



## Seasonal forecasts of wind power generation

Ll. Lledó<sup>a,\*</sup>, V. Torralba<sup>a</sup>, A. Soret<sup>a</sup>, J. Ramon<sup>a</sup>, F.J. Doblas-Reyes<sup>a,b</sup>

<sup>a</sup> Barcelona Supercomputing Center (BSC), Spain

<sup>b</sup> ICREA, Pg. Lluís Companys 23, Barcelona 08010, Spain



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### ABSTRACT

The energy sector is highly dependent on climate variability for electricity generation, maintenance activities and demand. In recent years, a few climate services have appeared that provide tailored information for the energy sector. In particular, seasonal climate predictions of wind speed have proven useful to the wind power industry. However, most of the service users are ultimately interested in forecasts of electricity generation instead of wind. Although power generation depends on many factors other than wind conditions, the capacity factor is a suitable indicator to quantify the impact of wind variability on production. In this paper a methodology to produce seasonal predictions of capacity factor for a range of turbine classes is proposed for the first time. The strengths and weaknesses of the method are discussed and the forecast quality is evaluated for an application example over Europe.

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## 1. Introduction

The energy sector is heavily impacted by atmospheric variability: energy demand and supply are conditioned by atmospheric conditions at several time scales ranging from small-scale turbulence through day-ahead weather or seasonal anomalies and up to climate change impacts [14,43]. Renewable generation from hydro, solar and wind power installations is specially sensitive to seasonal or multiannual climate oscillations and long-term trends [28,48]. Recent improvements in the field of climate prediction make it now possible to inform in advance of anomalous conditions for the months to come (i.e. seasonal prediction) [12,31]. Anticipating the future variability of energy sources beyond the first two weeks allows to take calculated, precautionary actions with potential cost savings. To foster the usage of those predictions, in 2015 the World Meteorological Organization (WMO) included energy as one of the priority areas in the Global Framework for Climate Service (GFCS) [23,52]. The GFCS set the basis for understanding user needs in terms of climate knowledge and building applications that transform climate model outputs to fulfill those specific user needs. Since then a few climate services have appeared that provide specific information for assisting decision making in the energy sector [6]. One of such examples is the RESILIENCE prototype

(resilience.bsc.es), developed specifically for the wind power industry under the EUPORIAS project [7,46]. In RESILIENCE the value of seasonal forecasts of wind speed issued one to three months ahead was explored according to the needs of various stakeholders in the sector: wind farm owners, operation and maintenance (O&M) teams, energy traders and transmission system operators (TSO).

The needs of those different user profiles regarding seasonal outlooks was explored through stakeholder interviews in EUPORIAS and S2S4E projects ([16,38,41]). After analysing 22 interviews and 69 survey responses, the needs of the wind energy sector proved to be quite diverse. For example, O&M teams need to perform maintenance activities under weak winds for safety reasons. For that purpose wind forecasts are directly useful and some recent research has already shown skill for seasonal wind predictions in some regions [3,9,46]. But most of the remaining stakeholders use the wind speed forecasts as a proxy to anticipate wind power generation either at site or country level: TSOs need to schedule alternative generation sources in advance to guarantee power supply, traders want to forecast power prices, owners need to be ready for cash flow shortages in case of mince revenues, and even O&M teams try to minimize generation losses due to turbine stoppings. Therefore direct forecasts of wind power generation would be beneficial to those stakeholders, as indicated in the interviews and surveys. However, efforts to transform seasonal predictions of wind speed to generation forecasts have received little attention so far and have only been considered very preliminarily in the work of MacLeod et al. [30].

\* Corresponding author.

E-mail address: [llledo@bsc.es](mailto:llledo@bsc.es) (Ll. Lledó).

While forecasts of wind power generation at lead times from minutes and hours to a few days ahead have been produced with very advanced methodologies (e.g. dynamical downscaling, machine learning or statistical downscaling [17]), a number of difficulties make the provision of generation forecasts at seasonal timescales challenging. Climate models have more complexity than weather models as they simulate and couple the different components of the climate system (atmosphere/hydrosphere/cryosphere/land surface/biosphere) and therefore demand enormous amounts of computational resources. This limits the effective temporal and spatial scales of the climate predictions that are currently available. Besides, climate predictions are affected by different sources of uncertainty than weather forecasts. Therefore some advanced methodologies that have been used with weather forecasts cannot be directly employed with climate model outputs. For instance, dynamical downscaling might be computationally prohibitive, and statistical downscaling usually requires long observational records that are scarce. Additionally, the vast differences among technologies that extract kinetic energy from the wind and convert it to electricity complicate physical approaches for computing wind power production. This paper explores all those challenges and difficulties, identifies gaps and provides reasonable choices whenever that is possible. The decisions are guided by the view of producing an indicator that can be computed from publicly available state-of-the-art seasonal prediction systems, covers the whole globe, is useful for estimating power production at wind farm level and general enough to serve any technology.

The paper is organized as follows: section 2 describes the indicator and the technological challenges. The limitations of seasonal forecasts to produce generation forecasts are presented in section 3. In section 4 the potential of the methodology is explored through an application example over Europe. Finally some conclusions are provided in section 5.

