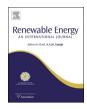


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Surface turbulence intensity as a predictor of extrapolated wind resource to the turbine hub height



Giovanni Gualtieri*

National Research Council, Institute of Biometeorology (CNR-IBIMET), Via Caproni 8, 50145, Firenze, Italy

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ABSTRACT

Based on power law (PL), a novel method is proposed to extrapolate surface wind speed to the wind turbine (WT) hub height, via assessment of wind shear coefficient (WSC), by only using surface turbulence intensity, a parameter actually regarded as a merely critical one in wind energy studies. A 2-year (2012–2013) dataset from the meteorological mast of Cabauw (Netherlands) was used, including 10-min records collected at 10, 20, 40, and 80 m. WT hub heights of 40 and 80 m have been targeted for the extrapolation, being accomplished based on turbulence intensity observations at 10 and 20 m. Trained over the year 2012, the method was validated over the year 2013.

Good scores were returned both in wind speed and power density extrapolations, with biases within 7 and 8%, respectively. Wind speed extrapolation was better predicted 10-40 m (NRMSE = 0.16, r = 0.95) than 10-80 and 20-80 m (NRMSE = 0.20-0.24, r = 0.86-0.91), while for power density even finer scores than wind speed were achieved (r = 0.98 at 40 m, and r = 0.96 at 80 m). Method's skills were also assessed in predicting wind energy yield. Application over sites with different terrain features and stability conditions is expected to provide further insight into its application field.

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1. Introduction

Increasing challenge in wind energy technology is leading to develop WT models as power rated as 6–8 MW, with hub heights regularly above 100 m [1]. In such a rapidly growing scenario, chasing the wind at steadily increasing WT hub heights by using the classical meteorological masts appears as a more and more expensive solution. The use of wind profilers such as LIDAR or SODAR is certainly more appropriate [2], yet largely increasing the costs of the wind power project, often making it economically not viable. In any case, during the earlier feasibility study, when to plan on-site wind measurement campaigns, the knowledge in advance with fair confidence of a site wind energy potential is crucial to cope with upper observations unavailability. In the past decades, various mathematical and modelling approaches have been implemented to estimate WT hub height wind resource at such feasibility stage. These include, e.g. reanalysis data downscaling numerical models [3], CFD models [2,4], and statistical techniques such machine learning [5] or artificial neural networks [6]. Aside from requiring a huge amount of input data, main drawbacks of these methods are that they might be computationally expensive, not sufficiently space—resolved, or — conversely — too site—specific. On the other hand, to increase the knowledge on wind speed extrapolation models appears preferable as allowing a wider application spectrum to predict wind resource at different WT hub heights. Among others, the use of this approach offers the advantage of merely using wind measurements routinely collected at surface heights (10 or 20 m AGL).

PL and LogL are the main laws achieving wind speed extrapolation [7–9], the former being the most widely used [10]. In wind energy studies, PL-based wind speed extrapolation, via assessment of WSC, is performed by means of two approaches: (i) extrapolation of wind speed time series (based on models, e.g. by SH [11] or PD [12]); (ii) extrapolation of wind speed Weibull distribution (according to the JM model [13]). The strict relationship among these two approaches has been earlier [14] and recently [15] investigated, and their mutual advantages and limitations compared.

In the current work, based on PL, a novel method is proposed to predict WSC, and thus extrapolate surface wind speed, by only using surface turbulence intensity. The latter is commonly regarded as a critical parameter in wind energy studies owing to various aspects, as it increases: (i) the load levels onto WTs, thus

^{*} Tel.: +39 55 3033743; fax: +39 55 308910. E-mail address: g.gualtieri@ibimet.cnr.it.

