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On the Development of Wind Market Values and the Influence of Technology and Weather: a German Case Study

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Abstract
Research into renewable energy market values is a popular field in energy economics. However, most contributions abstract from market values being highly individual and mostly study (nationwide) averages, usually based on a single or a "normal" wind year, if specifying wind conditions at all, and a limited set of technologies. However, market values of renewable energy resources are not monolithic but highly diverse. In this article, to shed light on this diversity, we illustrate the historical development of onshore wind's market value in Germany, from 2001 to 2019, for the fleet and all operating wind energy converters. We use highly granular wind speed data and a comprehensive database of wind capacities. Our results show the downward trend, the distributions, and the variance of market values. In this context, we explain why the performance of a single wind energy converter (compared to the fleet's performance) matters in the market premium model. Hereby, we also assess the magnitude of the outperformance of technologically advanced wind turbines as compared to less advanced turbines. In the second part of our research, we analyse the effect of the inter-annual weather variability on wholesale electricity prices, and market values. Our analysis is based on 19 different years of wind speeds, corresponding offshore and solar infeed, and an electricity market model to generate weather-congruent wholesale electricity prices.

Keywords Renewable energy · Wind power · Market value · Market premium model · Direct marketing · Electricity price modelling · Inter-annual variation

JEL-Classification American Economic Association: JEL Codes (aeaweb.org) C61 · Q21 · Q42

Supplementary material: https://github.com/BTU-EnerEcon/Price-effect-of-weather-years

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Zur Entwicklung von Marktwerten für Windkraftanlagen und der Bedeutung von Technologie und Wetter: Fallstudie für Deutschland

Zusammenfassung

Die Forschung zu Markwerten von Erneuerbaren Energien ist ein beliebtes Feld innerhalb der Energieökonomik. Die meisten Beiträgen lassen jedoch unbeleuchtet, dass Marktwerte sehr individuell sind, und analysieren zumeist (landesweite) Durchschnitte, die für gewöhnlich auf einem einzigen oder auf einem „normalen" Windjahr beruhen, sowie einer begrenzten Auswahl an Technologien. Um die Unterschiedlichkeit von Markwerten zu beleuchten, illustrieren wir im ersten Teil dieses Beitrags die historische Entwicklung der Markwerte von Windenergie an Land in Deutschland für die Jahre 2001 bis 2019, sowohl für die Flotte als auch für jede betriebene Windkraftanlage. Hierzu verwenden wir hoch aufgelöste Windgeschwindigkeitsdaten und eine umfangreiche Datenbank zu installierten Windanlagen. Unsere Ergebnisse zeigen den rückläufigen Trend, die Verteilungen sowie die Schwankung der Markwerte. In diesem Zusammenhang erklären wir, weshalb die sogenannte Performance einer einzigen Windkraftanlage im Vergleich zur Flotte im Marktprämienmodell von Bedeutung ist. Dabei zeigen wir auch, wie sehr moderne Windkraftanlagen weniger modernen Anlagen überlegen sind. Im zweiten Teil unseres Beitrags analysieren wir, welchen Effekt die Variabilität des Wetters auf Stromgroßhandelspreise und Marktwerte hat. Hierbei arbeiten wir mit 19 Jahren unterschiedlicher Windgeschwindigkeiten sowie damit korrespondieren Einspeisungen für Windenergie auf See sowie Photovoltaik, und einem Strommarktmodell, um auf das Wetter abgestimmte Großhandelspreise zu simulieren.

1 Introduction

The Paris Agreement has accelerated the quest for carbon neutrality in many countries. Consequently, the expansion of renewable energy sources (RES) is, together with nuclear power, many countries' answer to shaping future electricity production or at least one integral part of the transformation towards carbon neutrality.[1] One example is the European Commission's (2021) latest legislative package, called "Fit for 55", whereupon Member states shall achieve a 55% reduction of the net greenhouse gas emissions by 2030. To help meet this goal, the renewable energy directive increases the targeted share of renewable energy to 40% of total energy consumption by the end of 2030 (formerly 32%).

Building these required RES assets calls for huge investments from the private and state sector: ~4 trillion USD p. a. in clean energy projects by 2030 (IEA 2021). From an investor's point of view, assessing the cost and the revenue side of an asset is generally a crucial prerequisite to calculating a desired rate of return. In liberalised electricity markets, the revenue side of a power-producing RES depends on the market value of its infeed during its lifetime. However, this infeed fluctuates because RES do not constantly produce at their nameplate capacity but contingently on available wind or solar radiation, and infeed comes at a very low marginal cost. Therefore, in the short and medium run, wholesale electricity prices decrease with increasing RES infeed, widely studied as the merit order effect (Sensfuß et al. 2008; Cludius et al. 2014; Dillig et al. 2016; Kolb et al. 2020; Antweiler and Müsgens 2021; for the German market, Ortner et al. 2016, Woo et al. 2016; Bell et al. 2017; Halttunen et al. 2020; for international markets), and cannibalise their own "captured price" (market value) in the wholesale market.[2]

Along with its growing economic and political relevance, research into the market values and cannibalisation of renewables has become a popular field of research. Today, there is a comprehensive amount of research on the drivers affecting market values. To name probably one of the most influential and most studied drivers first: it has been shown that renewable market values drop with an increase of RES penetration level (Mills and Wiser 2012; Hirth 2013; López Prol et al. 2020), both empirically and for future scenarios based on computer models. Using computer models, many researchers study further parameters influencing market values such as gas and carbon prices, the power market's merit order, flexibility options, regional diversification, and policy design (Obersteiner and Saguan 2011; Hirth 2015; Winkler et al. 2016; Bistline 2017; May 2017; Blume-Werry et al. 2021; López Prol and Schill 2021), or focus on the parameters mitigating the reduction (Mills and Wiser 2015; Hirth and Müller 2016; Brown and Reichenberg 2021). Several authors have also shown that the market value of RES can be expressed as a function of the covariance between its fluctuating infeed and the market's electricity prices (Lamont 2008; Jägemann 2015; Genoese et al. 2016; Engelhorn and Müsgens 2018).

In any case, it is crucial to understand that there is no unitary market value, even though most research only stud-

[1] Because wind and solar power dominate governmental strategies for an RES expansion, we include only wind and solar in the term "RES".

[2] Antweiler and Müsgens (2021) show that in the long run, the market reduces overcapacity, and the effect disappears.

ies the average market value of an RES technology. In fact, each renewable asset realises its truly individual value, which can significantly deviate from the average (Engelhorn and Müsgens 2018). The reason for this is the nature of a renewable asset's infeed, which depends on location and technology (Klie and Madlener 2020; Eising et al. 2020). Location matters because wind speeds and solar radiation are different at different places at the same time for meteorological reasons (Grothe and Müsgens 2013; Schmidt et al. 2013; Becker and Thrän 2018; Pérez Odeh and Watts 2019). Technology matters because wind and solar inherit different infeed patterns due to their different technical design and energy transformation. Even within a technology like onshore wind, the design of an onshore wind energy converter (WEC), that is, the configuration and interplay of rated power, hub height and rotor, leads to differences in the infeed—and thus different market values at identical wind speeds (Hirth and Müller 2016; Dalla Riva et al. 2017; Johansson et al. 2017).[3] Hence, location and technology are important drivers of market values. In a greenfield simulation with two monolithic fleets in terms of WEC configuration, Hirth and Müller (2016) find that technically advanced WECs, that is WECs with high hub heights and very large rotors, systematically reach higher market values than non-advanced WECs—however, the difference owing to the status of technology has not been assessed for an existing market with a aplenty set of WECs and numerous locations, yet.[4]

Further, most studies on market values usually assume a normal wind year (with average wind resource), or at least do not vary the weather conditions. Yet, wind years can largely differ (Pryor et al. 2006, 2018; Wan 2012) and thus affect wind's generation, change infeed-price correlations, impact the merit order, and finally result in different market values (Ortner et al. 2016; Dalla Riva et al. 2017).

Therefore, our paper's contribution is to model and market values at the turbine level: historically and for changing weather patterns, in a real market. Within RES, we concentrate on onshore wind assets only, for the example of Germany. Onshore wind is one of the world's promising and important RES, and Germany is Europe's largest onshore wind market.[5] According to the German net development plan (Netzentwicklungsplan 2020), capacity is expected to grow from 53 to 87 gigawatts between 2019 and 2035. Further, we differentiate our results between WEC designs to quantify its today's influence on market values.

In our German case, a thorough understanding of the wind's market value is important for the following reason. Since 2012, wind operators have been obliged to sell a WEC's infeed in the wholesale electricity market to benefit from support payments (known as "direct marketing"). Therefore, wind operators and energy traders sign contracts to market the wind's infeed at a certain price for each unit traded. This way, there are two potential income streams for wind assets: revenues from governmental support and revenues from trading on the wholesale market. Governmental support is organised in a technology-specific benchmark regime and connects to the wholesale market: each month, the average market value of all onshore wind assets in Germany is documented[6]; building on that, the operator receives, for each unit of infeed, the difference between this average market value and the WEC's tariff as governmental support.[7] At the same time, the wind asset receives its individual market value in the wholesale market, which is set at a contracted price between the operator and the trader. Therefore, a wind asset receives a premium to its tariff if its individual infeed has a higher market value than the average of "competing" onshore wind assets but suffers a discount if its market value is below average.

In a nutshell, performance is the price difference against the average market value, and performance affects revenues. The system is called a market premium model, and the pros and cons are debated in the literature (Gawel and Purkus 2013; Klobasa et al. 2013; Purkus et al. 2015).

In this system, market participants are often interested in several recurring questions. For example: how did (or will) market values develop? Did (or will) a certain asset's infeed outperform the average? How large of an effect is out- and underperformance and how does it affect revenues? Which types of WEC perform well and where? What is the influence of changing weather patterns to market values?

Note that the trend towards power purchase agreements (cf. Kobus et al. 2021)—a way of financing without governmental support—will not outdate these questions. The topic is renewable asset valuation, and assessing the true value is key in any system that renumerates the marginal value of production (cf. Jones and Rothenberg 2019).[8]

[3] Also shaping a WEC's power curve: blade design, gearing, cut-in and cut-off speed.

[4] For the German market in years 2014 and 2015, Engelhorn and Müsgens (2018) showed that younger WECs reached higher market values than older ones.

[5] Onshore capacity 2019: 53 gigawatts; generation: 102 terawatt hours; share in RES generation: 42% (BMWi 2021).

[6] By transmission system operators imposed by the Renewable Energy Act (EEG 2021).

[7] Since 2017, the tariff is determined in a tender; before 2017, it was set by law. As this change does not interfere with the benchmark regime described and our analysis, we do not go into further detail about the German support mechanisms.

[8] The market value in power purchase agreements is even more important because the full risks of wholesale price turns need to be assessed—a risk the operator is shielded against in the market premium model.

With this chapter, we want to add to the understanding of market values. Our main contribution lies in the visualisation and the quantification of the magnitude of spreads in market values and performances, by investigating historical and fictitious realisations at the individual WEC-level for the German market for up to ~31,000 WECs. We do this from two perspectives:

- First, we present how individual market values and performances developed from 2001 until 2019. For years 2016 until 2019, we quantify and map the outperformance of technologically advanced WECs, and study performance stability.
- Second, we analyse the weather's influence on the market of 2019: how large of an effect can the inter-annual variability of RES infeed have on wholesale prices, market values and performances? Which locations are affected the most? We base our analysis on 19 years of reanalysis wind speed data (to model onshore infeed), and 19 years of hourly offshore and solar usage factors (to model offshore and solar infeed).