## 2. An indicator of wind power generation that is suitable for any kind of wind farm

### 2.1. Capacity factor

Wind power generation of a single wind farm depends on many factors. The most important ones are the number of installed turbines and the turbine model –which determine the maximum power that can be produced (also known as installed capacity)–altogether with the wind blowing at the site. Ideally, we are interested in an indicator as general as possible, that accounts for the impact of wind speed variations and is useful to as many stakeholders as possible. Therefore different turbine types and wind farm sizes should be accommodated. In conversations with a co-designer from the industry (an important wind power producer and project developer) the capacity factor was selected as a suitable indicator of wind power generation. The capacity factor (CF) is a widespread performance indicator in the whole energy sector that allows fair comparisons between power plants of different sizes and types. It is a typical way of assessing the relative performance or usage of any generating power plant. For a given period of time, it is defined as the ratio of total produced energy ( $E_{prod}$ ) to the maximum production that could be achieved if the plant were operating at full (installed) capacity during all the time ( $E_{max}$ ). Simple calculus shows that CF can also be computed as the average produced power ( $\bar{P}$ ) normalized by the installed capacity ( $C_{inst}$ ).

$$CF = \frac{E_{prod}}{E_{max}} = \frac{\bar{P}}{C_{inst}} \quad (1)$$

CF is typically expressed as a percentage, and can be also interpreted as the percentage of time that the plant would have to be working at full capacity to produce the same amount of energy actually produced. This amount of time is also known as equivalent hours, and sometimes used in the industry, although CF is more prominent.

For conventional technologies, typically the capacity factor depends on factors like the availability and cost of fuel, the electricity demand, the needs of the grid operator or the market prices, because the power output can be adjusted at discretion according to the needs of the plant operator. But in the case of renewable energies like wind or solar, the fuel cannot be directly controlled (nor stored for later usage as hydropower allows), and as the fuel has no cost, all the produced energy is fed into the grid without further considerations. So, the generation in wind and solar plants depends almost exclusively on meteorological factors such as wind or irradiation. These meteorological factors have a natural variability, and hence the power output from these plants is said to be intermittent and non-dispatchable. In this sense, capacity factor of an already installed wind farm measures how efficient the meteorological conditions have been for producing energy during a specific period.

The capacity factor is therefore independent from the number of turbines and their nameplate capacity, which is a desirable property. However it does depend on the efficiency of the specific turbine at extracting energy from the wind at different speeds (see section 2.2). The total generation of a wind farm during a period can be easily derived from its capacity factor just by multiplying it by the installed capacity and the number of hours in the period of interest.

$$E_{tot} = CF * C_{inst} * t \quad (2)$$

### 2.2. Computing capacity factor

There are multiple approaches to computing capacity factors. Power producers and TSOs simply obtain it directly from metering records of the energy that is fed into the grid and use equation (1). This capacity factor takes into account all energy losses in the wind farm and is therefore called net capacity factor [5]. An other approach is to estimate a theoretical capacity factor that would be achieved if there were no losses at all, i.e. all available wind was converted into energy according to turbine specifications. This is referred as gross capacity factor. The typical way of computing the gross capacity factor is using manufacturer-provided power curves that relate power output to steady 10-min winds blowing at hub height. Capacity factor can easily be derived from power curve values dividing the power output by the nominal capacity of the turbine.

It is important to understand differences between gross and net capacity factors. The main element that impacts gross generation is the flow speed that the blades receive, although other flow properties affect the turbine performance, namely wind shear, wind veer, turbulence and air density. If the flow is not steady and homogeneous through all the swept area the generation will slightly differ from the values provided in power curves [8,15,35,44]. Changes in air density (through temperature, humidity and pressure variations) also modify the available kinetic energy that goes through the swept area and can produce generation differences of up to 5% [49]. In this study we will neglect all the turbulence and shear effects and assume a standard density of  $1.225 \text{ kg m}^{-3}$ , which is the density reported in most power curves.

The list of factors affecting net generation, i.e. losses of all kinds,

is long and diverse: downtime due to maintenance or failures, grid curtailments, environmental curtailments (e.g. presence of birds or bats), electrical transport and conversion losses, icing conditions, accretion of dust or mosquitoes, blade degradation due to abrasion, control strategies, wakes from obstacles or nearby turbines, etcetera. Those losses vary greatly from one wind farm to another, and even from one period to another. Differing wind farm designs, country regulations, O&M strategies, risk appetites and other factors make big differences in the final losses. Just as a reference, total losses might be in the range of 7.8%–37% with a typical value of 18.5% [5]. In view of this diversity of losses, and for the sake of generality, an indicator of gross generation has been selected. Then each user is allowed to subtract the losses deemed necessary in order to obtain net generation estimates.

### 2.3. Handling a diversity of wind turbines

There are in the market several manufacturers offering a wide range of turbines, and each of them is suited for maximum efficiency at specific wind conditions. Since the advent of industrial wind turbines in the 1980's there has been a technological race to build taller turbines, with bigger rotor diameters and more powerful generators. However we are interested here solely in their efficiency in extracting energy from the wind, i.e. their normalized power curves. The international standard IEC-61400-1 [25] defines four classes of turbines suited for an average annual wind speed of 10, 8.5, 7.5 and 6 m s<sup>-1</sup> at hub height respectively (see Table 1). The mean wind speed is used in these standard to estimate the extreme 50-year gust that the turbine will receive, so all turbines of this class have to withstand such gusts. Classes are further subdivided by the turbulence in the site, which also impacts structural loads.

Typically turbines of type III are lighter than type II or I for the same nameplate capacity, because they do not have to withstand heavy loads. Therefore, they can produce energy with weaker winds. Conversely, turbines of type I are heavy, and they only produce energy with stronger winds. In general turbines of the same IEC class have similar normalized power curves, and this gives a chance to provide a simplified approach to a diversity of turbine models.

