WIND ENERGY
Wind Energ. 2009; **12**:640–659
Published online 22 January 2009 in Wiley Interscience
(www.interscience.wiley.com) DOI: 10.1002/we.315

Research Article

A Comparison of Methodologies for Monthly Wind Energy Estimation

E. García-Bustamante, Departamento de Energías Renovables, CIEMAT, 28040, Madrid, Spain and Departamento de Astrofísica y Ciencias de la Atmósfera, Universidad Complutense de Madrid, 28040, Madrid, Spain
J. F. González-Rouco*, Departamento de Astrofísica y Ciencias de la Atmósfera, Universidad Complutense de Madrid, 28040, Madrid, Spain
P. A. Jiménez, Departamento de Energías Renovables, CIEMAT, 28040, Madrid, Spain and Departamento de Astrofísica y Ciencias de la Atmósfera, Universidad Complutense de Madrid, 28040, Madrid, Spain
J. Navarro, Departamento de Energías Renovables, CIEMAT, 28040, Madrid, Spain
J. P. Montávez, Departamento de Física, Universidad de Murcia, 30071, Murcia, Spain

Key words:
wind speed;
wind energy estimation;
power curve;
linearity

Monthly wind energy estimations obtained by means of three different methodologies are evaluated. Hourly wind and wind power production data measured at five wind farms in the Northeast of Spain within the period spanning from June 1999 to June 2003 were employed for this purpose. One of the approaches is based on the combined contribution of the hourly wind speed frequency distribution and the corresponding power production. Several alternatives to represent the empirical wind power versus wind speed relationship are considered and their impacts on the error of monthly energy estimations assessed. Two more approaches derive monthly energy estimates directly from monthly wind values: one uses the theoretical power curve to obtain interpolated monthly wind power production values and the other consists in a simple linear regression between the observed wind speed and wind power monthly pairs, which serves as an approximation to the global power curve. The three methodologies reproduce reliably the total monthly wind energy. Results also reveal that linearity is a reasonable assumption for the relation between wind speed and power production at monthly timescales. This approach involves a simplification with respect to other standard procedures that require finer temporal resolution data.

Received 11 January 2008; Revised 04 November 2008; Accepted 14 November 2008

Introduction

Estimation of wind energy (*wE*) production from surface wind speed is not only interesting from a physical and engineering point of view. It also involves many ecological, economic and political aspects relevant for a society within a variety of timescales, ranging from hourly meteorological forecasts to long-term climate prediction. Short term *wE* forecast (hourly to daily scales) is important for electricity system management, particularly in liberalized markets, in order to ensure stability in the energy market.[1] Monthly and seasonal range prediction of *wE* can potentially allow electricity system operators to estimate the energy production availability from wind farms, and allow the electric network to conveniently adapt demand and resources.[2]

*Correspondence to: J. F. González-Rouco, Departamento de Astrofísica y Ciencias de la Atmósfera, Universidad Complutense de Madrid, 28040, Madrid, Spain.
E-mail: fidelgr@fis.ucm.es

Future changes in the regional and local wind fields as a result of the climate evolution within those spatial scales, though subjected to large uncertainties, can plausibly have significant impacts on energy resources which are worthy to be analyzed.[3] Therefore, evaluating the potential availability of *wE* resources,[4–8] their predictability[9,10] and variations[3,11,12] at different timescales are issues of interest in the context of renewable energy.

An understanding of the relation between wind speed and *wE* is desirable to attempt such evaluations and is often hampered in practical situations by the limited availability of historical power production records.

In the absence of available historical series of *wE* production, the relation between wind speed and *wE* is frequently established in terms of the associated *wE* density. In order to estimate it, different approaches are proposed within the literature,[13] the most extended one being the use of a theoretical probability distribution function (PDF) that fits the frequency distribution of wind velocity observations.[14–16] Subsequently, the estimated parameters of the PDF can be used to provide an idea of the expected energy that is carried by the wind.[17] In other cases, the dependence of *wE* on the wind speed is established through a discrete set of wind values and the corresponding outputs for a specific wind turbine or theoretical power curve (TPC) provided by the manufacturer.[3,18,19] Thus, an estimation of the energy that can be extracted from the wind may be obtained by means of the *wE* density calculation using only wind observations or additionally by incorporating technical information through the use of the TPC.

On the other hand, nowadays the wind energy market (facilities, wind energy conversion systems, energy policies, wind speed prediction, etc.) is widely developed in many regions of the globe, and some of them have been exploiting wind resources since a few decades ago.[20–25] Thus, admissibly long *wE* production series are now available for many locations and it is possible to use them to accurately validate the empirical relations between wind speed and power production at the various timescales of interest for resource assessments. For instance, García-Bustamante *et al.*[26] estimated monthly *wE* at several wind farms in the Northeast of Spain assuming a theoretical PDF (Weibull) would fit hourly wind speed observations. Using such a technique, the frequency terms are weighted by the corresponding power output, which can be derived from the TPC or some substitute of it. In that particular case,[26] the study is focused on the evaluation of the magnitude and nature of the error that the use of a Weibull distribution introduces in the estimation of monthly wind energy. This was done by using the historical records of power outputs to isolate the effects produced by the theoretical probability distribution. Celik[15,27] employed the measured *wE* values generated by a specific type of wind turbine and hourly wind observations to fit a third order polynomial curve that attempts to depict an experimental power curve, alternatively to the TPC. Availability of *wE* time series allows for a translation between wind speed and *wE* production for a specific site, helping to understand the underlying relation between both variables at every timescale. Such a relation can be used for instance in the assessment of the sustainability and predictability of wind resources.[2,4,6,8,14]

The target of this work is to illustrate the performance of several methodologies in estimating monthly *wE* production. This is done in an attempt to review some typical approaches for estimating wind power from wind speed and in doing so, exploring and understanding the relation between wind speed and wind power production at monthly timescales. For this aim, wind speed and *wE* production data from five wind farms sited in Northeast Spain (Figure 1) are employed. Three methods are compared in their ability to estimate monthly *wE* (wE_m). The first method examined is a common technique in wind resource evaluation that involves the fit of hourly wind data to a theoretical PDF and the use of a power curve that translates wind speed into wind power. The inspection of this methodology can be regarded as a continuation of the work by García-Bustamante *et al.*[26] where the impact of errors in the wind speed PDF distribution was analysed. Here, the impact of selecting a specific power curve on the estimations and the associated errors of wE_{m} is included. This method operating in hourly timescales is compared with other approaches that only use monthly resolution data. One of them adopts the strategy of estimating monthly *wE* by interpolating monthly wind speed values in the TPC. This rough approximation could be useful as a benchmark in the estimation of wE_m in the case that no historical *wE* production data were available at a particular site. The last procedure is based on the empirical relationship found between wind speed and wind power at monthly timescales and consists in assuming a linear relationship between wE_{m} and monthly wind velocity. Therefore, the standard approach providing

DOI: 10.1002/we

estimations of wE_m from hourly wind speed is compared with even more parsimonious approximations making use of coarser temporal resolution (monthly) information. This will allow for evaluating to what extent situations in which only monthly data are available could involve a loss of information in the estimation of wE_m.

This paper is organized as follows. The next section introduces the wind speed and *wE* datasets while the Methodology section describes and comments on the approaches employed to estimate *wE* from wind. The Results section presents and discusses results and finally, main conclusions are summed up in the Conclusions section. The acronyms used along the text are listed in the Appendix at the end of the manuscript.

Dataset Description

This work is focused on five wind farms (Alaiz, Aritz, El Perdón, Leoz and San Martín) situated in the Comunidad Foral de Navarra (CFN), a region with a considerable wind energy development located in the Northeast of Spain, in the southwestern side of the Pyrenees. Orographic features and wind farm locations are represented in Figure 1. The dataset consists of 4 years in the longest case (1999–2003) of hourly observations of wind speed and power production.

Original data have been subjected to a basic quality control in order to mitigate possible disturbances because of erroneous records in the performance of the methods used herein. Repeated values (duplicated dates/hours), missing information (dates, wind speed, etc.), unrealistic negative values or observations larger than physical thresholds supported by the instrument were identified and replaced with a missing code. The observations were not subjected to any other controls to filter out doubtful data like extreme wind speed or power production values (outliers). Thus, some dispersion in the representation of the hourly values can be expected as it is discussed further.

To elude any perturbation caused by the different number of observations within each month, 350 pairs of simultaneous hourly wind speed–wind power data (ca. 50% of observations) were selected from each month. The random selection is conditioned to follow a uniform distribution that allows for each value to have equal probability of being chosen. This approach, also adopted in García-Bustamante *et al.*,[26] enables a homogeneous and representative sampling representation of the variability of both wind speed and wind power within every month in the dataset. The number of extractions (350) was selected as a balance between decimating excessively the dataset or, alternatively, using potentially non-representative monthly mean values calculated from too few observations.