These two perspectives are taken up separately and referred to below as Part I and Part II. With it, we close a gap of research concerning the quantification of differences between advanced and non-advanced WECs in a large, existing market, and concerning the influence of an "exogenous driver"—the weather—of market values. Mapping our results, we uncover spatial dependencies within this complex matter. Our results are relevant for policy makers and researchers interested in wind energy's market value and design. Also, for operators and trading companies offering direct marketing services in the German wind market. Our illustration of the influence of weather patterns on wholesale prices and market values might be noteworthy for energy market modellers concerned with renewable asset valuation and risk simulations.

The remainder of this chapter is structured as follows: Section 2 presents the methodology and the data used. Section 3 shows the results of Parts I and II of the research. Conclusions are drawn in Section 4.

2 Methodology and Data

This section explains the basic definitions and the data to calculate our results.

To analyse historical developments in Part I, we link historical WEC-capacities with historical wind speed data of the respective year to model the historical infeed bottom-up and thereafter valuate it with historical wholesale electricity prices—in line with our definitions in Section 2.1.1.

To analyse the weather's influence in Part II, we link all WEC-capacities operating in 2019 with wind speed data from 2001 to 2019 to model nineteen years of infeed. This infeed serves as input for an electricity market model that runs with all power plants and commodity prices of 2019 to generate fictitious wholesale electricity prices. By keeping the market situation constant, we control for other effects impacting market values (as, for example, storage capacities, demand, and commodity prices) and thus carve out the weather effect. Then, we valuate this infeed with gained prices to measure the variability of our results due to weather changes, as is further explained in Section 2.1.2.

2.1 Basic Definitions

We first explain the definitions needed for Part I in the context of market values' role for traders and wind farm operators in Germany. Part II follows.

2.1.1 Research Part I

We define a WEC's market value as the energy-weighted average price of its infeed, being expressed as the sum of its hourly yield ($\text{yield}_{j,y,h}$ in MWh), multiplied by the hourly wholesale price ($p_{y,h}$ in €/MWh), divided by its annual yield (in MWh):

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

Similarly, the fleet's market value is defined as:

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

In Part I, index j,y identifies a distinct, unique WEC j that operates in the same *legal year* y, ranging from 2001 to 2019. Hence, summing over j for a each y gives the WEC-cohort of the respective year.

Market values are essential because operators are obliged by law to sell a WEC's infeed at the wholesale market to receive payments from the renewable support scheme.[9] Consequently, operators sign contracts with traders, usually for one year. Hence, an operator's revenue (OR in €) for a WEC j in a year y is composed of the revenue coming from the support scheme ($OR^{support}$) and the market (OR^{market}):

$$OR_{j,y} = OR_{j,y}^{\text{support}} + OR_{j,y}^{\text{market}} \tag{3}$$

[9] The motivation is to improve the integration into the electricity system.

$OR^{support}$ is determined by law (EEG 2021). Accordingly, it is the tariff diminished by the market value of all WECs in the market[10], which we simply call the fleet's market value (MV^{fleet} in €/MWh):

$$OR_{j,y}^{\text{support}} = \left(T_j - MV_y^{\text{fleet}}\right) \times \text{yield}_{j,y}, \quad \text{for } T_j \geq MV_y^{\text{fleet}} \tag{4}$$

Whereas the tariff is determined in a tender (before commercial commissioning) and fixed for 20 years (plus the first year), the fleet's market value is determined and published monthly on behalf of and according to rules set by the regulator.[11] At this point, we note that we show annual values and henceforth apply an approach of annual calculation, which does not derogate our results.[12]

The revenue coming from the market is settled in private contracts between the operator demanding and the trader offering the service; it can be expressed as the WEC's contracted market value ($MV^{contracted}$ in €/MWh) minus a service fee (F in €/MWh) for handling, multiplied by its yield. We do not account for the fee, because it is undisclosed information, making all our calculations gross values:

$$OR_{j,y}^{\text{market}} = \left(MV_{j,y}^{\text{contracted}} - F\right) \times \text{yield}_{j,y} \tag{5}$$

In a usual form of contract, the trader offers to buy the WEC's infeed from the operator at the price of the fleet's market value plus a premium or a discount for a one-year term. We refer to premium and discount as a WEC's performance (pf in €/MWh). Whereas the price level of the fleet's market value is not fixed but indexed to the official publication, the performance is fixed for the term of the contract:

$$MV_{j,y}^{\text{contracted}} = MV_y^{\text{fleet}}(\text{indexed}) + pf_{j,y}(\text{fixed}) \tag{6}$$

Performance is assessed by the difference in market values between the WEC and the fleet. It marks the comparative advantage of a WEC. and presents a premium if the trader expects the WEC to exceed the fleet's market value (outperformance) and a discount in the case it is expected to fall below the fleet's value (underperformance). It is in €/MWh and presents a price risk to the trader. Hence, the trader estimates the WEC's performance prior to the deal. In our research, we are interested in WECs historical realisations (not in the quality of traders' estimators) and henceforth model performance according to Eq. 7, interpreted as an infeed's historical realisation at the wholesale market:

$$pf_{j,y} = MV_{j,y} - MV_y^{\text{fleet}} \tag{7}$$

To give a feeling of the absolute revenues coming from premiums and discounts only, we multiply performance with yield, and get the competitive revenue of an operator ($OR^{competitive}$ in €):

$$OR_{j,y}^{\text{competitive}} = pf_{j,y} \times \text{yield}_{j,y} \tag{8}$$

Inserting Eq. 4 to (7) into Eq. 3 leads to the final revenue equations for an operator of a WEC in the German market premium model:[13]

$$OR_{j,y} = \left(T_j + pf_{j,y}\right) \times \text{yield}_{j,y}, \quad \text{for } T_j \geq MV_y^{\text{fleet}}$$
$$OR_{j,y} = \left(MV_y^{\text{fleet}} + pf_{j,y}\right) \times \text{yield}_{j,y}, \quad \text{for } T_j < MV_y^{\text{fleet}}$$

Summarising Eq. 9 for the first case: an operator receives the tariff-level (times yield) if the WEC's market value equals the fleet's value (corresponding to a performance of zero). In case of a higher (lower) market value than the fleet, the revenue for the operator is higher (lower) than the tariff by the level of performance. Summarising Eq. 9 for the second case: an operator receives the contracted market value (times yield).[14] In both cases, a general volume risk is untouched: a WEC's yield remains insecure for the operator and the trader.

We use Eq. 1, (2), (7) and (8) for our quantifications for Part I of the research. We group our results according to WEC classes to reveal the impact of WEC design. We measure stability by calculating the year-on-year changes. Section 2.2 explains the origin of yields and prices to be used in the equations. The grouping and its rationale are explained in Section 2.2.2.

2.1.2 Research Part II

The weather is a driver of market values in multiple ways. It directly affects solar radiation and wind speeds, and thus renewables infeed-patterns—in terms of hourly structure and overall generation, with the latter being often accounted for "penetration rate" or "market share". In turn, the infeed-pattern affects the merit order in the power market, and thus

[10] All operating WECs are included, irrespective of being eligible for support payments or not.

[11] Published on a website hosted by the transmission system operators (Netztransparenz 2021).

[12] If total revenues were calculated, this could make a difference, depending on the constellation of the tariff and the fleet's market value (cf. Equation 23 and Anatolitis and Klobasa 2019). Yet, we just change the timely resolution and present market values, as it is usually done (to account for seasonalities, cf. Dalla Riva et al. 2017), and for conveniance (to easily compare 19 years). Besides, the fleet's value will be determined annually for new WECs from 2023 onwards (EEG 2021).

[13] Service fee F omitted.

[14] This second case did hardly occur in our observation period.

hourly prices. Even though different weather-years may not differ much in market share, the difference in generation might be significant at regional levels, and the correlation between infeed and electricity prices will be changed.

The fact that the weather cannot be changed, and is hardly predictable in the long term, may be why this (exogenous) driver of market values is usually not investigated much. However, this may be worthwhile because statements on market values and performances could be deterred if they were highly dependent on the weather. It may also be interesting for pricing in direct marketing to investigate, whether locations and technology are affected alike, and how good of a proxy last year's market value can be.

To analyse the weather's influence, in Part II, index j identifies a distinct WEC that is part of the 2019 fleet. Market values and performances are calculated as already presented, for weather-year y, ranging from 2001 to 2019. This means the wind capacities are constant, but the wind speeds change. As is further explained in Section 2.2.4, the wholesale prices inserted in Eq. 1 and (2) are different from research in Part I in that they are "congruent" to the weather year (solar and offshore infeed also adapted) and based on market conditions of 2019. This way, we receive 19 different values for each German WEC operating in 2019.[15] Mapping the results is the base for our discussion.

2.2 Data

As shown in Eq. 1 and (2), calculating market values requires hourly electricity prices and hourly yields of wind capacities. Subsequently, we explain the origin of the data and how we group and process it.

2.2.1 Wind Speeds and Wind Market Data

Because there is no data set on the hourly yield of all WECs in the market between 2001 and 2019, we need to model it. Yield is determined by a WEC's power curve and the wind speed at its location and hub height.

Regarding wind speed data, we use commercial reanalysis data from the private company Anemos (Anemos GmbH o.J.). It is originally based on NCEP data but processed (downscaled, remodelled and verified) by the firm for higher accuracy. The data comprises wind speeds at an 80- and 140-metres hub height at a spatial resolution of 5 by 5 kilometres in a 30-minute time step from 2001 to 2019.

For the power curves, locations, and hub heights of wind capacities in the German market, we use the database of Engelhorn and Müsgens (2018), which provides wind market knowledge since the ramp-up of the market, enriched by public data of the regulator (Bundesnetzagentur 2020) and an update on power curves. The combined data set also provides us with the following useful information for each WEC: date of commissioning, rotor diameter, and rated power.

Given this data, we can assess which WEC j was part of the fleet in a certain year y and generate hourly infeed. The modelling is described in Section 2.2.3.

2.2.2 Grouping of WECs

WEC design has seen significant technological progress in terms of hub height, rotors, and rated power over the 19 years of data collection. Altogether, this progress changes a WEC's infeed: taller towers supply the turbine with higher and (usually) more steady wind speeds, leading to a higher and more steady power output; rotor- and power-scaling directly change the slope of a WEC's power curve. Today, there is a huge variety of WECs operating in the German market due to very different wind conditions.

Research indicates that technically advanced WECs reach higher market values than less advanced or so-called "classical" WECs (Hirth and Müller 2016; Johansson et al. 2017; Dalla Riva et al. 2017; Engelhorn and Müsgens 2018; Klie and Madlener 2020). What is advanced? In the literature, advanced WECs usually inherit two features: (very) tall towers in combination with low specific ratings, which is the ratio of rated power (in watt) and the rotor's swept area (in square metre). A lower rating is commonly achieved by significantly increasing the size of the rotor (rotor-scaling) or by a higher growth of the size of the rotor as compared to the growth of rated power (not by decreasing rated power). Both features (and hence the WEC itself) are also referred to as "system-friendly" because this design smoothens a WEC's infeed and thus the residual load in a way that it is less costly to serve (Hirth and Müller 2016). Theory (Hirth and Radebach 2016) and empirics (Engelhorn and Müsgens 2018) suggest that market values profit from less variation of the infeed.