From a sample of more than two-hundred turbine models, five have been selected to represent the different IEC classes. Capacity factors have been computed using those five power curves and will then be up to the users to select the one that most closely matches their turbine power curve. A first screening was carried out to select the most representative technologies. Several conditions were imposed: (a) consider only pitch-regulated turbines (i.e. the blade angle can be adjusted), (b) with nominal capacities around 2 MW, (c) available for installation at 100 m hub height (within the range 95–105 m), and (d) from the manufacturers with highest market shares in Europe: Vestas, Enercon and Siemens-Gamesa. Class IV is barely used in the industry, and Class S is for special designs not fitting any other class, so they have been discarded. Note that some

turbines can be certified as Class I and II or II and III at the same time, so we selected five turbines (see Table 2 and Fig. 1).

All the selected turbines start to turn and produce energy around 3 or 4 m s<sup>-1</sup> (cut-in speed). However, there are substantial differences in the wind speeds at which the five turbines reach the nominal power (rated speed). In the steeper section of the power curves, around 8 or 10 m s<sup>-1</sup>, differences of capacity factor reach more than 50%. It is also important to notice differences in the cut-out speed, i.e. the speed at which the turbine has to stop turning for safety reasons and stops producing energy (cut-out speed): the Vestas turbines for class II/III and class III stop producing at 20 m s<sup>-1</sup> while the others still produce energy up to 25 m s<sup>-1</sup>. Cut-out values are very important for sensitivity because small variations of wind produce ramps in capacity factor from 100% to 0%. Notice that there exist class III turbines with cut-out speeds of 25 m s<sup>-1</sup>, but these ones were selected to represent the widest range of differences amongst power curves.

### 3. Limitations of climate predictions to produce seasonal forecasts of capacity factor

Several centers produce operational climate predictions for the next months to come [20]. Typical settings cover up to six months ahead with some of the systems extending even one year ahead. These predictions are produced with coupled atmosphere/ocean/ice/land models. Although the atmosphere is very chaotic in nature and predictable only up to a few days ahead, the evolution of ocean temperatures, soil humidity, snow cover or sea ice extent evolves much slowly and in turn forces the atmosphere. This provides a chance to anticipate mean-state atmospheric anomalies [40]. To account for uncertainty, the predictions are repeated many times with slightly distinct but equally plausible initial conditions. This provides a set of ensemble members from which probabilities of occurrence of different situations can be estimated. Moreover, each prediction system is accompanied with a retrospective set of predictions for the past ten to thirty years, which is used to evaluate the quality of the predictions and adjust the biases.

These particularities of climate prediction result in huge amounts of data and expensive computational resource needs. Therefore all the producing centers carefully select the number of variables they generate, the spatial and temporal resolutions of their products as well as the number of ensemble members. Those compromises sometimes difficult the usage of the predictions for specific applications. The limitations that constrain our goal of producing capacity factor forecasts are detailed below.

#### 3.1. Spatial resolution

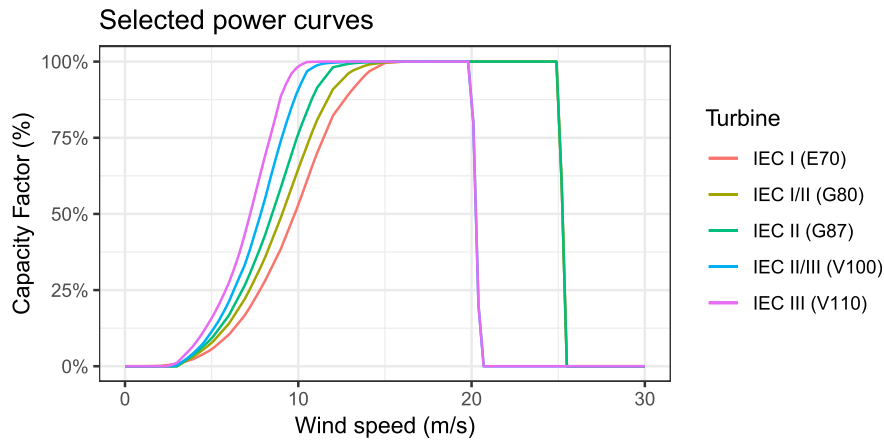
At small scales, the wind field near the ground is very spatially inhomogeneous. Turbulence, topography effects and obstacles can change the wind speed at distances of only a few tenths of meters. For that reason not all the turbines in a wind farm receive the same

**Table 1**  
Turbine classes defined in IEC-61400-1.

Class	Description	Annual average wind speed (m/s)	Turbulence intensity (%)	Extreme 50-year gust (m/s)
Ia	high wind & high turbulence	10.0	18	70
Ib	high wind & low turbulence	10.0	16	70
IIa	medium wind & high turbulence	8.5	18	59.5
IIb	medium wind & low turbulence	8.5	16	59.5
IIIa	low wind & high turbulence	7.5	18	52.5
IIIb	low wind & low turbulence	7.5	16	52.5
IV	very low wind	6.0	–	42.0
S	special	–	–	–

**Table 2**  
Technical characteristics of the selected turbines.

Turbine model	IEC Class	Rotor diameter (m)	Rated power (MW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-out speed (m/s)
Enercon E70_2.3 MW	I	70	2.3	2	16	25
Gamesa G80_2.0 MW	I/II	80	2.0	4	17	25
Gamesa G87_2.0 MW	II	87	2.0	4	16	25
Vestas V100_2.0 MW	II/III	100	2.0	3	15	20
Vestas V110_2.0 MW	III	110	2.0	3	11.5	20



**Fig. 1.** Selected power curves, normalized by maximum generation. Their specifications can be seen in Table 2.

wind speed at a given time. But the global models employed for producing seasonal predictions have grid sizes much bigger ( $\sim 50\text{km}$ ) than a typical wind farm extent, and therefore only provide one single wind speed value for all the turbines. Dynamical and statistical downscaling techniques can be used to refine the predictions [12, p.256]. Using microscale models one could adjust the wind speed to specific turbine locations [2], e.g. by computing a speed-up factor for each turbine location. However, this would require specific information on the wind turbine locations for each wind farm, which is not publicly available. Some authors have assumed a fixed distribution of speeds through the turbines to try to model this effect [42]. Other authors have used empirical power curves for the whole wind farm [18,29,37]. This approach also requires site-specific metering records of wind speed and production and cannot be employed to produce global forecasts. Although monthly or seasonal wind anomalies tend to be more homogeneous than the mean wind field and impact the whole wind farm in the same manner, power curves are sensitive to the absolute value of the wind, and therefore this effect can produce some differences in the monthly total generation of each turbine. The model employed here sticks to turbine power curves despite this limitation.