| Nomenclature | | ρ P | air density [kg/m³] wind power density [W/m²] | |
|------------------|--------------------------------------------------------|------------------------------|------------------------------------------------------------------------------------------------------------------------|--|
| Abbreviations | | c k | Weibull scale factor [m/s] Weibull shape factor [—] | |
| WT | wind turbine | AF | availability factor [%] | |
| AGL | above ground level | CF | capacity factor [%] | |
| PL | power law | FLH | full-load hours [h/y] | |
| LogL | logarithmic law | AEY | annual energy yield [MWh/y] | |
| LogLL | log-linear law | | | |
| WSC | wind shear coefficient | Statistica | Statistical skill scores | |
| SH | Smedman-Högström and Högström | N | number of observations | |
| PD | Panofsky and Dutton | O_i | observations | |
| JM | Justus and Mikhail | P_i | predictions | |
| | | $\mu_{O} = \overline{O_{i}}$ | mean observations | |
| Variables | Variables | | standard deviation of observations | |
| α | wind shear exponent [—] | $\mu_P = \overline{P_i}$ | mean predictions | |
| Z | height AGL [m] | σ_P | standard deviation of predictions | |
| ν | wind speed [m/s] | • | | |
| z_0 | surface roughness length [m] | NB | normalised bias = $\frac{1}{N}\sum_{i=1}^{N}(O_i-P_i)/\sqrt{\overline{O_i}\cdot\overline{P_i}}$ | |
| К | von Karman's constant [—], typically set to 0.4 | RMSE | root mean square error = $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i-P_i)^2}$ | |
| L | Monin-Obukhov length [m] | KIVISE | <u> </u> | |
| u* | friction velocity [m/s] | NRMSE | normalised root mean square error = $RMSE/\sqrt{\overline{O_i} \cdot \overline{P_i}}$ | |
| Ψ_m | Monin–Obukhov stability function [–] | IA | index of agreement | |
| I | turbulence intensity [%] | | $= 1 - [N \cdot RMSE^2 / \sum_{i=1}^{N} \left P_i - \overline{O_i} \right + \left O_i - \overline{O_i} \right)^2]$ | |
| σ_u | standard deviation of longitudinal v fluctuation [m/s] | r | correlation coefficient | |
| $\sigma_{	heta}$ | standard deviation of wind direction [deg] | | $= \frac{1}{N} \sum_{i=1}^{N} (O_i - \overline{O_i}) \cdot (P_i - \overline{P_i}) / \sigma_O \cdot \sigma_P$ | |
| T | temperature [°C] | NE | normalised error = $(O_i - P_i)/O_i$ | |
| P_a | pressure [mbar] | | | |

reducing WTs operational life [4,16]; (ii) the energy yield uncertainty, mostly as a result of WT power curve uncertainty [5,17,18]; (iii) energy losses, thus reducing the WT power output [16,18,19]. Conversely, turbulence intensity has been treated as a "positive" factor here by investigating the existence of a reasonable relationship with WSC in order to be used as a predictor of the latter. Observations from the 213 m tall meteorological mast of Cabauw (Netherlands) were used, including 10 min records collected at heights of 10, 20, 40, and 80 m AGL, A 2-year dataset (01/01/ 2012-31/12/2013) was processed. Turbulence intensity observations collected at two surface levels, 10 and 20 m, were used. Two WT hub heights, 40 and 80 m, have been targeted, since observations to test the model were available at those heights. A linear regression analysis by stability conditions was performed to train the model (2012), which was later validated over an independent 1-year period (2013) and its accuracy assessed in extrapolating annual mean wind speed, power density, Weibull distribution, and wind energy yield.

2. Background

2.1. Wind speed logarithmic law and power law

According to the LogLL, the ν vertical profile can be calculated as [20]:

$$v(z) = \left[u_*(z)/\kappa\right] \cdot \left[\ln(z/z_0) - \psi_m(z/L)\right] \tag{1}$$

The LogLL is a physical model incorporating the phenomenon of atmospheric stability and is valid over large ranges of altitude. For stability-dependent Ψ_m function, typical approximations are suggested (e.g. [21]). From ν_1 measurements, ν_2 can be estimated by transforming Eq. (1):

$$v_2 = v_1 \frac{\ln(z_2/z_0) - \Psi_m(z_2/L)}{\ln(z_1/z_0) - \Psi_m(z_1/L)}$$
 (2)

In the case of neutral stability ($\Psi_m = 0$), the LogLL reduces to the widely used LogL, which only depends on z_0 and is valid near the ground over relatively flat terrain [21]:

$$v_2 = v_1 \frac{\ln(z_2/z_0)}{\ln(z_1/z_0)} \tag{3}$$

Since the LogLL proved to be difficult to be used for general engineering studies, the far simpler PL equation is generally used for estimating ν vertical profile at WT hub height:

$$v_2 = v_1 \left(\frac{z_2}{z_1}\right)^{\alpha} \tag{4}$$

The exponent α , also known as WSC, depends on v, z_0 , atmospheric stability and the height interval [7,8,21]. Actually, Eq. (4) is an engineering, empirical formula, essentially amalgamating the stability correction and z_0 features into one single factor (i.e. α) [8,9], but has no physical basis. Its validity is generally limited to the lower atmosphere, upto 150–200 m [8].

From Eq. (4), α can be measured once records of v_1 and v_2 are available:

$$\alpha = \frac{\ln(\nu_2/\nu_1)}{\ln(z_2/z_1)} \tag{5}$$

2.2. Turbulence intensity

Wind turbulence is a critical parameter as dictating the operational life of WTs. It mainly generates from two causes, often

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