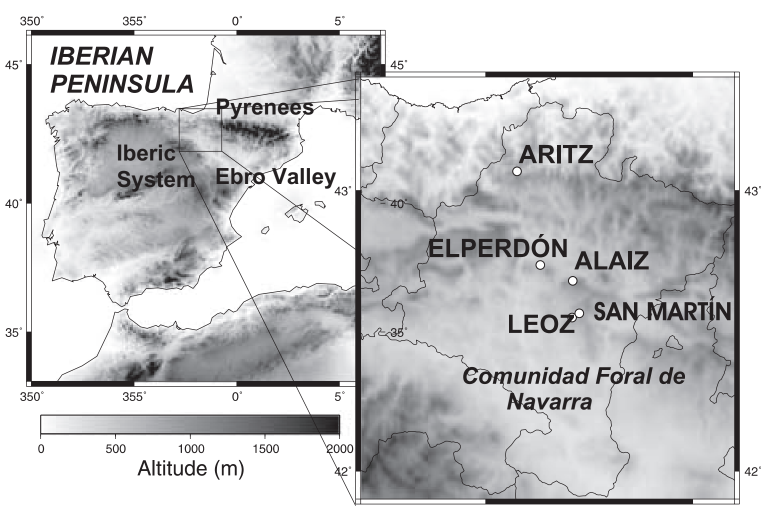

Figure 1. Orography (shaded) and wind farm locations (circles) in the CFN

DOI: 10.1002/we

In the case of the wind velocity, the hourly series were registered by anemometers located in weather stations within the wind farm, except for Leoz (Figure 1) where wind speed was measured at each wind turbine. For this site, a spatially averaged wind speed time series was calculated and considered to be representative of the whole wind farm.

The power production data were recorded at every wind turbine operating at the site. In Alaiz and Aritz, only one type of turbine is installed while in the case of El Perdón, Leoz and San Martín, several models are present (see García-Bustamante *et al.*[26] for further details). Since different models of turbine provide different power production for different wind speed levels, in the cases of wind farms with several turbine types, a power production series was calculated for each type of wind turbine installed. Hence, just one power production time series was calculated to represent Alaiz and Aritz, whereas three series were obtained for El Perdón and Leoz and two in the case of San Martín. The turbine model is identified with a code of the type GXX-YYY, where XX is the blade diameter (diameter of the area swept by the blade) in meters and YYY is the rated power (power output under nominal operating conditions) in kW.

The hourly power outputs from every wind turbine were averaged to obtain the corresponding number of series (as many as turbine types installed) representative for the whole location. The alternative to the use of a single series at each wind farm would be to use the records at every wind turbine. This strategy could potentially improve the estimation, as the information from each mast would provide a more realistic wind speed–wind power relation at individual turbines. Nevertheless, this work leans on the use of single average wind power series per farm. Several reasons have favored this simplified approach, as for instance, a small variation of the wind power production from turbine to turbine or the constraining fact that in this case study, four out of the five available wind farms have wind speed measurements available at only one location within the farm. This limitation is in practice not severe since changes in variability of power production among turbines are very small, particularly at monthly timescales. In addition, the ultimate goal of this text is to illustrate, in a parsimonious rather than sophisticated approach, the advantages and disadvantages of various strategies to estimate monthly wind power production.

Thus, it is worth to mention that the average relation between the hourly measured wind speed and wind power pairs is characterized by a large scattering (not shown, see Figure 4 in García-Bustamante *et al.*[26]). This hourly dispersion or deviation of the actual power outputs from the expected can be related to some extent to the methodological approach previously commented, i.e. the average over the total set of turbines to obtain the total power production, together with other methodological issues like the fact that in some wind farms, wind speeds are recorded at a meteorological mast instead of the exact turbine locations or the use of a single pair of wind speed and wind power series to represent the whole wind farm. In addition, the technical manipulations and some other local effects like the operational control on turbines, the effect of turbulence on short timescales,[28] shading between masts[29] or the influence of changes in air density could lead to deviations from the expected wind speed–wind power relationship.

Regarding the averaging of wind speed records from each turbine at the hub height (in Leoz) versus the use of a wind series recorded at each meteorological mast (the rest of wind farms), it is also worthy to remark that in Leoz, the hourly observations are less dispersed than in the rest of the locations. This evidence could point out that the power generated is sensitive to wind speed variations along distances within the wind farm dimensions and that using wind data from a single meteorological mast (i.e. less precise than measurements at each turbine location) could contribute to the mentioned scattering. Therefore, potentially more elaborated schemes could incorporate the use of wind observations at each turbine. This approach would not necessarily suffer from turbulence effects since wind speed observations recorded with specific instrumentation at hub height (e.g. nacelle anemometers in the case of Leoz) incorporate corrections from possible distortions caused by shading or wake effects among turbines.[29] Nevertheless, the analysis of the potential sources of scattering in the wind speed–wind power diagrams is of relevance since it helps to understand to what extent the TPC or any substitute of it is representative of the observations.

Correlations between the monthly power production series corresponding to the different turbine models are larger than 0.9 at El Perdón, Leoz and San Martín. For this reason, results concerning only one type of turbine (G42–600 kW) will be shown in the three sites for simplicity from here on. Additionally, the correlation values

DOI: 10.1002/we

Table I. Correlation between the monthly power production time series at each wind farm (wind turbines are type G42–600 kW, except for Alaiz where the model G47–660 kW is used)

	Alaiz	Aritz	El Perdón	Leoz	San Martín
Alaiz	1.00	–0.03	0.91	0.90	0.77
Aritz	–0.03	1.00	–0.22	0.21	0.39
El Perdón	0.91	–0.22	1.00	0.74	0.57
Leoz	0.90	0.21	0.74	1.00	0.95
San Martín	0.77	0.39	0.57	0.95	1.00

between the selected power production time series at each site in Table I present high values in the center of the CFN showing a similar evolution of wind power production variability. The production in Alaiz is strongly correlated with the other three wind farms (correlations of 0.8–0.9). El Perdón presents a correlation of 0.74 and 0.57 with Leoz and San Martín while these two locations present a 0.95 correlation coefficient. The exception is the most distant wind farm, Aritz, which presents a decoupled wind power production. The fact that power production in Aritz is uncorrelated with the rest can be attributed to its geographical situation to the north of the other four sites (Figure 1) that favors exposure to more Atlantic circulations while the others are more conditioned by the presence of the Ebro Valley.[30] The circulation regimes that influence the regional wind and wind energy as well as the climate variability in the CFN will be dealt with elsewhere (some information can be found in Jiménez *et al.*[30,31])

Expanded information about the dataset, as geographical location of wind farms, wind sensor heights, number and type of wind turbines, monthly wind speed and wind power means and deviations, etc., can be found in García-Bustamante *et al.*[26]

The estimation of the total wE produced in a month is the result of scaling the monthly power values with the total number of hours selected per month (350) and the number of wind turbines considered within each site to produce realistic total wE_{m} values. At this point, it is worthy to distinguish between the terms wind energy (wE) production and wind power production. The original data consist of hourly power production values (kW) but results are given in terms of energy production in kWh, since they are scaled with the number of hours within each month to obtain a total monthly production for each wind farm. Thus, power production values should be interpreted as the turbine output while wE is the total energy obtained from the wind farm.

Analysis of Methodologies

Three strategies are compared in their performance to derive estimations of wE_{m}.

The first strategy is based on a standard procedure[15,27,32–34] that takes into account hourly wind velocity data. It considers the observed wind speed frequency histogram, or a viable fit to a theoretical PDF of the frequency terms, and a transfer function representing the relation between wind speed and power production.

The other two strategies lean on the use of monthly wind and power production data. The second approach is based on the very rough assumption that the TPC would be valid at monthly timescales and thus, translates monthly wind values into monthly power production through an interpolation in the TPC. Some considerations addressing the validity of such an assumption are discussed in the next subsection.

The third approach is based on assuming that the relationship between wind speed and wind power is linear. Their monthly averages, as will be discussed in the subsection 'Linear Regression' (e.g. Figure 3) fall in the quasi-linear part of the TPC and are suggestive of a simple linear empirical relationship between them.

A more detailed description of the three methodologies is presented in the following subsections.

DOI: 10.1002/we

Estimation Based on Hourly Resolution Data

The first approach to estimate the total production of wE_m is based on the use of the hourly distribution of wind speed within each month and an estimate of the wind speed-wind power dependence such as the TPC or some substitute of it. This method has become relatively standard in obtaining wE estimates from high temporal resolution wind speed series[6,8,14,35] and allows to assess to what extent including hourly information refines results in comparison with the other approaches described below that only consider monthly time resolution. The estimation of the wE_m is obtained through:

$$wE_H = \Delta t N N_t \sum_{i=1}^{n} p_{out}(w_i) f(w_i) \qquad (1)$$

where wE_H is the total monthly wE production estimated from the hourly wind values, $f(w_i)$ is the expected frequency for each of the n wind speed class intervals represented by w_i and $p_{out}(w_i)$ is a transfer function for the power versus wind speed relationship which provides an estimation of the power production for a given w_i; Δt is the time resolution of the input wind speed data (1 h), N is the total number of hours per month and N_t is the number of wind turbines.