### 3.2. Temporal resolution

State-of-the-art seasonal prediction systems produce instantaneous outputs every six hours. Typically, those values are further aggregated to monthly or seasonal means, because predictability at seasonal timescales only arises when looking at long period averages: when averaging, the noise cancels and the forcing signal imparted by the ocean/land conditions can appear. In contrast, power curves are compiled with ten-minutal average winds as mentioned in section 2.1. As power curves are highly non-linear, using averages of wind speed to derive an average capacity factor can produce inaccurate results. Moreover instantaneous or ten-minutal wind speed distributions tend to be highly skewed

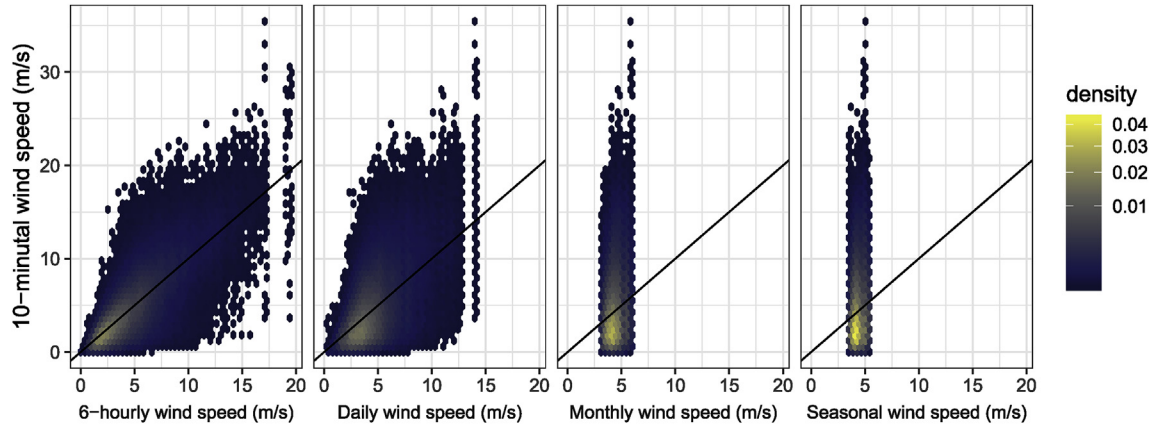
[33,34]. Therefore one might wonder what is the error incurred by using six-hourly sampled (instantaneous) winds or longer-period averages from the models with ten-minutal power curves. To illustrate this problematic, quality-controlled wind speed observations from 9 tall towers have been employed (see Table 3). For each location, ten-minutal wind speeds have been compared to its six-hourly, daily, monthly and seasonal averages. Fig. 2 shows the joint probability density of ten-minutal wind speeds and those longer period averages for one of those towers near Erie, Colorado and spanning 2006 to 2010. This plot reveals how apart are all the ten-minutal averages that compose a longer period average from the average itself. For six-hourly averages most of the ten-minutal values lie close to the  $y = x$  line. This means that for a given six-hourly period most of the ten-minutal values in that period are close to the six-hourly mean value, although a few of them can be quite apart. But for longer period aggregations the density peaks below the  $y = x$  line, and therefore a high number of ten-minutal values are lower than the period mean, with only a few of them above, although farther away. The analysis for the other 8 towers (see supplementary material) shows similar patterns. The non-linearity of the power curve complicates this further. The work of MacLeod et al. [30] discusses this issue in detail and finds that using daily averages is fair enough to produce accurate capacity factors. Six-hourly instantaneous values have been employed here. It is worth noticing that six-hourly instantaneous values from models are not directly comparable to six-hourly instantaneous samples from site observations. Global models at coarse scales do not represent adequately mesoscalar and turbulent motions and moreover the values provide a statistical value representative of a wide area. Therefore those six-hourly model outputs are much smoother than six-hourly instantaneous samples from anemometry, and tend to be closer to six-hourly averages [21].

### 3.3. Available variables

Another constraint for using power curves is that wind speed

**Table 3**  
Details of the nine tall towers employed.

Tower name	Country	Measuring height (m)	Period of record
BAO	USA	100	2007–2016
Butler Grade	USA	62	2002–2018
Cabauw	Holland	80	1986–1997 and 2001–2017
CVO	Cape Verde	30	2011–2018
FINO1	Germany	90	2004–2017
Ijmuiden	Holland	90	2011–2016
Lindenberg	Germany	98	1999–2017
NWTC M2	USA	80	1996–2017
WM01	South Africa	62	2010–2017



**Fig. 2.** Joint probability density function of ten-minutal and longer-period averages of wind speeds at Boulder Atmospheric Observatory. The black line is the  $y = x$  line.