The effect of rotor-scaling, and thus a lower-specific rating, can be seen in Fig. 1: due to rotor growth, the blue

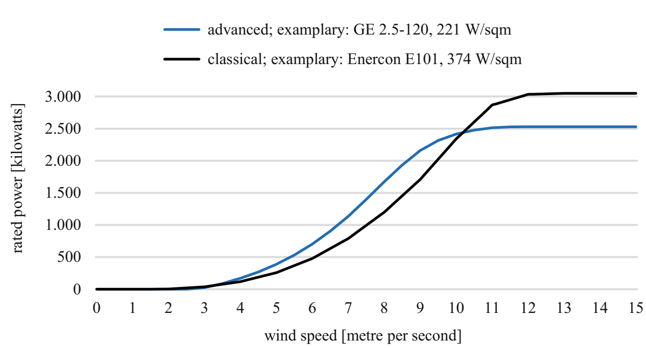


Fig. 1 Power curves of advanced and classical WECs

[15] Different weather conditions lead to different performances as infeed-price-correlations and yields vary with wind speeds.

		Hub height	
	Wind zone 1 and 2 (low wind)	< 120 metres	≥ 120 metres
	Wind zone 3 (medium wind)	< 105 metres	≥ 105 metres
	Wind zone 4 (high wind)	< 95 metres	≥ 95 metres
Specific rating	> 290 W sq m	Classical	Partly advanced
	≤ 290 W sq m	*Not considered*	Advanced

Fig. 2 Grouping of WECs

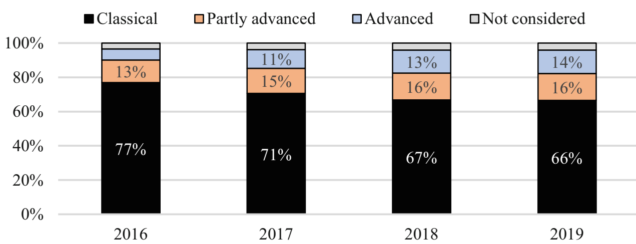


Fig. 3 Share of WEC groups in per cent of WECs installed

lined, advanced WEC has a higher power output at lower wind speeds than the classical one; yet its output, in our example, is curbed at lower power at high wind speeds, due to a smaller generator. Hence, rotor-scaling primarily serves low wind sites: more energy is harvested at low or modest wind speeds, full load hours increase, and production costs fall (if not compensated by higher capital costs).

Therefore, the blue lined type of power curve is mainly to be found in regions with lower winds (large parts of the German midland), and the corresponding WEC usually has a high tower.[16] Because rotor-scaling is technically applicable only in a limited way at high wind sites (due to turbulence and high load), the black lined type of power curve is mainly to be found in regions with high winds (near the German coastline), and usually at lower hub heights as compared to the midlands.

How can we transfer this to our research and quantify the differences in market values owing to turbine design in an existing market? To make the merits of modern turbine design visible and to keep the presentations of our results manageable[17], we build three WEC groups, partitioned by hub heights and specific ratings, as described in Fig. 2. Since there is no generally accepted definition what an "advanced" WEC is, we make assumptions. In terms of specific rating, we split our data by a value of 290 W per square metre, which is roughly the value that divides low from high wind turbines (Fraunhofer IEE 2018). In terms of hub height, we differentiate by wind zones: in low wind

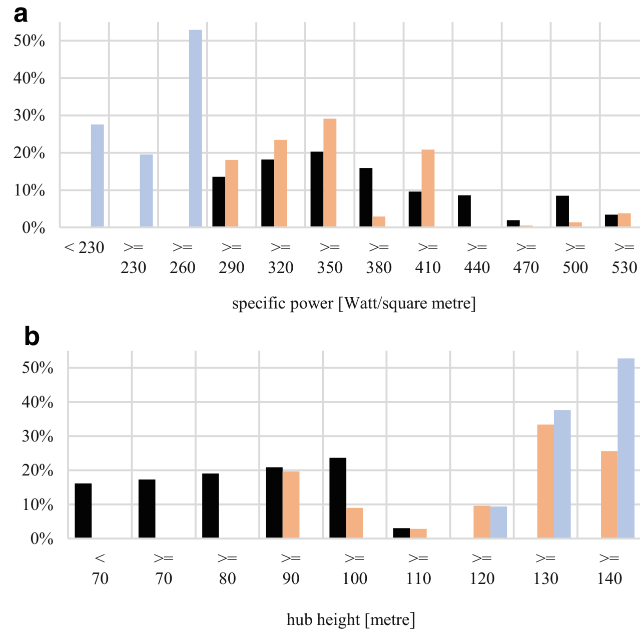


Fig. 4 Distribution of specific power [watts/square metre] (**a**) and hub heights [metres] (**b**) for different WEC groups

zones, hub heights need to be higher than 120 metres to be classified advanced; near the coastline the threshold is 95 m and for "transitional" zone 3 it is 105 m.

Figs. 3 and 4 show how the market is classified according to our definitions. Naturally, the largest share is made up by classical WECs, since advanced design is a more recent trend, roughly starting since 2012. We call WECs featuring high hub heights only "partly advanced". These are WECs, which are installed in any wind zone and have a rather medium specific rating (see Fig. 4). The share of advanced WECs only reaches 14% in 2019, which is large enough, though, to compare against classical WECs. In terms of capacity installed, this corresponds to 19%. There is a small fourth group of WECs (~3%) that features both low hub heights and low specific ratings. This group is not further considered in our analysis, because this configuration is regarded as too special to learn from it.

2.2.3 Wind Speed Processing and Yield Calculation

We follow the methodology described in Engelhorn and Müsgens (2018) for wind speed processing and hourly yield calculation. In brief, we take the following steps.

In the first data processing step, the wind speed data is aggregated to a spatial resolution of 10 by 10 kilometres (giving ~3500 raster nodes for the German landmass) and a temporal resolution of 60 min. Second, for each WEC location, the nearest wind speed node is detected, and new wind speed series are created by inverse distance-weighting, giving ~6000 wind speed time series at 80- and 140-

[16] Rotor-scaling and taller towers have a large share in driving down wind's levelised cost of energy and thus unlocking the potential of low-wind sites.

[17] ~500,000 observations in Part I and ~580,000 in Part II.

metres hub heights. Last, working with these time series at different heights, shear coefficients for any nodes are derived to vertically inter- and extrapolate wind speeds to any WEC's hub height.

To calculate hourly yields for Part I, individual wind speed series for each WEC are first created, using the shear coefficients, thus taking individual hub heights into account. Second, wind speed series are corrected for air density. Third, hourly yields for all WECs in the years 2001 to 2019 are calculated. Fourth, the fleet's annual infeed is compared with statistics; an annual wind speed correction factor[18] is implemented (to account for over- or underestimation, cf. Staffel and Pfenninger 2016) and steps three and four are repeated until the aggregated modelled infeed matches the historical infeed.

To calculate hourly yields for Part II, steps one to three are undertaken, except that we only use capacities of the wind market in 2019 and hence use the correction factor for 2019.[19]

At this point, we have calculated "real" hourly yields for each WEC operating between 01/01/2001 and 31/12/2019 and calculated "fictious" hourly yields of any WEC operating in 2019 for the case of the wind conditions in 2001 through 2019.

2.2.4 Electricity Prices

For Part I, we use the settlement prices of the German EPEX-spot day-ahead auction as historical wholesale electricity prices. This is a proxy as wind is also traded in the intraday market. We calculate market values, performances, and competitive revenues with our modelled hourly infeed and electricity prices of the same years.

For Part II, we need to determine hourly electricity prices that take into account the weather-driven renewable infeed. For this purpose, fundamental energy system models are well suited, as they are a widely used tool to generate market prices based on fundamental structural interdependencies of the power sector (e.g. Müsgens 2006; Eising et al. 2020). Therefore, we apply the "em.power" dispatch model to derive hourly prices of 2019.

Yet, feeding a model with the hourly infeed of the German onshore wind fleet for weather conditions of 2001 to 2019 does not suffice our goals. We also need the "weather congruent" infeed of onshore wind in other European countries, together with that of offshore wind and solar. The 23 countries covered by our electricity market model are most EU-27 member states[20], Norway, Switzerland, and the United Kingdom. Because we lack wind speed and solar radiation data for these countries and technologies, we model a proxy for the respective national infeed. To this end, we use data from the EMHIRES[21] project (Gonzalez-Aparicio et al. 2021) from regulators and transmission system operators. With it, we model the infeed for wind and solar for all countries for years 2001 to 2019.

EMHIRES provides hourly usage factors for the weather conditions of 1986 to 2015 for more than 30 European countries, in per cent of installed onshore wind, offshore wind, and photovoltaic capacities as of 31/12/2015. To receive aggregated hourly infeed for 2019 capacities, we multiply the factors with countries' 2019 capacities and thus transform historical weather conditions to our base year. To close the gap for required weather conditions in 2016 until 2019, we generate usage factors using data of national regulators and transmission system operators and multiply them analogously. This method is a proxy because the factors freeze the RES locations at the end of 2015; hence the fleet's infeed may be incorrect for countries with a large shift in locations used. However, because the European data is only used to generate export-import-flows for the German power market, we assume this to have only minor effects.

The "em.power" dispatch model is formulated as a linear optimisation problem that minimises the total costs of electricity production. The different countries are connected through net transfer capacities based on hourly day-ahead forecasts. The model constraints consider central techno-economic aspects of power systems, scheduled and non-scheduled hourly outages, linearised start-up costs and efficiency losses at partial load. The minimum electricity output of thermal plants is determined by combined heat and power plants, serving the demand for spatial heating, industry, and warm water supply. Owing to limited forecasting accuracy, the model is designed as a three-day rolling horizon model. As we base our analysis on the 2019 German onshore fleet, we refer all input data to it, such as demand, power plants, cost of fuel and CO_2; that is, we fully refer to historical parameters, except for the weather.

Applying this approach results in a perfectly competitive market outcome. The marginal market-clearing condition is interpreted as the hourly wholesale electricity price. All model formulations, applied data, and sources are offered in the supplementary material.

[18] On the NUTS-1 or NUTS-2-level, depending on data and year.

[19] Using the correction factors used for historical calibration leads to a strong trend in WECs' yields because the factors are close to 1 for weather-year 2001 and decrease continuously; the correction factor needs to suit the WECs installed.

[20] Bulgaria, Cyprus, Greece, Ireland, Iceland, Malta, and Romania are not included.

[21] European Meteorological derived HIgh resolution RES generation time series for present and future scenarios.

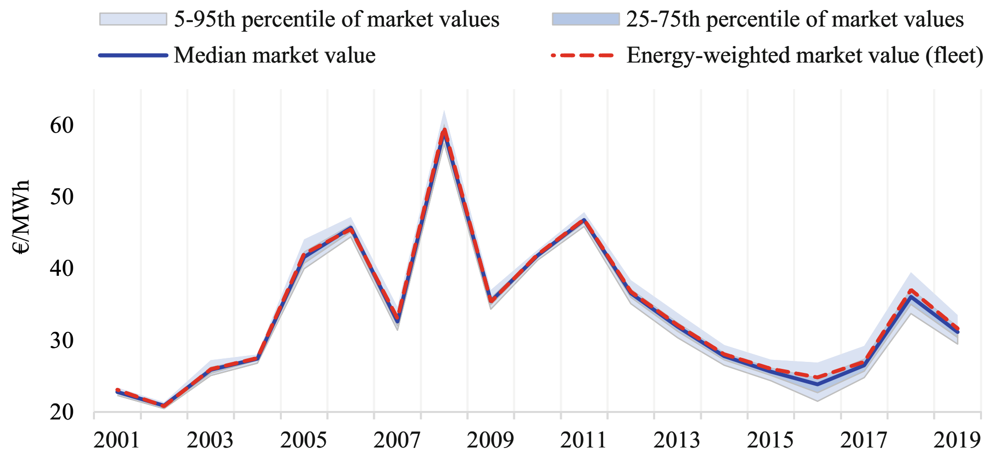


Fig. 5 Historical market values in €/MWh

At this point, we can valuate the infeed of Part I and II with hourly prices and gain market values, and performances.