Several comments can be made at this point concerning the estimations of $f(w_i)$ and $p_{out}(w_i)$. Of all possibilities, the most accurate estimation of wE for a given month should be the one calculated using the observed wind speed frequency, $f(w_i)$, and the observed relationship between power production and wind speed within each particular month, $p_{out}(w_i)$. The wind speed frequencies can be easily obtained from splitting the range of hourly wind observations into wind intervals, whereas the effective relationship between wind speed and generated power can be derived from the observation of the power production at each one of those intervals. This provides an empirical wind power versus wind speed curve that can be referred to as the effective power curve (EPC) and that can be used as $p_{out}(w_i)$. Such an estimation serves as a benchmark of the upper predictability that can be obtained using the procedure pointed out by equation (1) and provides an idea of the systematic error in the methodology associated with the discretization of the wind speed series into intervals. This estimate will be denoted herein as wE_{H-ref}.

However, many practical cases involve situations in which the precise knowledge of $p_{out}(w_i)$ and $f(w_i)$ is not available. In these practical situations, wE_H must be estimated by making approximations to the wind frequency distribution and the corresponding power output. A first approximation in such cases is the use of a specific theoretical PDF, like the Weibull function for instance[3,27,35–37] as a substitute for the observed wind speed frequency. This constitutes a first source of error when estimating wE_H in equation (1) to the extent that the specific wind distribution of a certain month deviates from the Weibull shape; the deviation being particularly relevant in the high wind speed range where the largest power production is achieved.[34] García-Bustamante *et al.*[26] evaluated to what extent the assumption of a Weibull distribution affected the estimation of wE through the procedure pointed out by equation (1). That study adopted the experimental relationship between wind and wind power (EPC) given by $p_{out}(w_i)$ and isolated the error impact of the Weibull approximation by substituting the observed frequency histogram with the one obtained from a fit to a Weibull distribution. Results suggested that even if the Weibull assumption was not substantiated for every site or time step, this does not necessarily imply a strong impact on the wE estimation errors.

A second source of error is provided by the assumptions made to estimate $p_{out}(w_i)$. One of the goals of the present work is the evaluation of the impact of using an approximation to the power terms on the wE estimations given by equation (1). With this purpose the observed frequency distribution is employed to provide the $f(w_i)$ terms (as in the case of wE_{H-ref}) and a set of variants for the power output terms were considered in order to isolate their influence on the wE_m estimations. These allows for the segregation of the two sources of error as previously performed in García-Bustamante *et al.*[26] but, in this case focused on the impact of the assumptions made about the power curve. Thus, in addition to wE_{H-ref} that provides information about the methodological error in equation (1), three more estimates of monthly energy production obtained with different versions of the wind speed-power relation are proposed here. The substitutes for the EPCs adopted herein are also considered to be representative of the whole wind farm, in spite of the fact that power production at each individual wind turbine within the wind farm is not identical to the rest.[38]

DOI: 10.1002/we

The first candidate for the $p_{out}(w_i)$ terms is the TPC. This is the simplest and roughest approximation since the TPC does not take into account the global wind farm effects (e.g shading between turbines). However, it has the advantage that historical data are not required. Bechrakis *et al.*,[8] Jaramillo and Borja[19] and Bivona *et al.*[39] for instance, have used commercial power curves (TPC) to obtain energy production. Hereafter the energy estimation produced using the TPC as an estimate of $p_{out}(w_i)$ will be denoted as wE_{H-TPC}.

Two more approximations of the EPC are considered: an *average power curve* (APC) and a third order polynomial fit curve (PFC). The APCs are calculated as the average of all the EPCs along the period of observation at each site, calculating for each wind speed interval the corresponding mean power production value. The PFC is the cubic polynomial that better fits the whole ensemble of EPCs. The use of these approximations is intended to explore the potential benefits of developing more elaborated models to substitute the EPC and that can be used as a realistic representation of the wind speed-wind power relationship. These approaches can incorporate some effects that are specific to the wind farm location and make use of the already existing information to face situations in which no data for a particular month are available. Even if these two new power curve models appear to be somewhat more elaborated than the EPC case, they are still conceptually simple since they do not take into account the effects of more complicated features like wind direction, the relative position of masts within a wind farm, the air density, etc. This will be commented on in the Results and Discussion section.

In order to keep independence between monthly WE_H estimations and the EPC averaging/fitting process through the methodological assessment, the data for the target month (the month for which the wE_H is going to be estimated) are excluded in the calculation of the APC/PFC curves. With this specification, a single APC/PFC is independently obtained for each particular month. This procedure can be compared with a cross-validation approach through which the temporal robustness of the empirical relation found between sets of predictand and predictor variables is assessed:[40] for each time step the estimation of the target-predictand variable (i.e. wind energy production herein) is obtained from the available predictor (i.e. wind speed) through the use of an empirical model (in this case, APC or PFC) that is built on the basis of the available information from all other time steps. The energy estimation in this case is denoted with wE_{H-APC}/wE_{H-PFC}.

Figure 2 illustrates the three approaches employed to represent the relationship between wind speed and wind power (TPC, APC and PFC) and therefore providing estimates for $p_{out}(w_i)$ in equation (1). December

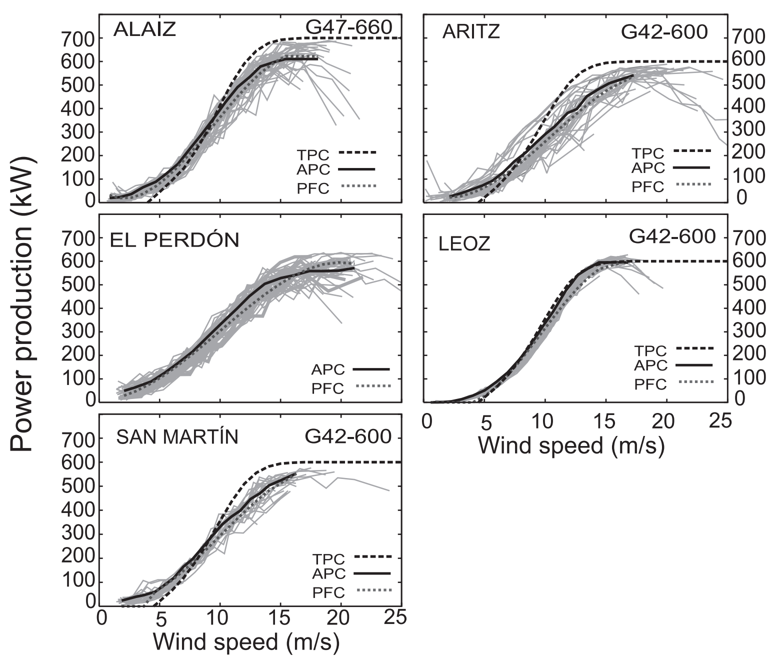

Figure 2. TPC (dashed), APC (solid) and PFC (points) for December 2001 at each of the wind farms; wind turbine types are G47–660 kW in Alaiz and G42–600 kW in Aritz, Leoz and San Martín. In El Perdón, no TPC was used (see text)

DOI: 10.1002/we

2001 is shown as a particular case example. The TPC generally underestimates the power generated at the lower wind speeds whereas it tends to overestimate it for the higher wind velocities. The weighting effect of the $p_{out}(w_i)$ terms in equation (1) is stronger for the highest wind speeds and thus, a global overestimation of the final wE_{H-TPC} should be expected. This point is further analyzed through the interpolation method in the next subsection. The APC and PFC are very similar though the PFC displays generally (not shown) smaller power values than the APC for the same wind.

The dispersion of the hourly wind speed–wind power pairs discussed in the Data section is also evidenced in the representation of the EPCs (Figure 2). Such an effect is, as expected, minimized in Leoz where the set of EPCs displays a much smaller monthly variability. A consequence of the spatial average over the set of turbines to obtain single power production series at each wind farm can be appreciated in the bended shape of some of the EPCs close to the cutoff wind part of the curve in Figure 2; for winds above the cutoff level, some turbines may be stopped in order to avoid damages because of high aerodynamic loads, but at the same time other turbines within the wind farm may still generate power at high wind velocities. The average overall muted and operating turbines produces the power decrease for high wind speed values in Figure 2 (for more details see García-Bustamante *et al.*[26]). Thus, as illustrated for the case of December 2001, the TPC, APC and PFC in this location provide an improved representation of the wind speed-wind power relation than in the rest of wind farms. An alternative to the PFCs calculation as it is done here could be the implementation of a polynomial fit over all the available hourly wind speed-wind power pairs.[27,32] However, the large dispersion of hourly observations leads to low signal to noise ratios that do not statistically support the fit to polynomial functions of orders higher than one. The generation of monthly EPCs from hourly data enhances signal to noise ratios (Figure 2) and allows for implementing higher polynomial orders that are consistent with the typical shape of a TPC. The TPCs cannot be established properly for El Perdón as a result of the frequent technical manipulations during the period of measurements and that probably contribute to a large dispersion of the wind speed–wind power pairs at this specific wind farm. Thus, the corresponding curve for this site is not shown in Figure 2.