should be provided at hub height. Modern turbines have hub heights in the range of 80–120 m, although many exceptions exist, especially with old wind farms that have lower hub heights. But current seasonal prediction systems only provide 10 m winds (or its components), which are obviously weaker than at those heights above ground. Some models also provide wind at standard pressure levels, but the changing orography and the sparse vertical levels make impossible to obtain wind at 100 m above ground. To estimate hub height winds from surface winds an extrapolation method is typically used. There exist two classical approaches: the power law and the log-profile [5,37]. For simplicity, we have selected here the power law and assumed a fixed hub height of 100 m, with a shearing exponent of  $\alpha = 0.143$  for land [47] and  $\alpha = 0.11$  for water [24]. Both shear exponents assume neutral stability (computing stability from existing forecast fields would be difficult if not impossible). Under these assumptions, wind at 100 m is obtained as:

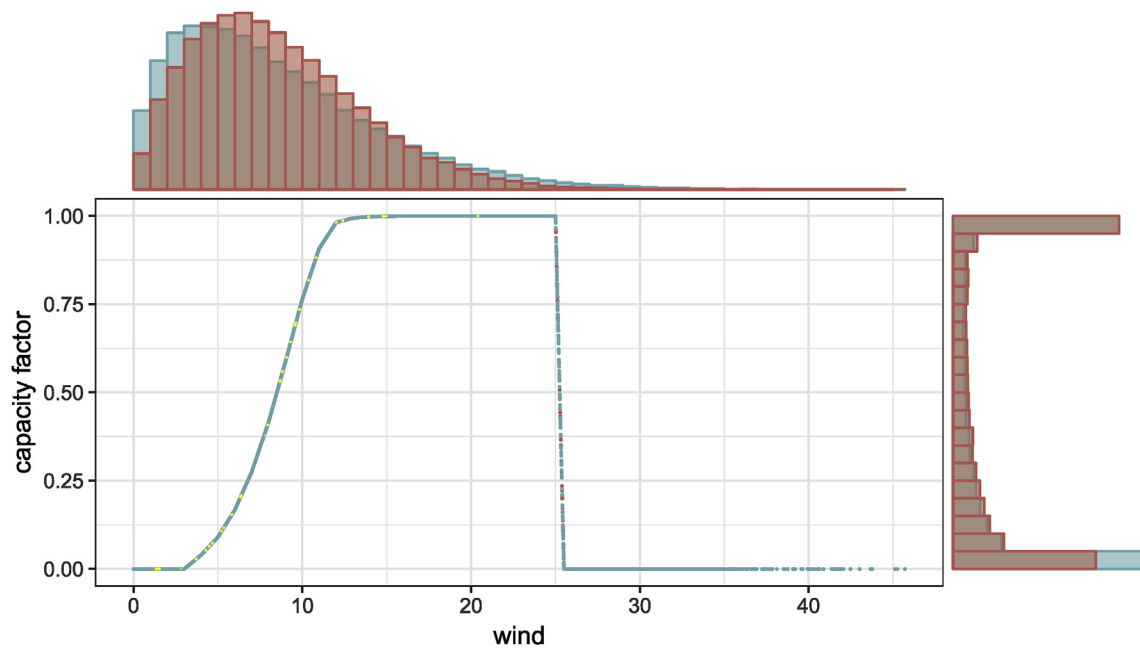
$$V_{100m} = V_{10m} * \left(\frac{100}{10}\right)^\alpha = \begin{cases} V_{10m} * 1.39 & \text{over land} \\ V_{10m} * 1.29 & \text{over sea} \end{cases} \quad (3)$$

Another not uncommon problem with available variables is the provision of time-averaged meridional and zonal wind components. As a result, computing the wind speed modulus from the average zonal and meridional components (using Pythagorean rule) produces much lower wind speeds than averaging the modulus directly. This limitation prevents the use of many seasonal forecast systems, for instance CFSv2 [39].

### 3.4. Model biases

All numerical prediction models have systematic biases due to many simplifications in the modelling of the complex behavior of

the Earth system. Those biases need to be adjusted before using forecasts for decision making or feeding impact models [46]. Moreover seasonal predictions might also exhibit drift [22] (i.e. non-stationary biases that change with the lead-time of the forecast), and need to be calibrated (i.e the spread of the ensemble adjusted to obtain reliable probabilities) [50]. There exist many bias adjustment methodologies for this purpose in the literature. For adjusting and calibrating monthly wind speed forecasts, the two methodologies described in Torralba et al. [46] are simple yet very effective. The general idea is to employ a set of retrospective forecasts (also known as hindcasts) and estimate the mean bias for each start date and lead time and subtract it from the corresponding monthly average forecasts. However, when trying to apply those methodologies to six-hourly winds some issues appear: when subtracting the monthly mean bias from six-hourly values, negative values can appear. Those negative values could be set to zero, but then the method would not entirely remove the bias. An alternative approach to avoid the negative values is to use a multiplicative approach, i.e. to compute a relative bias in percentage, and use this percentage to correct wind speed. But there is also a conceptual problem with these two approaches: they are designed to produce accurate monthly average wind speeds. However the goal here is to use the full range of six-hourly values to feed a (non-linear) power curve. Therefore it is not enough to correct the mean bias. Differences in variance and skewness of the wind distribution also have an impact on CF. Fig. 3 shows how two wind speed distributions with same mean but different variance result in a very different distribution of CF values. The narrower wind distribution produced less zero capacity factor values. From the example it is clear that the whole six-hourly forecast distribution needs to be adjusted. To that end, an empirical quantile mapping methodology has been employed [4,45]. This methodology aims to correct all of the moments of the distribution (ideally). As long as the adjusted



**Fig. 3.** Scatterplot of wind speed and corresponding capacity factor values obtained from two Weibull distributions with same mean (8.5 m/s) but different standard deviation (5 m/s in red and 6 m/s in blue), when the Gamesa G87 power curve is used for the conversion. The histograms on top are for wind, and the ones on the right for capacity factor values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

distribution of six-hourly wind speed values is similar to the observed one our capacity factor forecasts will be unbiased.