3 Results

Subsequently, we present our results derived with the methodology described in Section 2.

3.1 Research Part I: Historical Development

Fig. 5 shows the distribution of modelled market values in absolute terms [22]; the levels of the values varied quite largely, which is mainly an effect of the base level (cf. Table 1) and varying commodity prices. Only since 2012, the spread in market values becomes constantly visible. To better see the spread, Fig. 6 shows the development in per cent of the average annual wholesale price, also known as value factor. We interpret this quantification as follows.

Wind's value factor declined over time, though not linearly but with ups and downs. We divide this development in two phases: before 2012 and after 2012. In the first phase, the value factor mostly varied around 90% "plus x"; in the second it dropped well below 90%. It remains to be seen, if the current decade just started a new phase with value factors below 80%.

A common explanation for the decline is a rising share of wind generation (Pudlik et al. 2015; Hirth and Radebach 2016). Wind capacities, having very low marginal costs, let wholesale prices recede whenever they produce, and this price effect gets larger, the larger their generation becomes ("cannibalisation"). The amount of generation is basically influenced by the expansion of wind capacities in relation to other power producing capacities, their quality (technology and location) and the weather "hitting" these capacities installed, acting like an "error term". The results are condensed in wind's market share.

This explanation goes in line with our observation of the value factor and wind's market share as depicted in Fig. 6

Table 1 Historical market values of the fleet and yearly averages of wholesale prices ("Base")

Year	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*
Energy-weighted market value (fleet) (in %)	96	92	88	96	91	90	87	91	91	94
Energy-weighted market value (fleet) [€/MWh]	23.1	20.8	26.0	27.5	42.0	45.5	33.1	59.8	35.4	42.0
Base [€/MWh]	24.1	22.6	29.5	28.5	46.0	50.8	38.0	65.8	38.9	44.5
Year	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	**2020[a]**
Energy-weighted market value (fleet) (in %)	92	86	85	86	82	85	79	83	84	**78**
Energy-weighted market value (fleet) [€/MWh]	46.9	36.8	32.1	28.1	26.0	24.7	27.0	37.0	31.7	**23.9**
Base [€/MWh]	51.1	42.6	37.8	32.8	31.6	29.0	34.2	44.5	37.7	**30.5**

[a]2020 is not covered by our wind speed data. It was calculated with data from Netztransparenz

[22] The mean absolute error of modelled market values of the fleet vs empirical values is 0.49 percentage points.

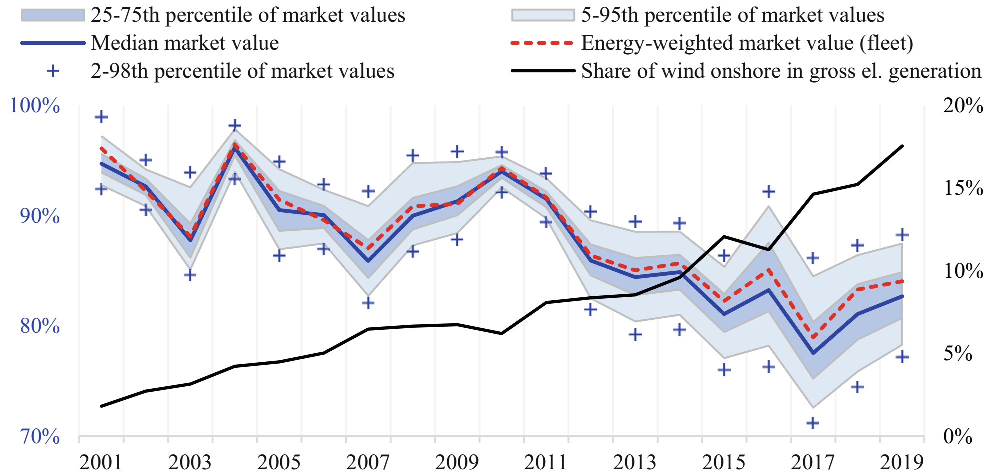


Fig. 6 Historical market value factor (primary axis) and wind's market share (secondary)

and 7. Yet, in the literature, there is a series of further explanation factors affecting wind's value factor, such as commodity prices, flexibility mechanisms (including interconnector and storage capacities), the composition of the renewable fleet (including technology design), the non-renewable power plant portfolio, as well as spatial diversification of wind capacities (cf. Eising et al. 2020; for a literature-based characterisation of value drivers). The latter ultimately influences the correlation between a single WEC's infeed and the wholesale price.

Given this series of complex and sometimes interdependent drivers, it is not surprising that there is no perfectly negative correlation between the fleet's value factor and the share of wind's generation. In our German case, the correlation factor (years 2001 to 2019) is—0.81. This means the raising and lowering of the value factor cannot be explained by the change in the wind's share alone; for example, the market value in 2019 is ~1 percentage point higher than in 2015, although the wind's share is six percentage points higher.

Second, there is a difference between the (energy-weighted) market value of the fleet and the median of market values, with the gap already existing ever since, yet

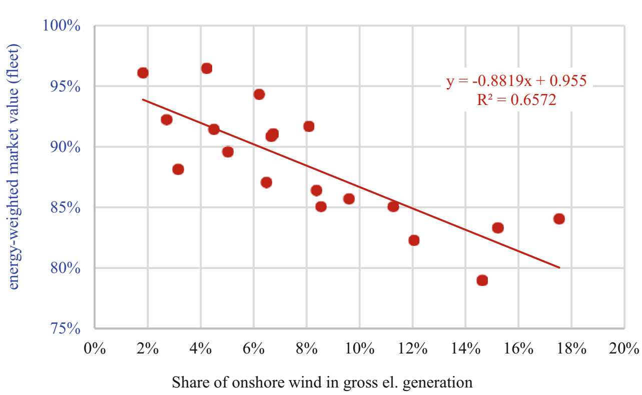


Fig. 7 Value factors by market share (penetration rate)

apparently becoming larger since 2015. Third, also since 2015, the spread in market values is constantly large and has grown further recently.

Findings two and three can also be seen in Fig. 8, which shows the distribution of performances in relative terms, that is performance divided by the fleet's market value of the same year (to better compare performance timewise). Even more clearly, we discover the spread becoming larger and the median of performances to be negative in 16 of 19 years. The latter means, that half of the market falls below of the fleet's market value most of the time. Concerning the spread: between 2016 and 2019, on average, 50% of performances are in a range of 6 percentage points (0.25 and 0.75 percentile) and 90% of performances are in a range of 14 percentage points.

How can these findings be interpreted up until here? The observed spread between the energy-weighted and the median values mean that (at least some) WECs with higher than average yields reach higher than average market values. In other words: higher(er) yields can go hand in hand with high(er) market values. This will be confirmed later, when mapping the spreads: even at the coastline, high performances can be reached, provided the "right" technology is used.

Further, the fact that this spread has grown in recent years, may be caused by a progress in the use of locations with good wind conditions and a favourable infeed pattern at the same time. This may apply to already developed areas for wind energy use and newly unlocked areas (offside the centre of capacities). Both the progress in technology and in regulation may be underlying reasons for this.

The growing distribution of market values and performances (finding three) might be caused by a technically more divers fleet, a growing number of locations used, or by a combination of both developments. In any case, given this dispersion, one should not assess a WEC's market value by relying on the fleet's value but take an individual look.

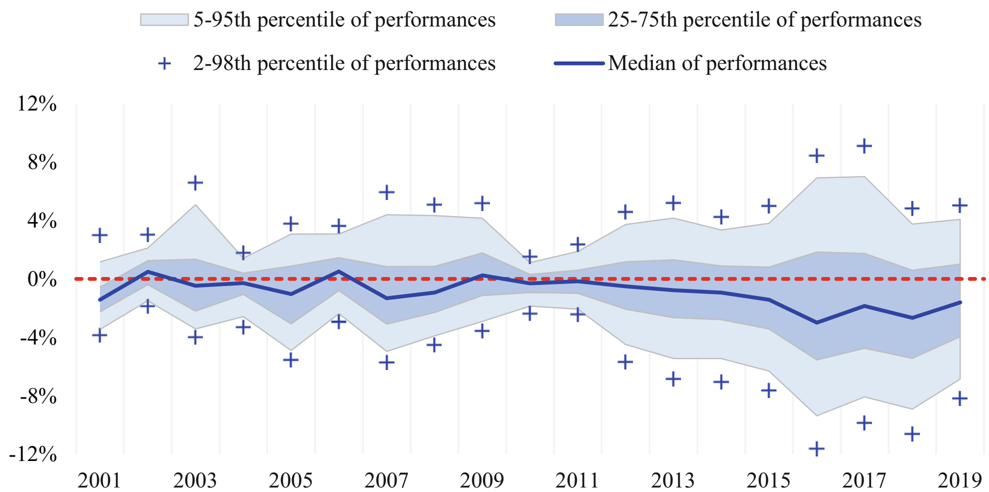


Fig. 8 Distribution of relative performance

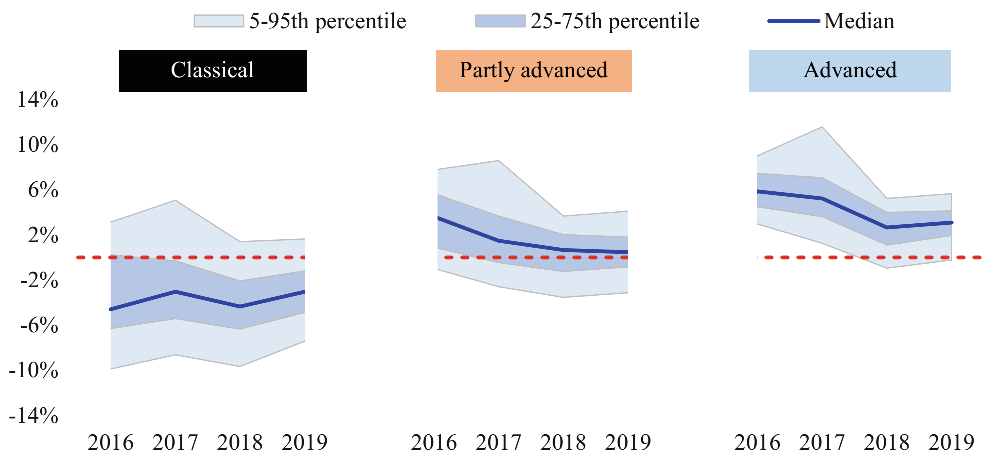


Fig. 9 Relative performance by WEC groups

To do so and to further investigate the spreads mentioned, we look at the performance of the WEC groups. We concentrate on the four recent years of our observation period. In terms of wind yield, 2016 to 2019 is characterised as extraordinarily weak, average, weak, and above average (Anemos 2017, 2019).