The comparison of wE_{H-ref} with the energy production calculated using the various estimates of the EPC (wE_{H-XXX}, with $XXX \equiv$ TPC, APC, PFC) allows for an evaluation of the errors associated to the $p_{out}(w_i)$ terms in equation (1). However, in order to compare the results of this approach with the ones described in the next subsections, it is desirable to provide an integral error estimation that includes also the effect of the $f(w_i)$ terms previously discussed. The evaluation of the error impact of the frequency terms is non-trivial since it depends on the theoretical PDF that wind speed is assumed to follow. For the sake of simplicity and consistency with previous work, this study adopts the Weibull distribution. Therefore the $f(w_i)$ terms are substituted by their corresponding Weibull estimates following the same procedure as in García-Bustamante *et al.*[26] The monthly energy estimations including both types of error will be denoted as wE_{H-XXXw} (with *XXX* ≡ *TPC, APC, PFC).*

Interpolation Using the Theoretical Power Curve

The TPC is the relationship between wind speed and power production, usually calculated using 10 min observations, provided by manufacturers and specific for each type of wind turbine.

The power that can be actually produced by a turbine does not increase with the cubic wind speed. As expected from basic theoretical considerations of wind kinetic energy, the available power carried by the wind is $P_a = \frac{1}{2}\rho A w^3$,[7,38] where ρ is the air density and A is the area swept by the rotor. The wind energy that could be generated by an ideal wind turbine (P_w) is P_a, increasing with the cubic wind speed up to the rated wind speed or the wind at which no increase in power production can happen.[7] Additionally, P_w is reduced by the rotor presence so that the power that can actually be generated results from balancing out the expected efficiency of the turbine, aerodynamic loads, turbulence, rated power and various other technical aspects. The

DOI: 10.1002/we

attenuation can be expressed as a percentage in terms of the power coefficient, $C_P(w)$, that depends on wind speed and shows a theoretical upper limit of ca. 0.59, given by the Betz limit.[41] Therefore:

$$P = \frac{1}{2} C_p(w) \rho A w^3 \tag{2}$$

is the actual power produced by a wind turbine as a function of wind speed.[38]

It could be argued that the actual power production (P) corresponding to monthly wind speeds would not deviate much from the manufacturer's reference value obtained by evaluating the TPC on the specific wind speed monthly averages. Such an assumption can serve as a rough benchmark estimation to be compared with the results of the somewhat more elaborated approaches described in the previous subsection and the next. On the basis of assuming the TPC as an appropriate candidate for a monthly power curve, monthly estimations of power production can be obtained by direct interpolation within the TPC:

$$P_{\text{Interp}} = P_0 + \frac{(P_1 - P_0)}{(w_{\text{m1}} - w_{\text{m0}})}(w_{\text{m}} - w_{\text{m0}}) \tag{3}$$

where w_m is the monthly mean wind, (w_{m0}, P_0) and (w_{m1}, P_1) are the two nearest points in the TPC and P_{Interp} is the monthly interpolated power output. From a formal standpoint, equation (3) cannot be supported since it is tantamount to considering that the non-linear TPC function that describes power production at high resolution timescales can also be used to estimate monthly power production when evaluated over monthly wind speed averages. This assertion would be necessarily incorrect since the monthly average of the non-linear TPC will not equate the result of the non-linear function evaluated on the monthly wind average. The results of applying equation (3) will illustrate the poorer performance of this assumption. Nevertheless, the estimates obtained can be useful to illustrate the error that can be made with such a crude approximation. In addition, equation (3) may be useful as a first rough estimate of the potential power production that can be expected in situations with no availability of historical wind power observations and having only monthly power records; this could be the case for instance of downscaling applications where only monthly estimations of wind variables are available.[42] On the basis of this rationale, P_{Interp} estimations have been included herein for comparison with the other approaches presented in the text.

The P_{Interp} values after interpolating the observed w_m at each wind farm, are shown, together with the corresponding TPC for comparison in Figure 3. Observed monthly averages span within the quasi-linear interval

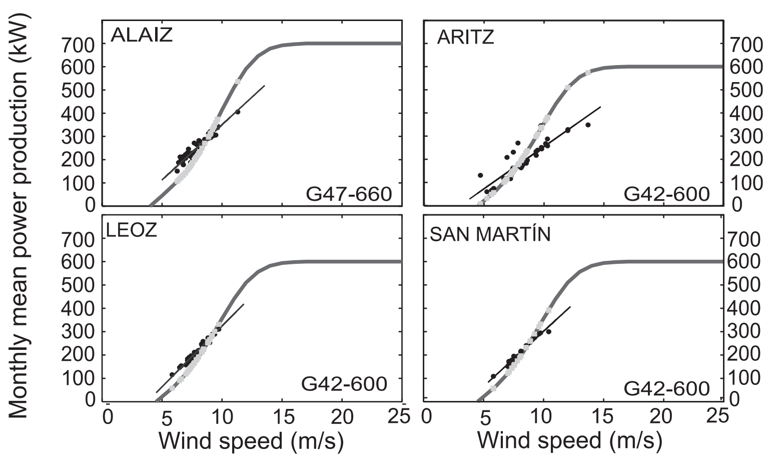

Figure 3. Observed monthly wind speed and wind power pairs (black points) and its linear fit (black solid line), TPC (gray line) and interpolated values of power production from monthly wind velocity in the TPC (light gray points). Notice that the TPC corresponding to turbine type G47–660 kW is shown in Alaiz while for the other sites G42–600 kW is used. El Perdón is not shown since it does not have a well-defined TPC

DOI: 10.1002/we

of the TPC. It is worth noting that the slope of the straight line that best fits the monthly observations is lower than that of the TPC, a consequence of the monthly averaging and the perturbations discussed. This larger tilt anticipates that any estimation of *wE* based on the TPC interpolation will likely overestimate the variance of observations, as was first discussed in the previous subsection.

The total monthly interpolated *wE* (wE_{Interp}) is calculated according to:

$$wE_{\mathrm{Interp}} = NN_{\mathrm{t}}P_{\mathrm{Interp}} \tag{4}$$

where N is the number of hours of each month (here 350) and N_{t} is the total number of wind turbines of the same type at the wind farm.

Linear Regression

Though the theoretical relation between wind and wind power at shorter timescales shows a cubic dependence of the P_a on the wind, monthly power production values have disclosed a significant linear relation (Figure 3). This linearity can be moreover appreciated in the monthly power and wind velocity standardized time series in Figure 4 at the five sites for which correlations are confined in the interval (0.89, 0.99). Additional arguments supporting a linear relation between monthly wind and wind power can be also found in the statistical properties of the Weibull distribution if this was considered to be representative of wind field properties or, from a broader perspective, in the relation between wind speed and its cubic power in equation (2).

In the light of this linear relationship between the monthly power production and wind speed values evidenced through Figures 3 and 4, a third approach based on a simple linear least squares fit between both variables is evaluated using:

$$P_{\mathrm{Linear}} = aw_{\mathrm{m}} + b \tag{5}$$

where w_m is the observed monthly wind speed and a and b are the regression coefficients.

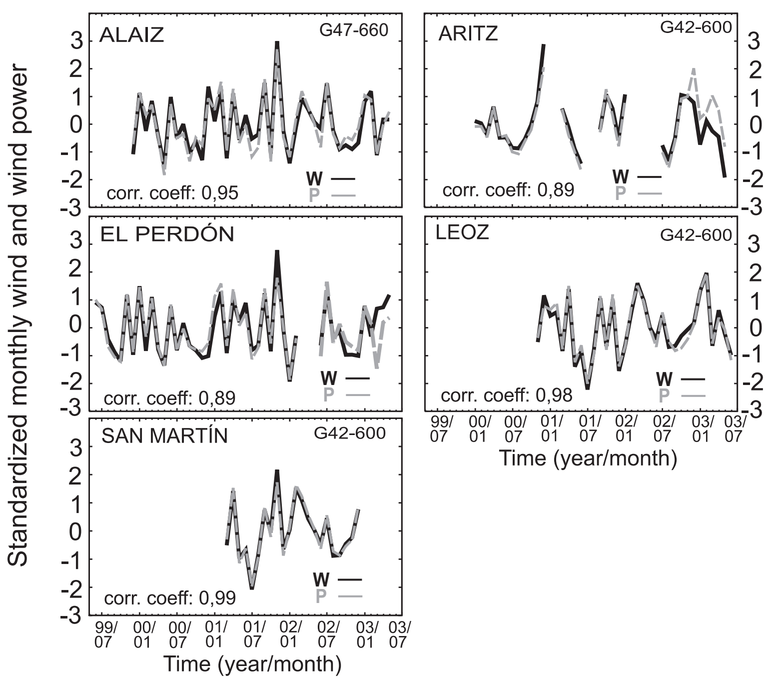

Figure 4. Monthly wind speed (w) and power production (P) time series in all wind farms. The series have been standardized by removing their mean and dividing by their standard deviation. Notice that the TPC corresponding to turbine type G47–660 kW is shown in Alaiz while for the other sites G42–660 kW is used

DOI: 10.1002/we

If theoretically it was assumed that the Weibull distribution appropriately describes the statistical features of the wind field, the idea of linearity stems from the properties of this frequency distribution,[43] for which the n order moments are defined by:

$$E(w^n) = c^n \Gamma\left(1 + \frac{n}{k}\right) \tag{6}$$

being w the wind speed, c the scale parameter and k the shape parameter. Then, the expected mean value, which would represent the monthly wind velocity, is defined as $E(w) = c\Gamma\left(1 + \frac{1}{k}\right)$, and the third order moment, that would be representative of the monthly wind energy carried by the wind if assuming a Weibull distribution is $E(w^3) = c^3\Gamma\left(1 + \frac{3}{k}\right)$. The correlation coefficients for the calculated monthly $E(w)$ and $E(w^3)$ series range from 0.94 to 0.97 (not shown). Thus, a good approach to linearity between the wind speed and the energy carried by the wind in the range of monthly values could be also considered if a Weibull distribution was theoretically assumed.

