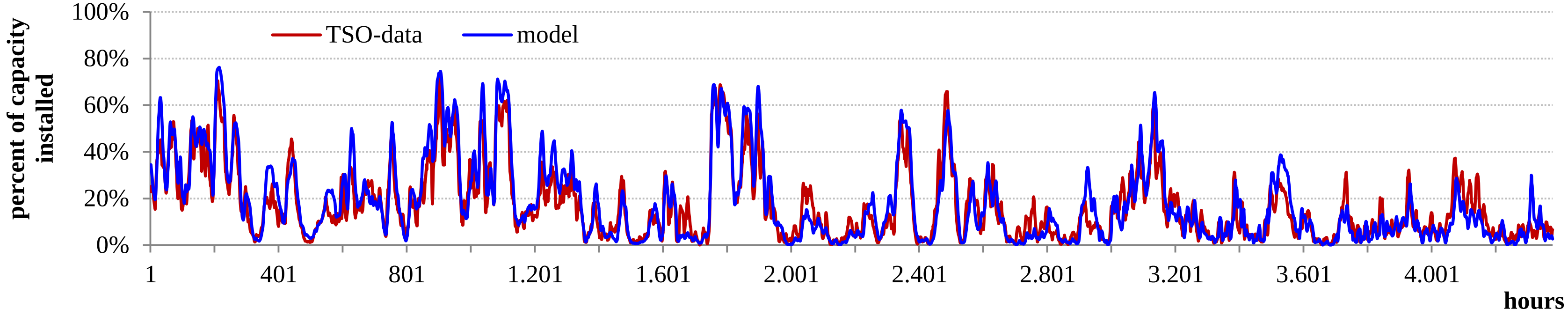
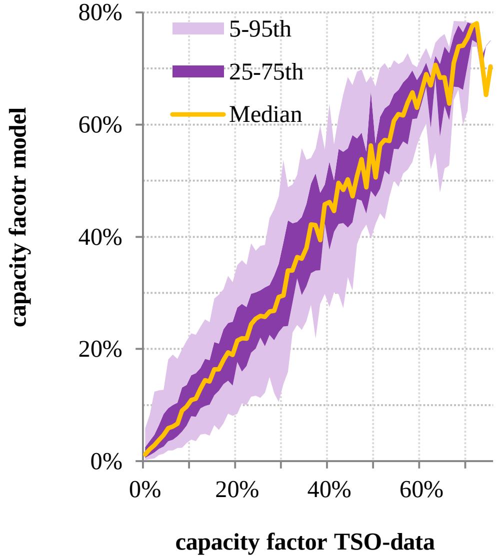
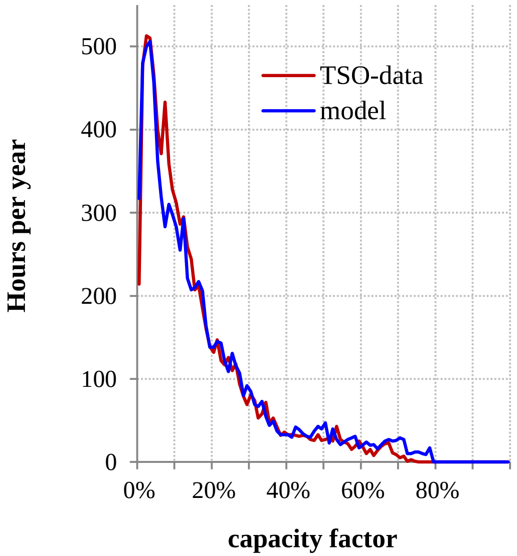


Fig. D1: Aggregated hourly infeed of the fleet: TSO data vs model [% of capacity installed], first half of year 2014.





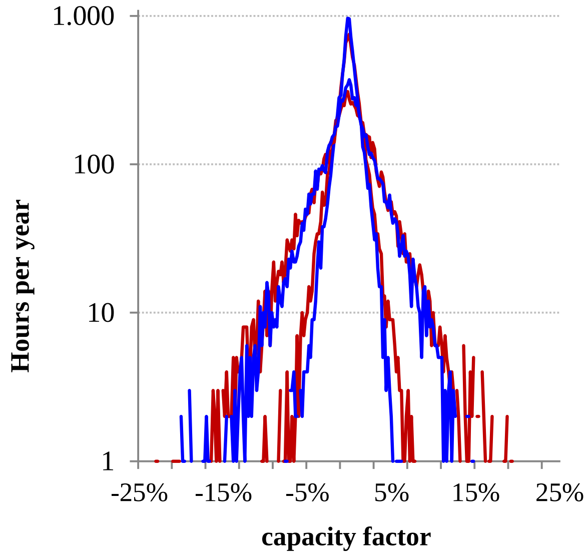


Fig. D2: Correlation of the fleet's infeed: TSO data (x-axis) vs model (y-axis), whole year 2014.

Fig. D3: Distribution of hourly infeed of the fleet in bins of capacity factors

Fig. D4: Histogram of the rate of change of capacity factors by the fleet's infeed: TSO data vs model, whole

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