We discover a strong link between performance and grouping of WECs, as shown in Fig. 9: advanced WECs perform significantly better than classical ones, and partly advanced WECs (high hub heights and medium to high specific ratings). There is hardly an advanced WEC featuring lower values than the fleet. This picture is inverted for classical WECs. Summing up until here, we can state that there is a clear split in market values and performances along the technology choice in the German market. In this context and remembering that the spread in market values gets larger since 2015, it is worth mentioning when advanced turbine design entered the market. Our data (and that of Fraunhofer 2018) shows that since 2012, specific ratings of newly installed WECs drop heavily (and hub heights keeps on rising). Put differently: the era of advanced turbines started somewhere around 2012. This development is also observed in the USA around that time (cf. Chabot 2015; who called this a "silent revolution"). This suggests that the recent divergence in market values is triggered by WEC design. We will later see that also an enlargement of (new) areas for wind energy use took place, yet this usage is closely linked to advanced WEC design, too: only advanced design made it possible to lift the potential of these areas.

How large is the difference between our groups? We find that, on average between 2016 and 2019, the spread in the median of performances (and thus market values) between advanced and classical WECs is ~8 percentage points.[23] The difference between advanced and partly advanced WECs is ~3 percentage points and roughly the same in any year. From this, we cannot conclude that advanced WECs are superior at any location, yet. This is because there are technical restrictions for the usage of these different technologies (see 2.2.2) and here, we compare different locations against each other. However, this represents a con-

[23] Annual values for 2016 to 2019 are 10, 8, 7 and 6 percentage points.

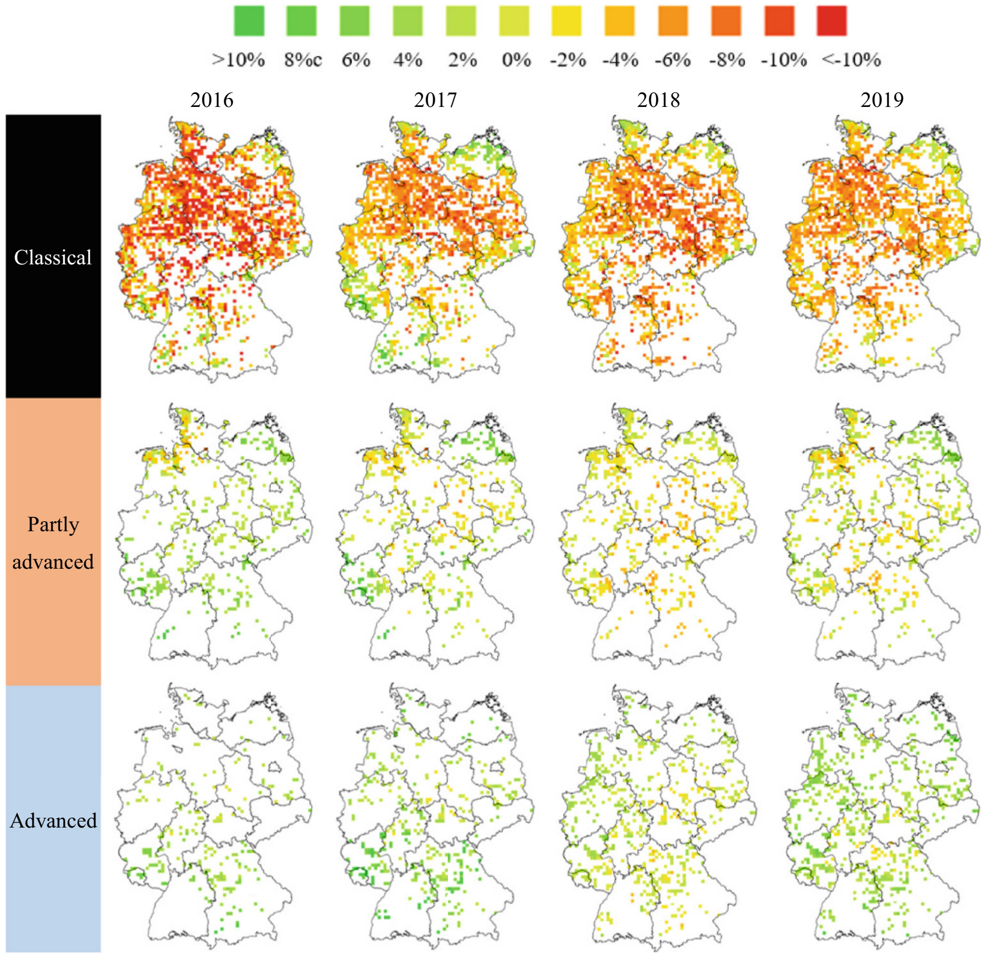


Fig. 10 Relative performance in a raster of 10 by 10 kilometres (median values)

firmation of theory and a first quantification for the spread in a real market.

Comparing the spread in the energy-weighted performances (and thus market values) between advanced and classical turbines (not depicted), the average difference declines to ~6.5 percentage points. This is because the values marginally decline for the advanced WECs, and marginally increase for the classical WECs. This means that within the advanced (classical) group, WECs with comparatively higher yields reach comparatively lower (higher) performances. This value of 6.5 percentage points can be compared to an analysis by Hirth and Müller (2016), who estimated the difference to be between 4 and 5 percentage points for a comparable market share of wind in Germany, simulating a total monolithic classical fleet versus a total monolithic advanced fleet, on a ~80-kilometer wind speed grid.

Also noticeable is the spread between the 0.95 and the 0.05 percentile within each group (Fig. 9). Compared to classical WECs, the spread within (partly) advanced WECs is 40% (30%). However, this result may be caused by the larger number of classical WECs in our data (see Fig. 3), their larger spatial distribution (Fig. 10), and our classification: the variety of configurations (hub heights and specific ratings) is also larger than for the two other groups (Fig. 4). Consequently, given that location and technology matter, the spread in performance ought to be higher, too.

Turning to revenues in direct marketing stemming from performances only: the spread in performances translates into a larger spread of competitive revenues. This is evident because competitive revenue (Eq. 8) is defined as the WEC's performance times its yield, and our group of advanced WECs mainly feature modern turbines with large towers, large rotors, and still comparatively high-rated powers. On the contrary, the classical group is, to a great deal, made up by old and comparatively small WECs. To give a feeling: The difference in full load hours between the three groups is roughly 500, meaning that advanced WECs have ~1000 full load hours more than classical WECs. Therefore, we are not interested in the difference between groups, but in absolute figures for the "best in class", that is advanced WECs. For them, competitive revenues are on median levels ~7700 € per WEC and year (average between 2016 and 2019). 50% of advanced WECs (within the 0.25 and 0.75 percentiles), reach between ~4500 € and 11,700 €. Top performers (0.95-percentile) reach 17,000 €.

How do these competitive revenues compare to investment costs? For an approximation, we refer to Wallasch et al. (2015), who report a scale of 1.2 to 1.4 million € per megawatt as main and 0.4 million € per megawatt as ancillary investment cost for WECs commissioned in the German market in 2016 and 2017. Their reporting is even more detailed, giving cost figures according to combinations of two different rated powers and four hub heights. We take up their detailed values for advanced WECs commissioned between 2016 and 2017, assume their competitive revenues of direct marketing to remain constant in real terms during the support period, calculate the net present value (NPV)[24], and relate it to investment cost. As a median value, we obtain ~140,000 € as NPV or ~2.8% of total investment cost. Half our values (within the 0.25 and 0.75 percentiles) are between 1 and 4% of investment cost. The 0.05 and the 0.95 percentile are around 0% and 6% of investment cost. To further contextualise these figures: in a sensitivity analysis Wallasch et al. (2015) also note that a 10% increase (decrease) in investment cost leads to a 5% increase (decrease) in the levelised cost of energy (LCOE). Hence, the median NPV of competitive revenues corresponds to a ~1.4% decrease of LCOE.

In competitive tenders, considering these benefits may be worthwhile for some WECs, though. At this point, it is worth mentioning that the absolute level of market values after the support period (not the comparative advantage along the way) surely has a larger influence on the NPV. Against the background of the future development being highly insecure and disputable, given a series of complex drivers, we leave it to further research to determine how market values affect bidding strategies or project sourcing.

Next, we turn to the regional dispersion. Fig. 10 shows the median values of relative performance[25] per group for four years. Since performance is the comparative advantage of a WEC, the colours also reflect, which type of WEC achieve high or low market values and where (yet, without reflecting its absolute levels). Two observations are striking: the colour split and the development of locations for advanced WECs.

In recent years, the number of locations used by advanced WECs increased clearly. This has already been indicated by Fig. 3, yet now, we see that the roll-out started in the south (wind zones 1 and 2) and quickly proliferated to the north. Between 2019 and 2016, the share of advanced capacities installed in Baden-Württemberg and Bavaria recedes from around a quarter to 17%. This reflects a common trend in the industry, which is the "triumph" of advanced WECs even at sites with better wind conditions.

Irrespective of "going north", advanced WECs perform better than less-advanced ones, seemingly everywhere, even, though reduced, in the heartland of wind farming (Lower Saxony) and near the coastline. Though on a lesser extent, much of this is true to partly advanced WECs: even at the direct coastline, they do not fall below the fleet's value, on median levels. Classical WECs offer the most colourful picture. They have their lowest performances in the central area of Germany (ranging from Westphalia in the west to Brandenburg in the east, also covering large areas of Lower Saxony), which is also the centre of capacities. Locations seems to make a bigger difference for classical WECs, since larger than average market values can be reached aside of this centre, namely in the southwest and in the very east.

Our results indicate that clustering of performances by a two-dimensional interpretation of location only (latitude, longitude), without considering WEC types, is probably not enough to understand the complexity of market values. Further, we confirm and update prior research (Eising et al. 2020; Engelhorn and Müsgens 2018) in our findings on regionality. Following prior research on drivers of this, we conclude:

- due to prevailing weather conditions, a WEC operating in the core area exhibits an infeed-price correlation which is more in line with the correlation of the fleet than the same type of WEC operating in a non-core area, provided wind speeds are not synchronised—an effect that amply applies for (a country the size of) Germany (Mono and Glasstetter 2012; Schmidt et al. 2013 already detect this for Austria). This can particularly be seen for classical WECs. A high correlation with the fleet implies a negative infeed-price correlation (high infeed at times of low wholesale prices), and low market values. Engelhorn and Müsgens (2018) find the lowest infeed-price correlation in the centre, and the highest in the south.
- WECs with higher hub heights (partly advanced), and even more, WECs with both higher hub heights and lower specific ratings (advanced) seem to be able to counter this locational driver. At locations with very unfavourable correlations, technology acts like a "reliefer", cushioning the value drop (see German midlands). At locations with more favourable correlations, technology acts like a "booster" (see southeast) Research indicates that this technology effect goes back to a smoothened infeed, which diminishes output variation and thus positively affects market values (Hirth and Radebach 2016; Engelhorn and Müsgens 2018).
- It remains unclear, whether higher hub heights also positively affect infeed-price correlations. This might be the

[24] Wallasch et al. (2015) assume a weighted average cost of 3.6 to 4.4% depending on wind site; we use 4%.

[25] Performance divided by the fleet's value.