Furthermore, the previous argument can be generalized for any frequency distribution, by calculating the correlations between the monthly wind speed and the available monthly power carried by the wind (P_a), represented by means of the monthly-averaged cubic wind speed. These correlation coefficients between both variables are 0.93 for Alaiz and Leoz, 0.94 for Aritz, 0.92 in El Perdón and 0.95 for San Martín, respectively, thus supporting that linearity can be a parsimonious assumption for the relation between wind speed and P_a for the typical monthly range of values at the various sites.

The difference between P_a and the power generated by an ideal wind turbine (P_w) is that, in the case of P_w, the power production increases with the cubic wind up to the rated wind speed.[7] Finally, the differences between P_w and the actual power generated are mainly because of the $C_p(w)$ power coefficient. This factor, at the range of values considered at monthly timescales and for the turbine types previously described, can be approached as constant (e.g. Vestas[44]). Thus, linearity can be a plausible assumption that is worth testing also from this perspective.

In order to ensure independence in the building of the model in equation (5) a similar process as in the case of the hourly based method [equation (1)] was performed: each monthly P_{Linear} estimation is obtained by inserting the corresponding w_m value into the linear regression previously calculated, incorporating all the remaining monthly wind speed-wind power pairs after excluding that of the target month. This procedure was carried out consecutively for each month and separately for each one of the groups with similar wind turbines at farms with more than one type of turbine. The total monthly wind energy estimation (wE_{Linear}) is computed from equation (4), replacing P_{Interp} with P_{Linear}.

Results and Discussion

Estimations Based on Hourly Data

Figure 5 (left column) shows the observed temporal evolution of wE_m production at each wind farm and the wE_m estimations obtained from hourly resolution data using the approaches described in the subsection 'Estimation Based on Hourly Resolution Data.' It is worth noting that months with large production alternate with months with less power generation which is a sign of interannual variability potentially related to atmospheric circulation. It is apparent that all methodological variants capture the overall structure of the temporal variability at all sites. The differences among the various energy estimations are smaller than the range of intra- and interannual variability. The different power production ranges at each wind farm seem to be also well

DOI: 10.1002/we

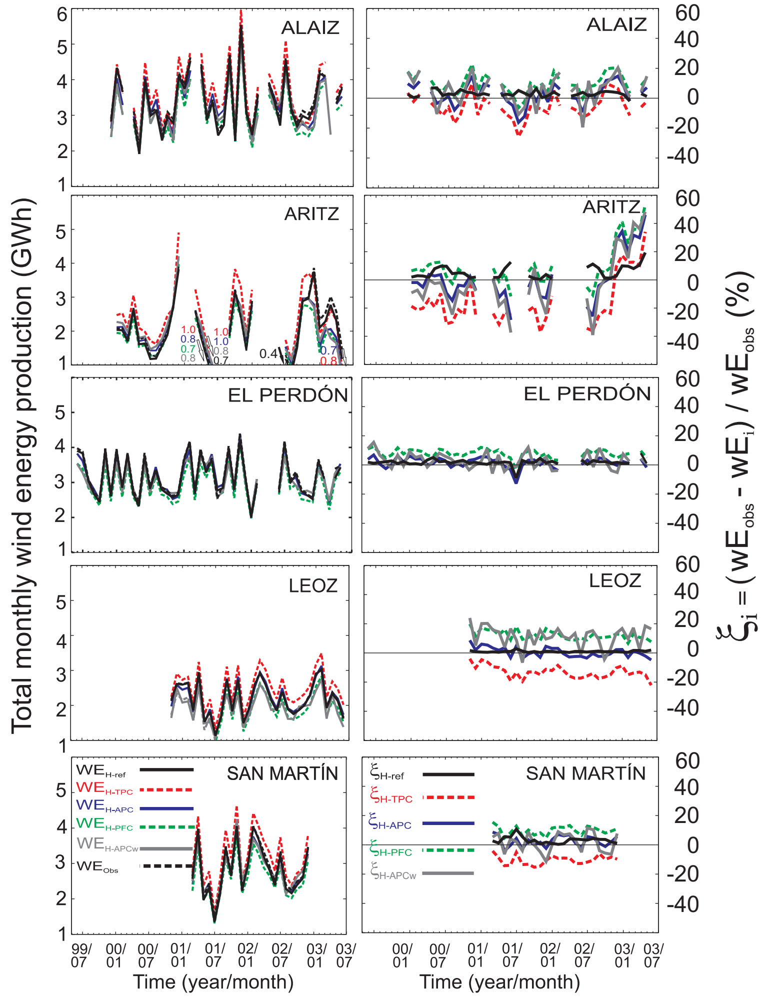

Figure 5. Observed and estimated total monthly wEm time series (left column) for all wind farms using hourly resolution data as described in the first subsection of the Methodology. The optimal methodological estimations using the actual monthly EPC and histogram, $wE_{H\text{–}ref}$ is compared with other variants, wEH–XXX, incorporating XXX ≡ TPC, APC, PFC as estimations of the effective power curve. $wE_{H\text{–}APC_w}$ estimations including APC as an estimate of EPC and a Weibull fit for the frequency terms are also shown. The corresponding estimation relative errors are represented in the right column

represented. The two methodological variants that produce the larger discrepancies are the ones incorporating the TPC and the PFC ($wE_{\mathrm{H}\text{–}TPC}$, $wE_{\mathrm{H}\text{–}PFC}$).

The similarity between energy estimations and observations can be quantified with the correlation (ρ) and the Brier skill score (β) statistics that measure the concordance between observations and estimations and an estimate of the observational variance that the model accounts for, respectively[40] (Table II).

The $wE_{\mathrm{H}\text{–}ref}$ estimations show the largest values of ρ and β (Table II) indicating that, as expected, they reproduce best the variability in observations. The methodological variants incorporating the TPC, APC and PFC curves still deliver very high ρ and β values. The performance in terms of the β score is best for the $wE_{\mathrm{H}\text{–}APC}$ estimations and worst for the $wE_{\mathrm{H}\text{–}PFC}$ case. This suggests that assuming the TPC as a simple estimate of the relationship between wind speed and power production or the average of all

DOI: 10.1002/we

available monthly power curves (APC) can produce a good performance or even better than more elaborated polynomial fits.

The additional use of Weibull estimates for the frequency terms further deteriorates monthly energy estimations and provides a more realistic estimation of the error associated to this approach, due both to the $f(w_i)$ and $p_{out}(w_i)$ terms. For simplicity reasons, results in Figure 5 and Table II are only shown for the case of incorporating the APC power curve ($wE_{H\text{–}APCw}$), which has produced the best results so far. It is noticeable that in general the $wE_{H\text{–}APCw}$ estimation falls within the variability of the ensemble of methodological variants, thus suggesting that incorporating the error in the frequency terms is, in general, of less relevance than changing the estimation used for the power terms. This comparatively smaller impact does not necessarily point out a good quality Weibull fit.[26]

Figure 5 (right column) illustrates also the different performance of the methodological variants previously discussed by showing the temporal evolution of the relative error: $\xi_I = (wE_{obs} - wE_i)/wE_{obs}$. As indicated in Table II, the smallest errors are produced by the reference methodological estimations, $wE_{H\text{–}ref}$. The case of incorporating the APC power terms provides the second best estimations and the TPC and PFC cases tend to present negative (overestimation) and positive biases (underestimation), respectively. This is because of the over- (under-) estimation of $p_{out}(w_i)$ terms by the TPC (PFC) for large monthly wind speeds (see Figure 2). In Figure 5, this reveals a systematic behavior for which specific corrections could be developed at each wind farm, thus improving the performance of these model variants. Some methodologies can be found in the literature regarding potential improvements that could be used to derive more refined estimates of the power curve at each site than the ones used herein. For example, Pinson *et al.*[45,46] applied non-parametric techniques providing probabilistic estimates of the power production to evaluate the uncertainty associated with the wind power estimates and to derive a more accurate estimation of the power curve. Some other works use non-parametric statistical methodologies for different issues related to the wind speed modeling, as for instance, in wind tunnel experiments[47] or to correct bias, scattering or inhomogeneities in data coming from a model.[48]