For the forecasts to be successful it is still needed to have some degree of skill in predicting the 6-hourly distribution shape. Although seasonal predictions do not provide correspondence between forecast and observations at daily or sub-daily scales it is possible to obtain skill in predicting the whole distribution of six-hourly winds in a longer period. Note that quantile mapping does not correct errors in the ensemble spread, so calibration might be needed separately (this has not been done here). Also, quantile mapping is known to worsen verification scores in areas where there is not any forcing signal [53].

### 3.5. Accuracy of reanalysis data as observational reference

The impact model we propose to compute capacity factor is very sensitive to the absolute value of wind speed that it receives. For that reason, the accuracy of the observational dataset used to bias adjust predictions needs to be as good as possible. Seasonal predictions are typically bias adjusted with reanalysis datasets [51], due to the need of having both global coverage and long records. Those global reanalysis datasets are good at representing variability at monthly, daily or sub-daily scales [10], but they suffer from similar problems than seasonal predictions, as far as they are produced also with modelling techniques. Although some of them provide hourly outputs and at higher spatial resolutions, and even some provide winds at 50 or 100 m above ground, the long-term mean wind speeds at hub height derived from them are biased when compared with tall tower observations. Wind atlases, such as DTU's Global Wind Atlas (GWA) or the New European Wind Atlas [1,36], incorporate information from mesoscale and microscale models and even from some observational sites and provide refined estimates of mean wind speed at relevant hub heights and for a finer grid. The 1981–2015 100 m mean wind speed difference between GWA and ERA-Interim [11] is shown in Fig. 4 as a percentage. According to GWA, over most of the continents the ERA-Interim 100 m wind speed needs to be increased. In some mountainous

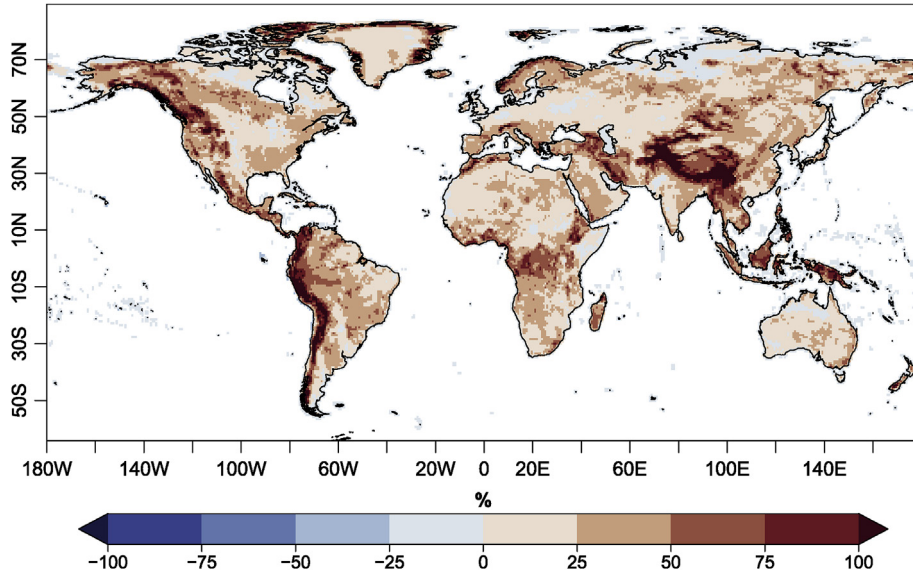
regions the correction is very high (more than 100%). Probably the GWA winds are too high in this case, as this is one of the known limitations of the GWA methodology that have been reported in Badger et al. [1] and Beaucage et al. [2]. To incorporate the mean wind speed information from a wind atlas but not lose the temporal variability that reanalyses provide, the ERA-Interim extrapolated 100 m wind data has been multiplied by the GWA to ERAI ratio. This adjustment can indeed be understood as a refinement at each location of the shearing exponent employed in equation (3) when extrapolating wind speed to hub height.

Another issue with global reanalyses that can be corrected with a wind atlas is the representativeness problem. Wind farms tend to be located in ridges or places where the wind is higher than its surroundings, therefore using the mean wind speed of the ERA-Interim grid box, even corrected by GWA mean wind speed in the grid cell, might be inaccurate. If the coordinates of the wind farms are known then the wind atlas value for the specific location can be used, instead of an average. This has not been done here.

Despite the mentioned difficulties, estimates of capacity factor for the past years have already been produced at hourly and six-hourly resolution from several global reanalyses datasets in the literature [13,19,42].

## 4. Application of the methodology over Europe and verification results

To illustrate the potential of the proposed methodology, it has been applied retrospectively for the winter season (DJF) with a hindcast of ECMWF System4 seasonal predictions [32] issued on November and covering 1981/82 to 2015/16 winters. Table 4 summarizes the main characteristics of this prediction system. The employed predictions from November have an extended integration up to 13 months and a hindcast with 51 ensemble members. Winter is the season with the highest inter-annual variability in Europe and therefore most seasonal prediction applications focus in this period. An overview of the steps that have been followed to produce the CF forecasts can be seen in Fig. 5. Details on



**Fig. 4.** Percentual difference between 100 m mean wind speeds from GWA and ERA-Interim over the period 1981–2015. ERA-Interim winds at 100 m were extrapolated from 10 m winds using a power law.