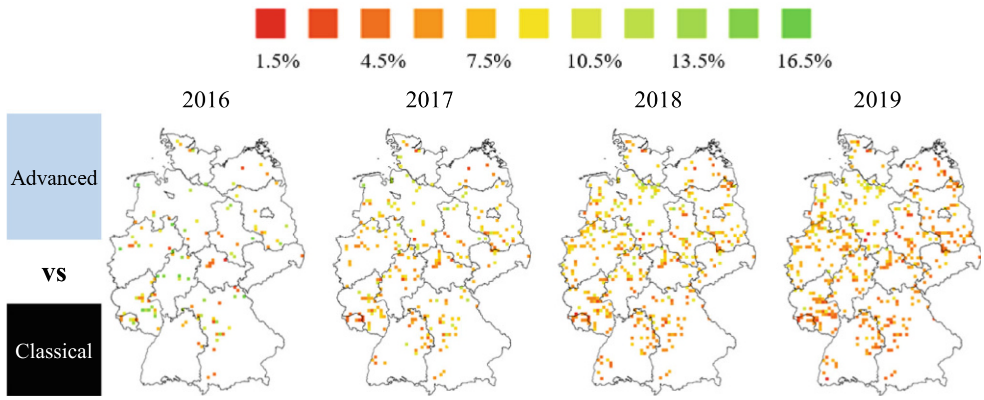


Fig. 11 Difference in relative performance: advanced vs classical WECs (median values)

case, if considerably different wind speed patterns appeared at higher heights (which is out of scope in our analysis).

At this point it is worth mentioning the benchmarking character of the market premium model and the interpretation of performance as a competitive advantage. With more and more advanced WECs entering and classical WECs leaving the market, we expect a stronger harmonisation of technologies used, because the potential for ever lower specific ratings and higher hub heights is limited (though today's large spread in the distribution of performances indicates, that the market is still very divers). Yet, over time, the market will presumably become less divers and advanced WECs the dominating group. Accordingly, performances for advanced WECs might shrink in the future. This is not a contradiction to research on market values stating that advanced turbine design leads to higher market values. This is because performance is a relative measure and market value an absolute one. Shrinking spreads may be counteracted by an enlargement of locations used. In any case, concerning the development of future performances (not market values), we expect technology to become less and location to become more important, as an explaining driver for the dominating WECs. For the shrinking fraction of classical WECs, the future seems gloomy: becoming "renegades" implies being punished in this benchmark system. We leave this to further research.

Up until here, we compared performances across WEC groups irrespective of their location. This way, a larger fraction of advanced WECs installed in the south are compared against a larger fraction of classical WECs installed in the north. Consequently, technology and location come into question as explaining drivers. To remedy this and to sharpen the comparison across technologies, Fig. 11 shows the difference between advanced and classical WECs only for raster at which both technologies are used (119 raster in 2016, and 449 in 2019). Outperformance of advanced WECs is given at any level. Naturally, the difference is most large in the central region, and lowest in the south. This can be explained by the fact that classical WECs are already closer to advanced WECs from a technically point of view in the south than it is in the centre. Hence, the empirical, pure technology advantage is smaller in the south. Fig. 12 builds on this, showing the distribution of relative performances as a graph. The technology advantage, at comparable raster[26], amounts to 5–6 percentage points (on median level).

Performances differ by years, WEC design and regions. For both traders and operators, the performance stability of

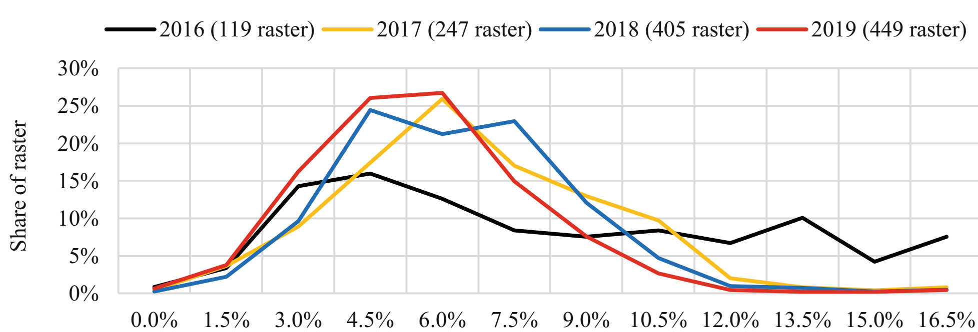
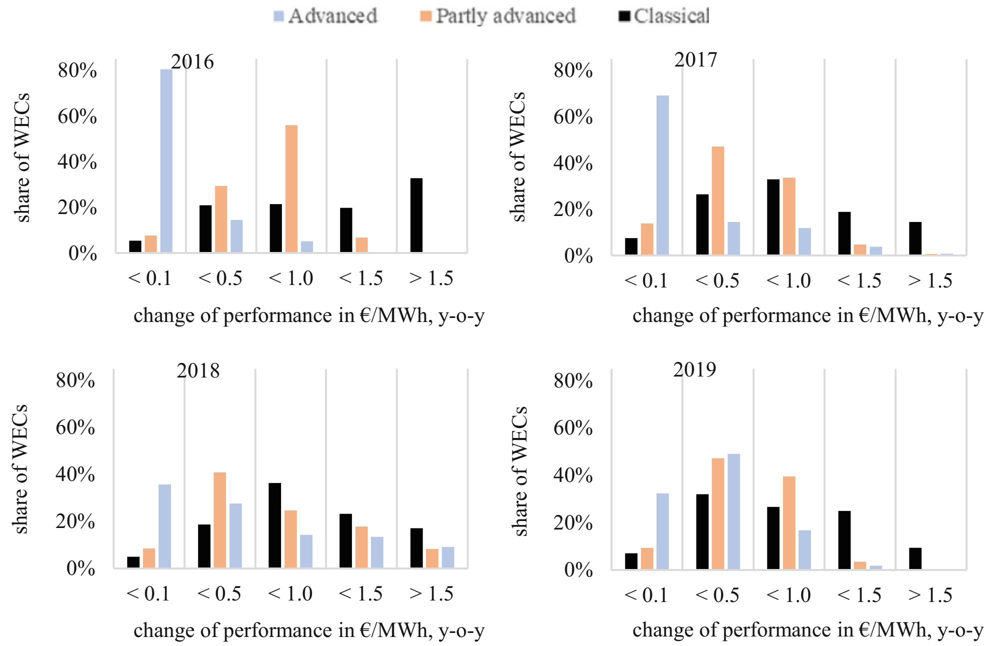


Fig. 12 Distribution of differences in relative performance: advanced vs classical (medians)

[26] Within raster of 10 by 10 kilometres, orography and wind speeds can still vary and thus influence correlation.

Fig. 13 Stability of performance. **a** 2016, **b** 2017, **c** 2018, **d** 2019



an individual WEC is important, too. And a volatile comparative advantage surely not a "quality label" for a WEC. To develop an approximation of the volatility of individual performances, we calculate each WEC's year-on-year change.

From Fig. 13, we find that historically, most performances of partly advanced and advanced WECs varied up to 0.5 €/MWh. Volatility is highest among classical WECs: ~40% of observations within this group had year-on-year changes of more than 1 €/MWh (period 2016–2019). Partly advanced WECs suffered from the second-highest year-on-year changes. However, with more observations of advanced WECs in our sample (2019 vs 2016), distributions are more similar.

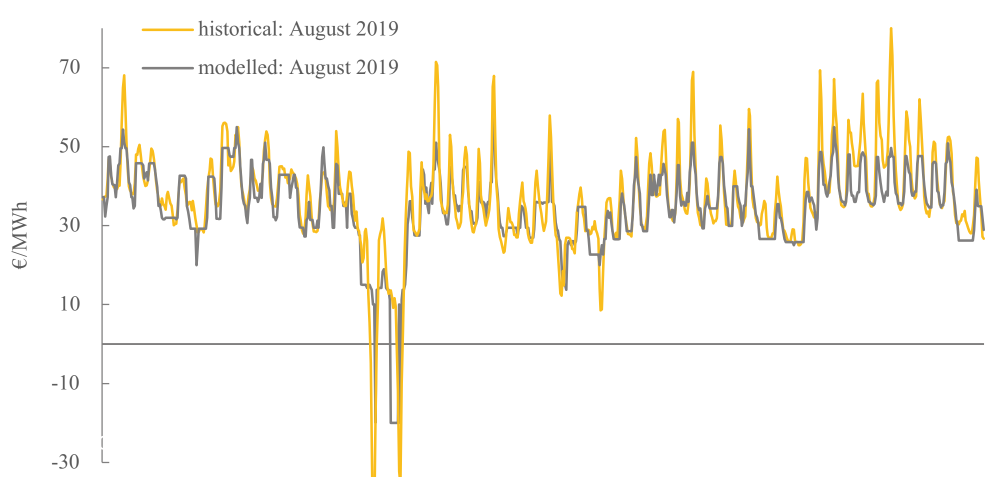
This learning on volatility is also relevant to traders. It means that—in the absence of any other information than a WEC's historical track record in the wholesale market—historical performances of advanced WEC are a better proxy (for the near future) than it is the case with less modern ones (remember that performance is commonly fixed for the term of contract in direct marketing). Also, it suggests that, for classical WECs, the performance, offered by the trader to the operator in the contracted market value (cf. Equation 6) should be given a higher deduction for risk.

3.2 Research Part II: Weather Influence

The goal of Part II is to investigate the effect of the inter-annual variability of RES infeed on wholesale prices, market values and performances.

With different weather patterns for onshore wind, offshore wind and solar capacities, wholesale electricity prices

Fig. 14 Hourly wholesale prices: empirical vs modelled, exemplary



change on hourly, monthly, and yearly resolutions. We first present these price effects before turning to the impacts on market values.

Fig. 14 shows how our modelling fits empirical hourly prices for the example of August 2019. Generally, the hourly pattern is matched well, yet modelled prices do not fully retrace the peaks and lows. The mean average error (MAE) for 2019 (modelled vs empirical) is 6.5 €/MWh; the root mean squared error (RMSE) is 9.2. Comparing these values with other models in the same modelling class, we find that our model generates good price estimates. Qussous et al. (2022), for example, generate market prices for the year 2019 and report a MAE of 6.7 €/MWh and a RMSE of 10.9. For the year 2015, Eising et al. (2020) report a MAE of 4 €/MWh and a RMSE of 8.3.[27]

For three weather patterns, Fig. 15 shows that hourly prices vary significantly, though monthly prices are within reach (38 and 39 €/MWh). The maximum hourly deviation in the example is 70 €/MWh (107 vs 34 €/MWh), only depending on RES infeed.

Monthly prices are also subject to significant variations (Fig. 16). The spread is largest in winter (January, February, December) when wind's yield can be very high; January exhibits the largest spread (19 €/MWh), mainly driven by two weather years (2007, 2005) with very high January yields. In August the spread in prices is lowest (5 €/MWh) All weather years show a common seasonal pattern with decreasing price levels in spring and increasing levels in winter, quite close to each other.