An overall perspective for the error at each site is provided in Table III where the average of relative and total errors is shown. For the calculation, absolute values at each time step have been considered to avoid

Table II. Correlation (ρ)/Brier (β) skill score for the different methods

ρ/β	Alaiz	Aritz	El Perdón	Leoz	San Martín
$wE_{H\text{–}ref}$	1.00/0.98	1.00/0.98	1.00/0.98	1.00/1.00	1.00/0.98
$wE_{H\text{–}TPC}$	0.96/0.87	0.90/0.71	—/—	0.99/0.68	0.99/0.83
$wE_{H\text{–}PFC}$	0.96/0.67	0.89/0.60	0.99/0.66	0.99/0.63	0.99/0.72
$wE_{H\text{–}APC}$	0.95/0.88	0.89/0.73	0.98/0.94	0.99/0.98	0.99/0.94
$wE_{H\text{–}APCw}$	0.92/0.76	0.84/0.72	0.96/0.85	0.94/0.59	0.96/0.91
wE_{Interp}	0.94/0.56	0.81/0.52	—/—	0.97/0.82	0.98/0.83
wE_{Linear}	0.94/0.88	0.76/0.47	0.96/0.92	0.98/0.95	0.98/0.96

Table III. Averaged absolute relative ($\overline{|\xi_r|}$) and total ($\overline{|\xi_t|}$) errors in monthly *wE* estimation at each wind farm

$\overline{|\xi_r|}(\overline{|\xi_t|})$	Alaiz % (MWh)	Aritz % (MWh)	El Perdón % (MWh)	Leoz % (MWh)	San Martín % (MWh)
$wE_{H\text{–}ref}$	2.6 (89)	5.0 (102)	1.7 (55)	0.9 (20)	2.9 (80)
$wE_{H\text{–}TPC}$	7.8 (265)	21.7 (434)	—(—)	13.1 (288)	10.5 (294)
$wE_{H\text{–}PFC}$	10.2 (347)	11.9 (238)	8.0 (256)	12.2 (268)	9.9 (277)
$wE_{H\text{–}APC}$	6.2 (211)	11.8 (236)	2.9 (93)	2.9 (64)	3.7 (104)
$wE_{H\text{–}APCw}$	9.2 (313)	14.8 (414)	4.8 (153)	10.0 (264)	6.0 (168)
wE_{Interp}	18.1 (615)	24.3 (486)	—(—)	13.4 (295)	11.8 (330)
wE_{Linear}	6.6 (224)	17.5 (350)	3.5 (112)	4.1 (90)	3.9 (110)

DOI: 10.1002/we

cancellation of errors by changes in sign. The worst estimations are obtained at Aritz for all methods. The average error ranges between 0.9 and 5% for the five wind farms in the best case scenario for the hourly resolution method ($wE_{\text{H}-ref}$) and between 7.8 and 21.7% for the roughest power curve approximation case ($wE_{\text{H}-TPC}$). As previously discussed, $wE_{\text{H}-APC}$ produces the best results of the three tested approximations with values ranging between 2.9 and 11.8%; these errors increase to values between 4.8 and 14.8% when the Weibull approximation is included. As previously mentioned, this comparatively small increase suggests that, in general, the contribution to error of assumptions made in the power terms is more important for the sites studied herein than those concerning the fit to a theoretical probability distribution. Yet two amendments should be made to this statement. The first one is that a clear exception takes place in Leoz where the average error increases from 2.9 to 10.0% after the introduction of the Weibull approximation. This is also shown clearly in Figure 5. The reason for this behavior is the poorer quality of the Weibull fit at this site that is a result of a large underestimation of observed frequencies at high wind speeds (see García-Bustamante *et al.*[26] for details).

The second amendment to the last statement stems from the fact that the errors associated to the frequency terms have been included in $wE_{\text{H}-APC\text{w}}$, considering the optimal monthly fit to a Weibull distribution as was done in García-Bustamante *et al.*[26] However, there is a conceptual difference between this approach and the incorporation of errors in the $p_{\text{out}}(w_{\text{i}})$ terms performed in this text. For the latter, the estimation of the power curve for each monthly case involved an independent assessment based on the exclusion of data belonging to the target month whereas for the $f(w_{\text{i}})$ terms, the best fit was developed using the hourly data of the target month. This means that the error associated to the inclusion of the Weibull assumption represents only the contribution of substituting the observed histogram by its Weibull fit and not the impact of estimating the Weibull parameters from information independent of the target month. This issue would expectedly increase in practical situations the error associated to the $f(w_i)$ terms in the $wE_{\text{H}-APC\text{w}}$ estimations.

A couple of final comments are worth concerning Figure 5. It is apparent that all energy estimations, except for $wE_{\text{H}-ref}$, tend to produce a similar pattern in the temporal evolution of errors, an exception being Leoz, where the impact of errors in the $f(w_{\text{i}})$ terms is comparatively larger. This suggests that all approaches fail to conveniently reproduce some of the specific features of the monthly variability in the $p_{\text{out}}(w_{\text{i}})$ terms. This common pattern of errors can be understood if it is recalled that the power curve models employed in the different energy estimations do not consider the influence of several factors like the wind direction or the air density, etc. The elaboration of a power curve that is valid for the whole wind farm can involve many physical and engineering aspects to be taken into account in order to represent in detail the global wind speed–wind power relation.[38] Previous work has attempted to illustrate, for instance, the uncertainty in the energy production estimation that arises from the use of a specific wind turbine power curve.[49,50] Also, Pinson *et al.*[46] employ an advanced nonparametric statistical approach to adequately estimate the conversion function from wind speed to wind power. Such a refinement of the energy estimations or the inclusion of specific corrections for each power curve model is out of the scope of this work and from such perspective the power curve models used herein are parsimonious and all omit a number of complexities that can lead to the common pattern of errors in Figure 5.

It is also interesting to highlight the increase of error produced by all methodological variants, including $wE_{\text{H}-ref}$, in Aritz at the end of the observational period. The causes for this overall failure that produces the largest errors have not been elucidated. This behavior suggests problems with the quality of data as a plausible cause that would deteriorate the performance of the reference estimate $wE_{\text{H}-ref}$ and consequently also of the others.

Estimations with Monthly Data and Comparison with the Hourly Case

Figure 6 allows for extending the assessment to the performance of the two very simple approaches described in the last two subsections of the Methodology (wE_{Interp} and wE_{Linear}). Results for ρ and β as well as for relative error averages are also shown in Tables II and III. For clarity purposes, only the $wE_{\text{H}-APC\text{w}}$

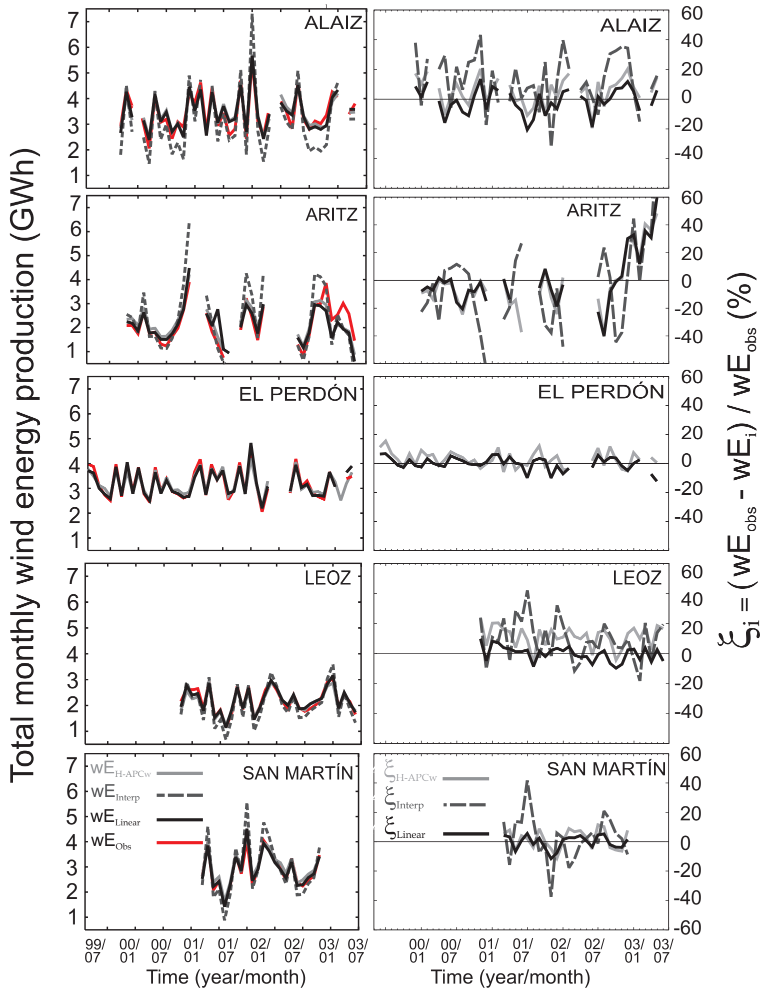

Figure 6. Observed and estimated total monthly wE ($wE_{H\text{–}APC_w}$, wE_{Interp} and wE_{Linear}) time series (left column) for all wind farms. The corresponding relative errors are represented in the right column

variant, which involves the more realistic assessment of errors in Figure 5, is included in Figure 6 for comparison.