**Table 4**  
Main characteristics of ECMWF System4 prediction system, as described in Molteni et al. [32].

<b>System components</b>	
Atmosphere	IFS (model cycle 36r4)
Ocean	NEMO
Land	HTESSSEL
Sea ice	Prescribed from climatology
<b>IFS configuration</b>	
Horizontal resolution	$T_L255$ (~ 78km)
Vertical levels	91 levels up to 0.01 hPa
<b>NEMO configuration</b>	
Horizontal resolution	~ 1 × 1deg
Vertical levels	42 levels
<b>Operational configuration</b>	
Start date	1st of each month
Issue date	8th of each month
Ensemble members	51
Integration	7 months
Extended runs	extend 15 members up to 13 months (only Feb, May, Aug & Nov)
<b>Hindcast</b>	
Ensemble members	15 (Jan, Mar, Apr, Jun, Jul, Sep, Oct & Dec)
Period	51 up to 7 months and 15 up to 13 months (Feb, May, Aug & Nov) 1981 to 2010

most of the steps have already been covered in the previous sections. The only step that has not received attention so far is the final presentation of the probabilistic forecast results (step 5). The information from the fifty-one ensemble members has to be summarized in an informative way to be useful for decision-making. The standard approach in the climate prediction community is to provide probabilities for three tercile-defined categories: above normal CF, normal CF and below normal CF. The thresholds that define the three categories are computed as the percentile 33 and 66 of an observational historical record.

**4.1. Verification**

A verification has been undertaken employing reanalysis-derived CF values as verification truth. Therefore this verification

does not quantifies the quality of the impact model itself but of the whole capacity factor forecasts. Leave-one-out cross-validation has been employed to ensure that for each single forecast, the corresponding observations are not included in the bias adjustment procedure (i.e. each year is adjusted using the biases from all other years). The probabilistic nature of the seasonal predictions requires specific verification metrics [27]. The Ranked Probability Score (RPS) measures the quality of probabilistic forecasts presented in form of tercile probabilities. To gain a better understanding of the results, scores are typically compared to a baseline forecast and expressed as improvement over the baseline (known as skill scores). The Ranked Probability Skill Score (RPSS) compares the RPS of the seasonal predictions from System4 with the RPS of a climatological forecast. A climatological forecast uses observed values from previous years to derive probabilities for each tercile category

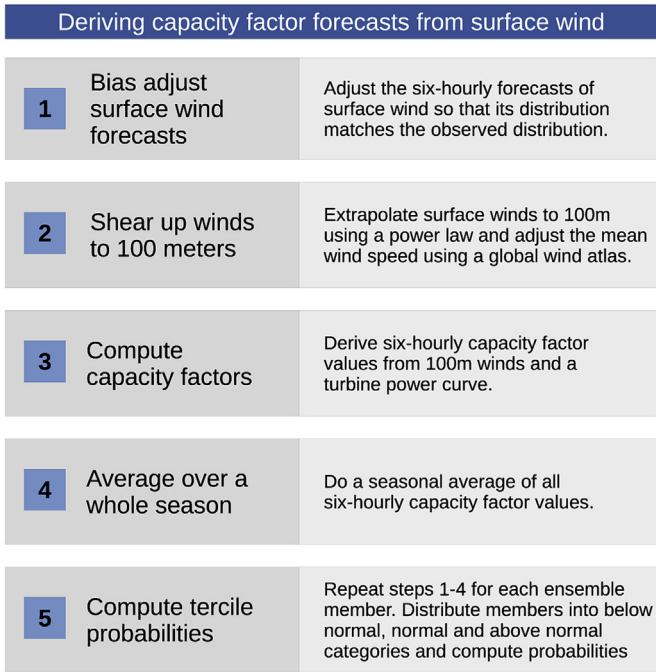


Fig. 5. Flow diagram of the steps followed to compute capacity factor forecasts.

(i.e. 1/3 of probability is always assigned to each tercile). Positive RPSS values represent an improvement over the climatology, while negative values discourage the usage of this forecasts. Fig. 6 presents RPSS values over Europe for both surface wind predictions (adjusted with the calibration method in Torralba et al. [46]) and capacity factor forecasts for IEC1, 2 and 3 classes. The skill for surface wind is modest in this region, but still positive in some spots, reaching up to a 17% of improvement over Finland. When looking at capacity factors, there is a slight increase of skill in many areas compared to surface wind. Especially in the British Isles, northern Germany, western France, and Scandinavian peninsula the seasonal predictions perform better than the climatology and offer some options to employ those forecasts for decision making.

5. Conclusions

A methodology to compute wind power generation seasonal forecasts employing manufacturer-provided power curves has been described. Several challenges related to how seasonal predictions are made available and how wind turbines generate electricity from wind speed have been addressed. A summary of those challenges and the proposed solutions follows below:

- CHALLENGE: generation of a wind farm depends largely on the number of turbines and the total installed capacity.