Fig. 15 Hourly wholesale prices: effect of different weather years, exemplary

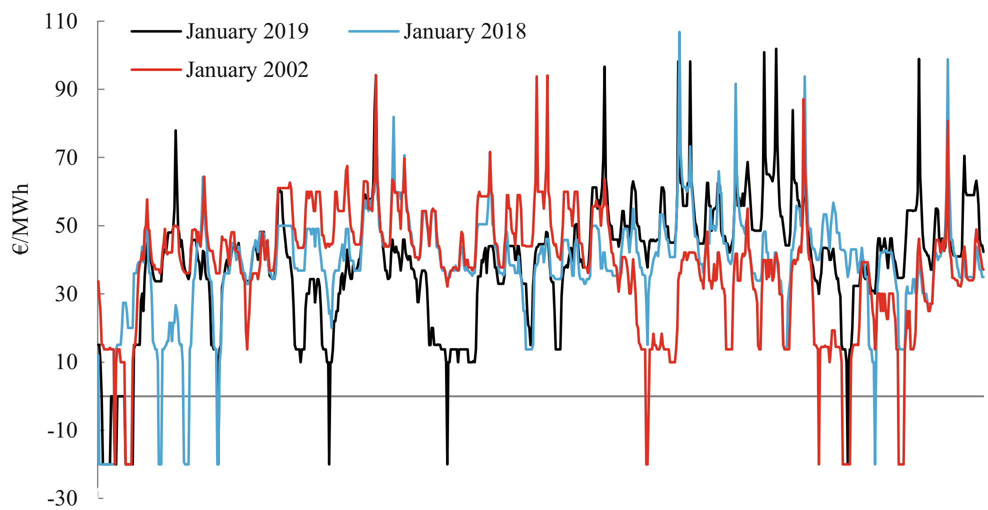
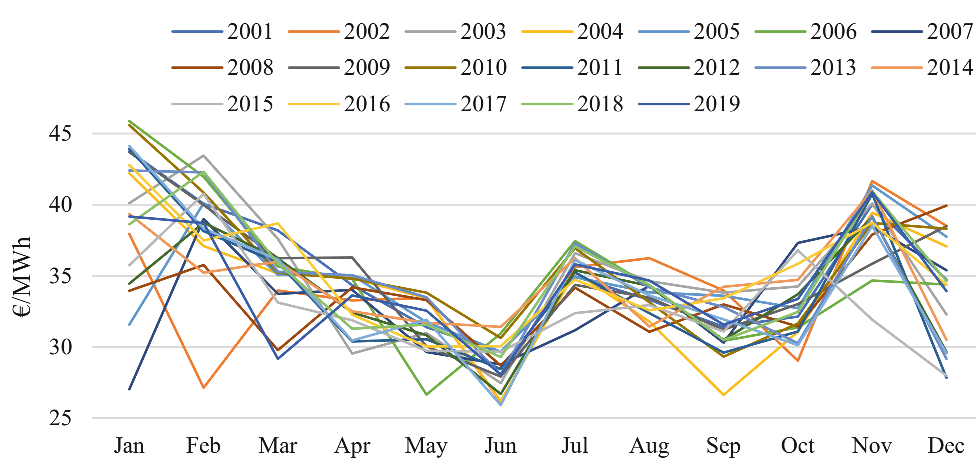


Fig. 16 Monthly wholesale prices based on different weather years



[27] Note that the error strongly depends on the respective year. Eising et al. (2020) collect error measures of energy system models for different years and report a range for the MAE from 1.91 to 7.88 €/MWh and for the RMSE from 2.81 to 39.09.

Table 2 Yearly wholesale prices and German RES generation for different weather years

Weather year	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*
Base [€/MWh]	35.3	34.0	35.0	34.2	34.7	34.8	33.2	33.6	35.0	35.7
Onshore wind [TWh]	94	108	89	105	99	102	112	113	97	93
Offshore wind [TWh]	24	23	22	23	24	22	24	22	24	21
Solar [TWh]	44	41	36	41	42	42	41	45	42	39
RES infeed [TWh]	162	172	147	169	165	166	177	180	163	153
Weather year	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	**2019[a]**
Base [€/MWh]	33.7	33.5	34.9	34.5	32.8	35.1	33.9	34.9	34.3	**37.7**
Onshore wind [TWh]	106	108	98	101	111	95	102	99	105	**105**
Offshore wind [TWh]	21	24	23	22	23	24	22	24	22	**24**
Solar [TWh]	39	44	41	36	41	42	42	41	45	**42**
RES infeed [TWh]	166	176	162	159	175	161	166	164	172	**171**

[a]Empirical

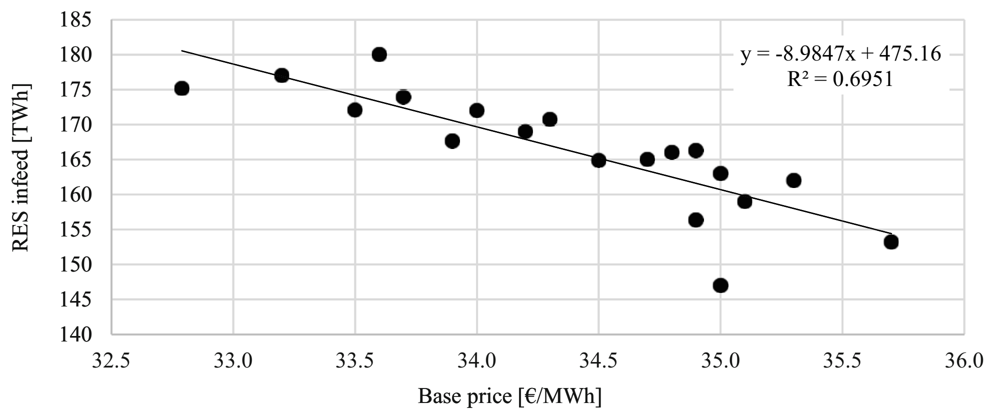


Fig. 17 RES infeed-price-relationship

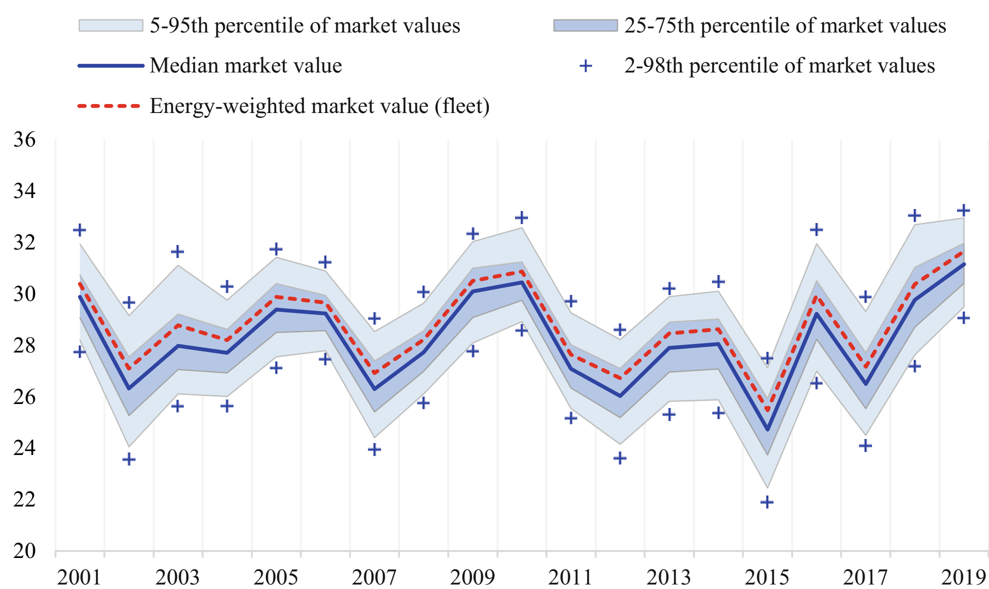


Fig. 18 Distribution of market values in €/MWh (changing weather years, market conditions of 2019)

On a yearly level (Table 2), the range in (base) prices, driven by the variation in RES infeed, is ~3 €/MWh (minimum 32.8, maximum 35.7), with an expected (average) price of 35 €/MWh. The years with the highest and lowest infeed are close to the observed lowest and highest years of annual prices, echoing the price-decreasing effects of RES infeed (Fig. 17). National onshore wind production varies between 88 and 111% of the average infeed of 102 terawatt hours (TWh). Solar production varies between 88 and 112%, and offshore wind varies between 97 and 106%. In

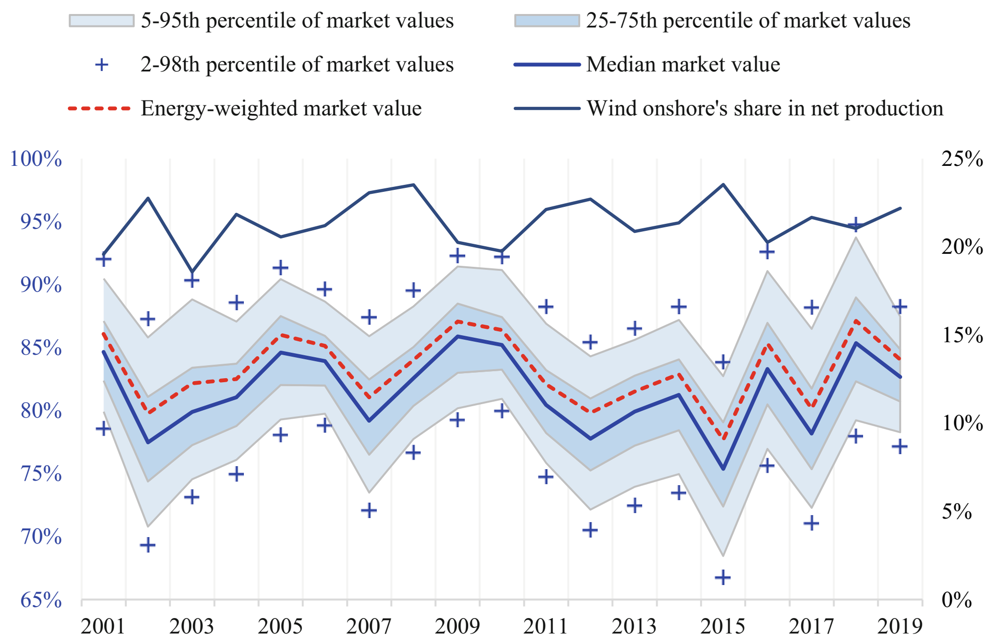


Fig. 19 Market value factors (primary axis) and wind's market share (secondary) (changing weather years, market conditions of 2019)

sum, this leads to an inter-annual variation of RES infeed between 94 and 103%.

Fig. 17 summarises the relationship between RES infeed and prices. This highlights the dispatch of different plant types in the merit order, measuring the swing in electricity prices for a fixed power plant portfolio, "come rain or shine". For our exemplary year 2019, an additional infeed of ~9 terawatt hours [TWh] let wholesale electricity prices drop by 1 €/MWh. Our 19 different weather-years induced a swing of ~33 TWh (minimum 2003: 147 TWh; maximum 2008: 180 TWh). The years with minimum and maximum RES infeed are not identical with the years of minimum and maximum prices, because average price levels rather depend on hourly timing and composition of the RES infeed during a year.

Turning to market values (Fig. 18), the range of annual values for the fleet is ~5.5 €/MWh (minimum 25.5, maximum 30.9) and thus a bit larger than the spread in base prices, with an expected (average) market value of 29 €/MWh.

Looking at market values in per cent of the wholesale electricity price (value factors, Fig. 19), we see a varying distribution with a quite constant range over the weather years and a spread of 9 to 15 percentage points between the 0.95 and 0.05 percentiles. This constant spread, even for wind years below average, such as 2010, is in contrast to corresponding historical spreads for the same weather-years (see. Fig. 6), and thus might stem from modelling effects and or the deployed power plants of 2019.

The fleet's value varies between 13 percentage points or put differently, between 78 and 91% of the respective wholesale electricity price. This is one of our central results of Part II.

Weather-year 2015 represents weather conditions with the lowest market value factors and the highest infeed of onshore wind; weather-years 2014 has the highest market value factors, yet a moderate level of infeed; 2009 and 2018 show the second highest market value factors and are among the lowest infeed of onshore wind. Weather-years 2002 and 2018 feature the highest spread of market value factors (0.95 to 0.05 percentiles) (Table 3).