It can be appreciated in Figure 6 (left column) that both wE_{Interp} and wE_{Linear} reveal quite a good performance in comparison to $wE_{\text{H–}APCw}$ in spite of the rough approximations adopted. In particular, it is worth to note that the wE estimation obtained through the interpolation of monthly wind speed values in the TPC (wE_{Interp}), although it overestimates the variance of the observations as previously discussed, is able to replicate their temporal structure and reasonably captures the variability of observed time series in the wind farms (the explained variance is 89, 66, 95 and 96% for Alaiz, Aritz, Leoz and San Martín, respectively). The $wE_{\text{H–}APCw}$ and wE_{Linear} estimations are very similar in all cases and they are additionally very close to the observed values. This is also evidenced in Figure 6 by the relative errors of the different estimations ($wE_{\text{H–}APCw}$, wE_{Interp} and wE_{Linear}) and in the statistics in Tables II and III. The interpolation method presents the largest errors, as shown in Figure 6 (right column), in the higher error averages of Table III and in the decrease of the Brier score

DOI: 10.1002/we

values in Table II. This is a result of an overestimation of variability by this method produced by the larger tilt of the TPC relative to the observed wind speed–wind power relationship at monthly timescales (see Figure 3). It can be argued that the TPC is calculated to represent the relationship between wind speed and wind power for 10 min resolution data. Its use as an estimation of the EPC in $wE_{\mathrm{H}-TPC}$ in an hourly resolution data approach is admissible in view of the results shown in Figure 5 and Tables II and III. The use of monthly averages involves changes in the relationship between wind speed and wind power (Figure 3) that are not well captured by an interpolation in the TPC. The reason behind addresses the use of the averaging operator (which is linear) over a curve that is essentially not linear, except at the intermediate range of wind values where it can be approached as a quasi-linear curve (see discussion in the last subsection of the Methodology). Nevertheless, wE_{Interp} still captures the temporal variability in the observations (Figure 6) and thus, it may prove useful when monthly wind energy estimations are required in situations of no availability of power production observations.

The more interesting feature in Figure 6 is perhaps the fact that $wE_{\mathrm{H}-APC\mathrm{w}}$ and wE_{Linear} produce a similar performance. wE_{Linear} performs worse in Aritz (see Tables II and III) and compares well or outperforms $wE_{\mathrm{H}-APC\mathrm{w}}$ in the rest of the sites. In Leoz, where the impact of the frequency terms produces larger deviations in $wE_{\mathrm{H}-APC\mathrm{w}}$, wE_{Linear} does visibly better (Figure 6, right column). In addition, in practical situations the error associated to $wE_{\mathrm{H}-APC\mathrm{w}}$ could be expected to increase if we recall the fact that these estimations incorporate only a lower limit estimation of the error in the frequency terms (see independence arguments previously raised). This argument further endorses the performance of a parsimonious simple linear regression in comparison with more elaborated approaches. Therefore, not only does the linear approach achieve comparably good results, but also it performs as a simple and robust methodology operating on monthly resolution data.

It is also interesting to notice that the temporal evolution of errors in Figure 6, in particular those of $wE_{\mathrm{H}-APC\mathrm{w}}$ and wE_{Linear}, is correlated (values not shown). Such changes in wE_{Linear} can only stem from deficiencies in the representation of the monthly variability of the slope in the linear regression. Therefore, this supports the idea that in the case of $wE_{\mathrm{H}-APC\mathrm{w}}$ and the methodological variants included in Figure 2, the common temporal structure of error derives from common deficiencies in the representation of the tilt of the power curve.

Conclusions

In this work, three methods have been compared in their performance to estimate monthly wind energy. The first strategy makes use of hourly resolution data and builds estimates based on the wind speed frequency distribution and on a transfer function that expresses the relationship between wind speed and wind power at these timescales. Different estimates have been analysed: the observed monthly power curves (EPCs), the TPCs provided by manufacturers, the average of the available EPCs (APCs) or a polynomial fit to them (PFCs). Observed frequency histograms have also been replaced by Weibull estimations to take into account the influence of the frequency terms. The selection of these power and frequency estimates has been done on the basis of their simplicity and/or standard use.

In the second approach, the TPC has been used to obtain monthly values of power production through an interpolation procedure using directly the monthly wind velocity. Some evidences of the linear relationship existing between wind and power production at monthly timescales are shown, in spite of the expected cubic relation between both variables. Thus, the last approach here considered consists in a simple linear regression calculated over the monthly wind speed–wind power pairs.

All methods and methodological variants used pick up the intra-and interannual variability of energy production at all wind farms. The hourly approach produces minimal errors when the EPC and monthly frequency histograms are used in $wE_{\mathrm{H}-ref}$ and they are raised most often below 20% (below 15% on average) when power curve and frequency approximations are used. The APC provides a simple and straightforward estimation for the power terms that leads to the best results.

DOI: 10.1002/we

The inclusion of the Weibull approximation raises the error, particularly at sites where the quality of the fit is clearly bad as in the case of Leoz. The results achieved in this work suggest that the choice of a power curve is more critical than the errors stemming from using a Weibull fit to the data.

The interpolation-based method provides wE_{Interp} estimations that tend to overestimate monthly wind energy variability because of a larger tilt in the TPC than in the observed relationship between wind speed and wind power at monthly timescales. Nevertheless, monthly energy estimations with this approach may be useful in situations of unavailability of power production data.

The hourly-based and linear regression methods perform comparably in spite of the simplicity of the linear regression approach. This supports the use of regression estimates in estimations of energy production from monthly resolution data.

Estimating the *wE* production from the wind at monthly timescales based on the robust knowledge of the wind speed–wind power relationship can be useful in the medium- and long-term framework. For instance, in an empirical or dynamical downscaling context, the wind speed is derived through its relation with the large-scale circulation and afterwards the wind energy can be estimated from the wind velocity. Some previous works that assess the past variability of the wind and wind energy density and evaluate possible changes in the wind energy resources in potential climate change scenarios can be found in the literature.[12,17,35,42,51] The empiric linearity between the two variables at monthly timescales involves an additional interesting alternative: the direct estimation of the wind energy production from its relation with the synoptic atmospheric flow. It can be expected that such a relation presents similar properties as the relation between the wind and the atmospheric circulation at monthly timescales as a result of the empirical linearity observed between wind velocity and power production at these timescales.

Acknowledgements

The authors wish to thank Acciona Energía and especially Manuel Calleja for providing the data employed in this work. A special recognition for many interesting and enriching comments to Dr. M. Montoya, Dr. E. Zorita, Dr. D. Bray and Dr. L. von Bremen. The authors also thank the collaboration covenant no 2003/89 between Universidad Complutense de Madrid and Centro de Investigaciones Energéticas Medio Ambientales y Tecnológicas (CIEMAT) for supplying funding and a framework for cooperation to both groups. JFGR was funded by the Ramon y Cajal program.

Appendix: Nomenclature

β	Brier skill score
c	Weibull scale parameter
CFN	Comunidad Foral de Navarra
C_{p}	power coefficient
EPC	effective power curve
$f(w_{\text{i}})$	wind speed frequencies for the i class interval
k	Weibull shape parameter
P	actual power produced by a wind turbine
P_{a}	available power carried by the wind
PDF	probability density function
P_{Linear}	monthly linearly fitted power output
P_{Interp}	monthly interpolated power output
$p_{\text{out}}(w_{\text{i}})$	transfer function for the power *vs.* wind speed relation for a given w_i
P_{w}	wind power generated by an ideal wind turbine

ρ	correlation skill score
Sw_m	monthly mean wind speed standard deviation
S_{wEm}	monthly mean wind energy standard deviation
TPC	theoretical power curve
w	wind speed
w_i	wind speed representative for the *i* class interval
$\bar{w}$	monthly mean wind speed
wE	wind energy
wE_{Linear}	total monthly wind energy estimated from the monthly linear fit
wE_{Interp}	total monthly wind energy estimated from the monthly interpolation
wE_{H-APC}	total monthly wind energy estimated from hourly wind speed using the APC
wE_{H-APCw}	total monthly wind energy estimated from hourly wind speed using the APC and the Weibull expected frequencies
wE_{H-PFC}	total monthly wind energy estimated from hourly wind speed using the PFC
wE_{H-ref}	total monthly wind energy estimated from hourly wind speed using the EPCs
wE_m	monthly mean wind energy
ξ_i	estimation error using the *i* method