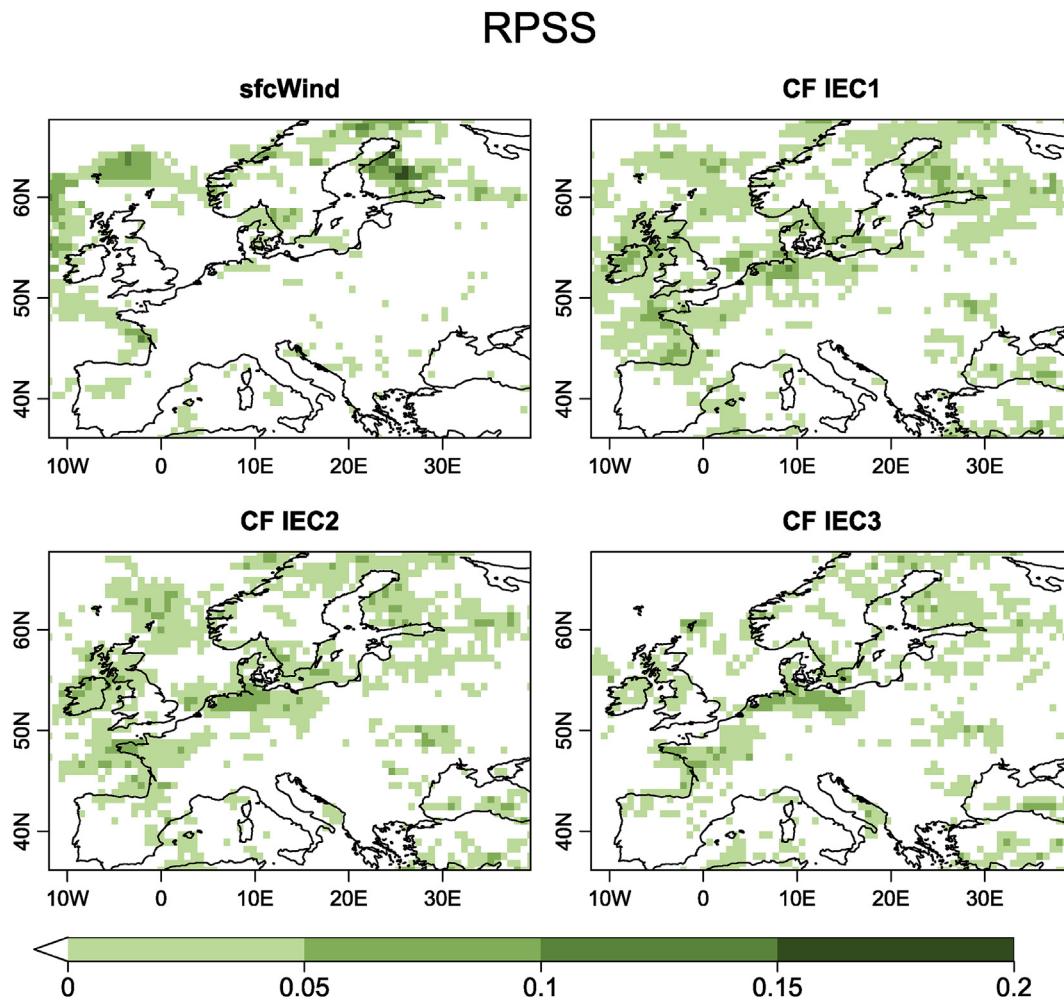


Fig. 6. Ranked Probability Skill Score of surface wind speed and capacity factor forecasts from ECMWF System4 issued in November and valid for next DJF season over Europe. The scores have been estimated from a hindcast covering 1981–2015, and employing ERA-Interim-derived capacity factors as verification truth.



**PROPOSED SOLUTION:** capacity factor provides normalized generation dividing by the installed capacity. Each user can derive total generation forecasts for a wind farm multiplying capacity factor by the installed capacity.

- **CHALLENGE:** a large number of turbine models exist with differing efficiency curves.

**PROPOSED SOLUTION:** capacity factor is computed for three different turbines representing three turbine classes suitable for low, medium and high wind speed conditions.

- **CHALLENGE:** wind farm losses are highly specific to each project.
- PROPOSED SOLUTION:** provide net capacity factor estimates and let each user subtract the losses deemed necessary.

- **CHALLENGE:** Seasonal predictions are produced at a coarse scale.

**PROPOSED SOLUTION:** Employ the predictions at the provided resolution. Statistical downscaling techniques cannot be applied without long on-site observational records. Dynamical downscaling is not feasible in terms of computational resources. Anomalies at monthly or seasonal time scales tend to be spatially smoother than short-term variability, therefore the local scale is not so relevant for seasonal predictions as might be for meteorological (e.g. day-ahead) prediction.

- **CHALLENGE:** power curves are valid for 10-minutal wind speeds, while most seasonal prediction systems produce monthly mean outputs and only a few of them provide daily or 6-hourly values at most.

**PROPOSED SOLUTION:** Employ six-hourly instantaneous values directly with the 10-minutal power curves. This effectively restricts the number of systems that can be used with this methodology.

- **CHALLENGE:** power curves are valid for wind speed at hub height, but only surface wind is available from state-of-the-art seasonal prediction systems.

**PROPOSED SOLUTION:** surface wind is adjusted at hub height with a simple power law, assuming a hub height of 100 m and fixed shearing exponents valid over land and sea under neutral stability.

- **CHALLENGE:** seasonal prediction systems have biases and drift in time.

**PROPOSED SOLUTION:** employ a lead-time dependant empirical quantile mapping bias adjustment technique. These method corrects the shape of the distribution.

- **CHALLENGE:** surface wind from reanalysis models, which is employed as observation for bias adjustment, is also biased, with the extrapolation at 100 m adding even more uncertainty.

**PROPOSED SOLUTION:** long-term mean wind speed from a high-resolution global wind atlas has been employed to adjust reanalysis winds at 100 m.

The methodology has been applied over Europe employing ECMWF System4 wind speed predictions. Those capacity factor predictions for the winter season proved to be better than using a climatological forecast in some regions, especially around the North Sea region. The method, although simple in some aspects, proved to be able to produce skillful forecasts of wind power generation one to three months ahead. Further developments could transform those generation forecasts into wind farm revenue forecasts or region/country aggregate forecasts that would be useful for TSOs and traders.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.renene.2019.04.135>.

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