Table 3 Market values based on different weather years

Weather year	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*
Energy-weighted market value (fleet) (in %)	86	80	82	83	86	85	81	84	87	86
Energy-weighted market value (fleet) [€/MWh]	30.4	27.1	28.8	28.2	29.9	29.7	26.9	28.2	30.5	30.9
Weather year	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	**2019**[a]
Energy-weighted market value (fleet) (in %)	82	80	82	91	78	85	80	87	83	**84**
Energy-weighted market value (fleet) [€/MWh]	27.6	26.7	28.5	37.3	25.5	29.9	27.2	30.4	28.4	**31.7**

[a]Empirical

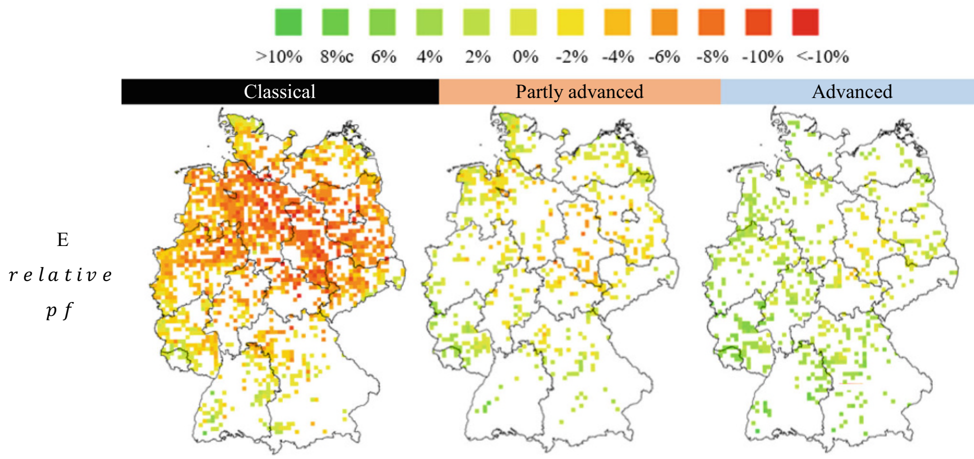


Fig. 20 Expected relative performance in raster of 10 by 10 kilometres (median values)

Finally, we look at individual WEC performances in 19 weather years. The following measures of dispersion are calculated for each WEC's 19 performances: the expected performance (E pf_j), the minimum–maximum spread (range pf_j) and the standard deviation of performances (std. dev. pf_j). The expected performance is the average of observations. The range can be interpreted as the maximum price risk for a trader, and the standard deviation gives a feeling on the dispersion of observations. We show our results per WEC group and raster on a map (median values per raster). This way, we can see spatial and technological effects of the weather's influence.

Fig. 20 condenses the picture already seen for the historical development (see. Fig. 10): the clear nuance in terms of technology and the spatial appearance of good and bad relative performances (and thus also market values above or below the fleet's average). Yet alone, the historically good performances for classical WECs in Mecklenburg-West Pomerania are partly diminished by taking more weather years into account. As a basic takeaway, we state that the four historical weather-years already gave a good indication what can be expected in the long run (given market conditions of 2019). On median levels, advanced WECs reach a relative performance of 4%, partly advanced 1%, and classical WECS –4%, thus taking on the spreads already observed in Part I. We like to point out that for classical WECs, significantly better performances can be reached in the very north and in the southwest, aside off locations with alike turbines already installed. For brevity, we refer to the discussion of this in Section 3.1.

More interesting is the spatially illustration of ranges and standard deviations of relative performances. Low ranges and low standard deviations can be interpreted as performances being weather-invariant, and thus mark stable locations (note that the green shade stands for "low" and red for "high").

Mapping median levels (Figs. 21 and 22), we find more of a difference in the centre of capacities, yet a comparatively identical picture anywhere else. For all WEC groups, the performance variation is lowest in the centre (ranging as a green-yellow, diagonal belt from the northwest of Lower Saxony to Saxony in the east), where expected performances are also among the lowest. The highest variation across all groups is found in the southwestern part of Germany—which is also the region with the highest (expected) performances (and market values). Here, comparatively few

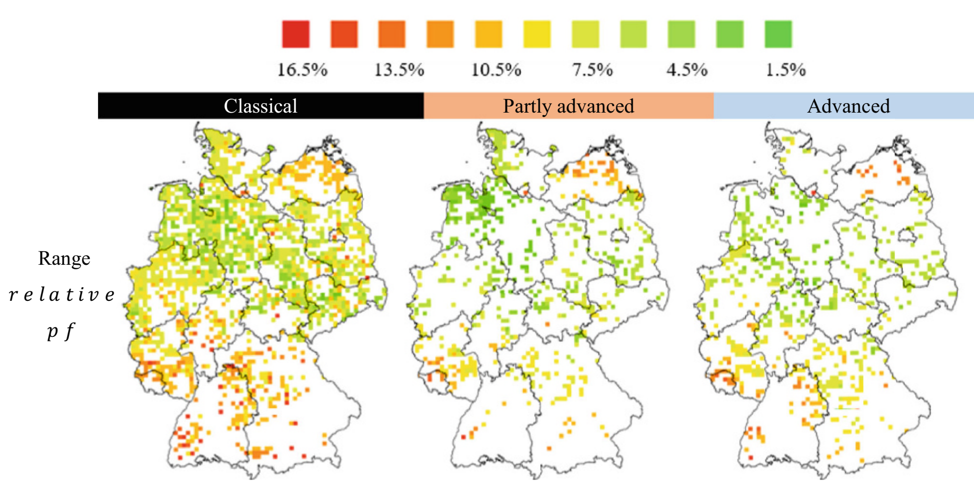


Fig. 21 Range of relative performance in raster of 10 by 10 kilometres (median values)

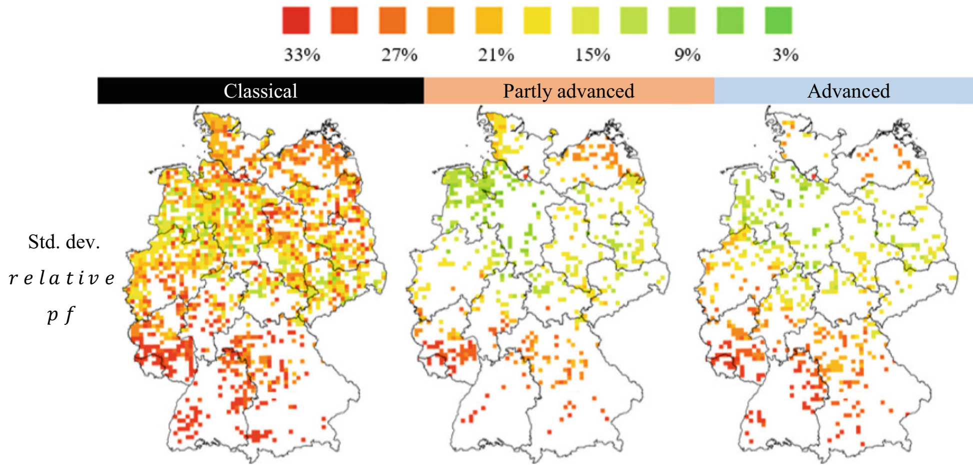


Fig. 22 Standard deviation of relative performance in raster of 10 by 10 kilometres (median values)

WECs are installed, and the sites feature a more complex orography (hills, forest). Somewhat less of this effect can be explored in the north and northeast, close to the coastlines.

Put differently: for our specific setting (market conditions of 2019), changing weather has the lowest impact in regions, with the lowest performances (and market values). On the contrary, regions with comparably high performances are affected the most by the weather. Put differently, again: if performance is below average—"do not hope for changing weather!". If it is (very) good—"be aware of changes in the weather!". This finding might be interesting for operators, traders, and for asset valuation. Apparently, to assess the value of a comparative advantage in today's wind market, building on a series of different weather-years is more important for WECs in the southwest than it is for WECs in Lower Saxony, for instance. Given the overall colourful shades for classical WECs, building on a series of weather-years might be worthwhile at any location, since they are affected the most by the weather. Or, in case of relying on one weather-year only, be given a higher deduction for risk in direct marketing contracts.

Numerically comparing distributions of ranges and standard deviations across WEC groups, we do not find much of a difference: the values in each percentile are very similar, meaning that the levels of performances are equally dispersed. This suggests that the weather leaves the structural advantages of advanced WECs unchanged.

3.3 Conclusion

In this paper, we first modelled the hourly infeed of up to ~31,000 onshore wind energy converters (WECs) operating in the German market for the years 2001 to 2019. We analysed the development of market values, performances, and competitive revenues, sorted by differently advanced WEC groups.

We found that absolute market values varied significantly, as did annual wholesale electricity prices. Wind's value factor, that is the captured price of WECs in per cent of the average wholesale electricity price, showed a downward trend. Further, we focused on historical performances, defined as the difference between the fleet's and an individual WEC's market value (comparative advantage). Historically, 50% of WECs' performances were within a spread of 6 percentage points and 90% were within a spread of 14 percentage points. We assume the growth in the spread of performances to be caused by a more divers fleet in technological respect, and a larger spatial dispersion of wind sites used.

We illustrated that advanced WECs, that is WECs with a low specific rating and high hub heights, exhibited significantly higher performances (and market values) than classical ones. Geographically, advanced WECs performed better than the whole onshore wind market, and nearly everywhere, whereas the classical WECs only outperformed in the southeast and small areas in the northwest of Germany. This way, we updated and confirmed prior research on regional clusters and showed the spatial effects of performances connected to turbine design.

Comparing advanced to classical WECs, we quantified the historical difference in market values to be 8% on median level, and 6.5% if weighted by the groups' respective energy output, with both values being deduced irrespective of location. Comparing these types of WECs on raster-levels, that this in spatial proximity, advanced WECs reached 5–6 percentage points higher market values.

We also analysed that year-on-year changes, across all versions of WECs, mostly occurred in a range of 0.1 to 0.5 €/MWh, and the classical WECs suffered from the largest absolute year-on-year changes.

In terms of ("competitive") revenues stemming from realised performances, we found that half of the advanced

WECs reached between 4500 and 11,700 € per year (median 7700 €), in years 2016 to 2019.

Second, we modelled the (fictitious) infeed of WECs operating in 2019 for 19 different weather years and corresponding wholesale electricity prices for the German market. We found that an additional 9 TWh of RES infeed decreased wholesale electricity prices by 1 €/MWh. On hourly and monthly resolutions, the weather effect is significant (5 to 19 €/MWh on monthly basis), whereas, on a yearly basis, the spread in annual prices falls to ~3 €/MWh. However, the spread in market values for the fleet's level is somewhat higher with ~5.5 €/MWh. The distribution of individual market values is in a quite constant range over the years: 90% of market values are in an interval of 3 to 5 €/MWh. The (market) value factors for the fleet vary between 78 to 91% of the base price, with a 90% of values ranging between 9 and 15 percentage points.

The variety of weather years did not change the ranking in performances; that is, the outperformance of advanced WECs was confirmed. We also measured the minimum–maximum spread and the standard deviation of performances. We found the weather effect to be largest in the south, and lowest in the heartland of wind farming (high ranges and high standard deviations). In the light of our results, market participants should take different wind years into account when estimating the performance of a WEC in direct marketing, especially when pricing WECs in the southeast of Germany. Likewise, researchers on the future development of market values and asset valuators should consider the inter-annual variability of the weather to broaden the base for a well-grounded revenue prospect to onshore wind assets.

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