References

1. Kariniotakis G, Pinson P, Siebert N, Giebel G, Barthelmie R. The state of the art in short-term prediction of wind power—from an offshore perspective. *Proceedings of 2004 SeaTech Week* 18–22 October 2004: Brest, France.
2. Weisser D, Foxon TJ. Implications of seasonal and diurnal variations of wind velocity for power output estimation of a turbine: a case study of Grenada. *International Journal of Energy Research* 2003; **27**: 1165–1179.
3. Palutikof JP, Davies PM, Davies TD, Halliday JA. Impacts of spatial and temporal windspeed variability on wind energy output. *Journal of Climate and Applied Meteorology* 1987; **26**: 1124–1133.
4. Jamil M, Parsa S, Majidi M. Wind power statistics and an evaluation of wind energy density. *Renewable Energy* 1995; **6**: 623–628.
5. García A, Torres JL, Prieto E, de Francisco A. Fitting wind speed distributions: a case study. *Solar Energy* 1998; **62**: 139–144.
6. Mathew S, Pandey KP, Kumar A. Analysis of wind regimes for energy estimation. *Renewable Energy* 2002; **25**: 381–399.
7. Chang TJ, Wu YT, Hsu HY, Chu CR, Liao CM. Assessment of wind characteristics and wind turbine characteristics in Taiwan. *Renewable Energy* 2003; **28**: 851–871.
8. Bechrakis DA, Deane JP, McKeogh EJ. Wind resource assessment of an area using short term data correlated to a long term data set. *Solar Energy* 2004; **76**: 725–732.
9. Mengelkamp HT. Wind climate simulation over complex terrain and wind turbine energy output estimation. *Theoretical and Applied Climatology* 1999; **63**: 129–139.
10. De Rooy W, Kok K. A combined physical-statistical approach for the down-scaling of model wind speed. *Weather and Forecasting* 2004; **19**: 485–495.
11. Pryor SC, Barthelmie, R. Long-term trends in near-surface flow over the Baltic. *International Journal of Climatology* 2003; **23**: 271–289.
12. Pryor SC, Barthelmie RJ, Schoof JT. Inter-annual variability of wind indices across Europe. *Wind Energy* 2006; **9**: 27–38.
13. Balouktsis A, Chassapis D, Karapantsios T. A nomogram method for estimating the energy produced by wind turbine generators. *Solar Energy* 2002; **72**: 251–259.
14. Weisser D. A wind energy analysis of Grenada: an estimation using the Weibull density function. *Renewable Energy* 2003; **28**: 1803–1812.
15. Celik AN. Weibull representative compressed wind speed data for energy and performance calculations of wind energy systems. *Renewable Energy* 2003; **44**: 3057–3072.
16. Li M, Li X. MEP-type distribution function: a better alternative to Weibull function for wind speed distribution. *Renewable Energy* 2005; **30**: 1221–1240.

DOI: 10.1002/we

17. Pryor SC, Schoof JT, Barthelmie R. Climate change impacts on wind speeds and wind energy density in northern Europe: empirical downscaling of multiple AOGCMs. *Climate Research* 2005; **29**: 183–198.
18. Seguro JV, Lambert, TW. Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis. *Journal of Wind Engineering and Industrial Aerodynamics* 2000; **85**: 75–84.
19. Jaramillo OA, Borja MA. Wind speed analysis in La Ventosa, Mexico: a bimodal probability distribution case. *Renewable Energy* 2004; **29**: 1613–1630.
20. Ackerman T, Soder L. An overview of wind energy-status 2002. *Renewable and Sustainable Energy Reviews* 2002; **6**: 67–128.
21. Jager-Waldau A, Ossenbrink H. Progress of electricity from biomass, wind and photovoltaics in the European Union. *Renewable and Sustainable Energy Reviews* 2004; **8**: 157–182.
22. Flowers LT, Dougherty PJ. Wind powering America: goals, approach perspectives and prospects. *SAMPE Journals* 2004; **40**: 44–46.
23. Kenisarin M, Karsli VM, Caglar M. Wind power engineering in the world and perspectives of its development in Turkey. *Renewable and Sustainable Energy Reviews* 2006; **10**: 341–369.
24. Faulin J, Lera F, Pintor JM, García J. The outlook for renewable energy in Navarre: an economic profile. *Energy Policy* 2006; **34**: 2201–2216.
25. Fairless D. Renewable energy: energy-go-round. How did a little Spanish province become one of the world's wind-energy giants? *Nature* 2007; **447**: 1031–1142.
26. García-Bustamante E, González-Rouco JF, Jiménez PA, Navarro J and Montávez JP. The influence of the Weibull assumption in monthly wind energy estimation. *Wind Energy* 2008; **11**: 483–502.
27. Celik AN. Energy output estimation for small-scale wind power generators using Weibull-representative wind data. *Journal of Wind and Industrial Aerodynamics* 2003; **91**: 693–707.
28. Aubrun S, Koppman R, Leitl B, Mollman-Coers, Schaub A. Physical modelling of a complex forest area in a wind tunnel—comparison with field data. *Agricultural and Forest Meteorology* 2005; **129**: 121–135.
29. Barthelmie RJ, Frandsen ST, Nielsen MN, Pryor SC, Rethore PE, Jorgensen HE. Modelling and measurements of power losses and turbulence intensity in wind turbine wakes at Middelgrunden offshore wind farm. *Wind Energy* 2007; **10**: 517–528.
30. Jiménez PA, González-Rouco JF, Montávez JP, García-Bustamante E, Navarro J, Valero F. Surface wind regionalization in complex terrain. *Journal of Applied Meteorology and Climatology* 2008; **47**: 308–325.
31. Jiménez PA, González-Rouco JF, Montávez JP, García-Bustamante E, Navarro J. Climatology of wind patterns in the Northeast of the Iberian Peninsula. *International Journal of Climatology* 2008: DOI: 10.1002/joc.1705.
32. Celik AN. Assessing the suitability of wind speed probability distribution functions on wind power density. *Renewable Energy* 2003; **28**: 1563–1574.
33. Biswas S, Sraedhar BN, Singh YP. A simplified statistical technique for wind turbine energy output estimation. *Wind Engineering* 1990; **19**: 147–155.
34. Celik AN. On the distributional parameters used in assessment of the suitability of wind speed probability density functions. *Energy Conversion and Management* 2004; **45**: 1735–1747.
35. Pryor SC, Schoof JT, Barthelmie RJ. Empirical downscaling of wind speed probability distributions. *Journal of Geophysical Research* 2005; **110**: D19109.
36. Tuller SE, Brett CA. The characteristics of wind velocity that favor the fitting of a Weibull distribution in wind speed analysis. *Journal of Climate and Applied Meteorology* 1984; **23**: 124–134.
37. Dorvlo ASS. Estimating wind speed distribution. *Energy Conversion and Management* 2002; **43**: 2311–2318.
38. Noorgard P, Holttinen H. A Multi-Turbine Power Curve Approach. *Nordic Wind Power Conference,* Chalmers University of Technology, 2004.
39. Bivona S, Burlon R, Leone C. Hourly wind speed analysis in Sicily. *Renewable Energy* 2003; **28**: 1371–1385.
40. von Storch H, Zwiers F. *Statistical Analysis in Climate Research*. Cambridge University Press: Cambridge, 1999.
41. Bergey KH. Lanchester-Betz limit. *Journal of Energy* 1979; **3**: 382–384.
42. Kaas E, Li T-H, Schmith T. Statistical hindcast of wind climatology in the North Atlantic and northwestern European region. *Climate Research* 1996; **7**: 97–110.
43. Conradsen K, Nielsen LB. Review of Weibull statistics for estimation of wind speed. *Journal of Climate and Applied Meteorology* 1984; **23**: 1173–1183.
44. Vestas. *General specifications 600 kW variable slip wind turbines*. Vestas-American Wind Technology technical note 941615.R3 25 pp., 1996.
45. Pinson P, Nielsen HA, Moller JK, Madsen H, Kariniotakis GN. Nonparametric probabilistic forecasts of wind power: required properties and evaluation. *Wind Energy* 2007; **10**: 497–516.
46. Pinson P, Nielsen H Aa, Madsen H, Nielsen TS. Local linear regression with adaptive orthogonal fitting for the wind power application. *Statistics and Computing* 2008; **18**: 59–71.

47. Hwang-Dae K, Robinson TJ, Wulff SS, Parker PA. Comparison of parametric, nonparametric and semiparametric modeling of wind tunnel data. *Quality Engineering* 2007; **19**: 179–190.
48. Caires S, Sterl A. A new nonparametric method to correct model data: application to significant wave height from the ERA-40 re-analysis. *Journal of Atmospheric and Oceanic Technology* 2005; **22**: 443–459.
49. Lange M. On the uncertainty of wind power predictions: analysis of the forecast accuracy and statistical distribution of errors. *Journal of Solar Energy Engineering* 2005; **27**: 177–184.
50. Lackner MA, Rogers AL, Manwell JF. Uncertainty analysis in MCP-based wind resource assessment and energy production estimation. *Journal of Solar Energy Engineering* 2008; **031006**: 1–10.
51. Pryor SC, Barthelmie R, Kjellström E. Potential climate change impact on wind energy resources in northern Europe: analyses using a regional climate model. *Climate Dynamics* 2005; **25**: 815–835.

DOI: 10.1002/we