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Identification of optimum wind turbine parameters for varying wind climates using a novel month-based turbine performance index

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Abstract

The capacity factor (CF) and power coefficient (C_p) are two important wind turbine characteristics. CF describes the power generation capacity during a given period, and C_p describes the efficiency of the wind turbine. Both quantities depend on the rated wind speed. Determining the optimal rated wind speed that maximizes a function of CF and C_p that is directly related to a wind turbine's output wind power density thus is of utmost importance as it leads to a maximum energy output. This paper proposes a novel Month-based Turbine Performance Index ($MTPI$) that considers the hourly mean wind speed data month-wise and enables the evaluation of this desired optimum rated turbine speed ($V_{r,opt}$) for a given site. Here, the 2-parameter Weibull distribution is employed as a single tool to parameterize the wind speed data and determine the wind speed probability density function, wind power density, vertical wind shear, CF, and C_p of the wind turbine. The examined stations taken for the analysis are from Trivandrum, Ahmedabad, and Calcutta in India. Our index is especially important in regions with intra annular variability, since it is the first to consider monthly instead of annual data.

Introduction

The capacity factor (CF) and power coefficient (C_p) are two essential wind turbine characteristics that play a vital role in defining the performance of a wind turbine generator. On the one hand, CF predicts the duration of operation of the wind turbine in a year. On the other hand, C_p indicates the efficiency in the conversion of the wind power potential to the final electric power generation [50]. The higher C_p is, the more efficiently the wind turbine converts the available wind energy into an energy output. A high CF can be achieved using a wind turbine with a relatively large rotor size and a small generator size. However, its efficiency is reduced, resulting in a lower electricity generation. In contrast, for the same rotor size, a large generator leads to a higher efficiency, but the total duration of power generation is less, i.e., *CF* is reduced. These two turbine characteristics are basically a function of a single wind turbine parameter, namely the rated wind speed (V_r). Therefore, optimization of rated wind speed that yields a high energy output for a longer duration of time is of utmost importance before designing and installing the wind turbine at a given site so that the feasibility of greater power generation and economic viability of the power plant can clearly be evaluated for the wind power plant (WPP).

The wind regime at a particular site, therefore, determines the performance of the wind turbine, which has, besides V_r, two further speed parameters, namely cut-in (V_c) and cut-out or furling (V_f) speed. Lanzafame and Messina [33] have revealed that the performance of a wind turbine is maximal at a particular rated wind speed, and this performance decreases rapidly for all other wind speeds. Therefore, designing the wind turbine with optimum speed parameters is the prime requirement to maximize the wind energy harnessed at a particular site. Particularly, wind speeds that are rated too low lead to much energy lost for higher-speed winds. In contrast, wind speeds that are rated too high lead to the turbine operating at its capacity, which, in turn, loses too much energy at the lower-speed winds [1]. Therefore, the evaluation of optimum rated wind speed $V_{r,opt}$ is essential for the turbine to yield higher energy output at a higher *CF*. To estimate the optimal rated wind speed, this paper proposes a novel formulation regarding wind turbine performance indicated as month-based turbine performance index (*MTPI*). This novel *MTPI* has the capability to select the optimized rated wind speed of the turbine, which in turn enables the optimization of a function of the capacity factor and power coefficient of the wind turbine and can yield high-energy output. Moreover, our *MTPI* looks at hourly mean wind speed data month-wise, which is particularly relevant for regions with strong climatic changes within a year. Nevertheless, it can also easily be adapted for handling hourly mean wind speed taken on annual basis.

The output wind power density (WPD_{output}) of the wind turbine yields maximal power for a long duration of time only when it has high *CF* and C_p. However, several researchers, including [[3], [5], [6], [18], [28], [35], [36], [41], [44], [47], [53]] have focused only on the maximization of *CF* for yielding higher energy output, neglecting the importance of C_p or considered it to be a constant. However, the best suitable wind turbine for a particular site is judged only when it yields a higher energy production for a longer duration of time, i.e., yields higher C_p with higher *CF*, which results in the maximization of the energy output [19]. Cooney etal. [20] use both *CF* and C_p to assess the performance of a wind turbine, further underlining that these two quantities are equally important when defining the optimal wind turbine parameters.

In this paper, we have focused to calculate *CF* and C_p analytically, though simulation and modeling using computational fluid dynamics (CFD) models is another way to calculate *CF* and C_p. However, there is no perfect model in the CFD to simulate wind characteristics due to its stochastic nature [52]. We believe that using the statistical approach is handier. Both *CF* and C_p can analytically be estimated using speed parameters of the turbine in combination with the universally accepted Weibull distribution.

Several researchers [2,4,8,43,48] have proposed various models for wind speed data, including the Weibull, Inverse Weibull, Lindley, skewed generalized error, skewed *t*, and Johnson S_B distributions. Ouarda etal. [37] compared different models and found that the 2-parameter Weibull distribution is the best to describe unimodal wind speed datasets, while mixture models are preferred for bimodal data. The 2-parameter Weibull distribution is a flexible model and has the advantage that if the wind speed follows the Weibull distribution with shape parameter *k* and scale parameter *s*, then the cube of the wind speed also follows the same distribution with shape and scale parameters *k*/3 and s^3, respectively [17]. This, in turn, enables the estimation of the wind power density at a particular site. Several utilizers [[9], [10], [11], [12], [16], [21], [22],

[24], [29], [32], [38], [40], [45], [46]] also found Weibull distribution a most suitable distribution compared to other unimodal distributions to define the wind regime of several parts of the world. Recently, Baseer etal. [13], used the Weibull parameters to study the wind power characteristics of selected stations in Saudi Arabia, and Wais [49] concluded that the 2-parameter Weibull distribution provides a suitable tool for wind power analysis.

For validating the appropriateness of the Weibull distribution to model wind speed data of the concerned Indian locations (cities), we have compared four distributions, namely, the Exponential, Inverse Gaussian, Lognormal, and Weibull distributions via the Akaike Information Criterion, see Table 1. The hourly mean wind speed data for all the years, as mentioned in Table2, has been taken for analysis. From Table 1, we can see that the Weibull distribution is the best distribution to model the wind speed data for these three stations of India.

On the basis of the above evidence and discussion, we use as well the Weibull distribution in the present paper. Its probability density function $f_w(v)$ and cumulative distribution function $F_w(v)$ are respectively given by $f_w(v)=\left(\frac{k}{s}\right)\left(\frac{v}{s}\right)^{k-1}\exp\left[-\left(\frac{v}{s}\right)^k\right]$; for $v>0$ and $k,\ s>0$ $F_w(v)=1-\exp\left[-\left(\frac{v}{s}\right)^k\right]$ where v is the wind speed, k is the dimensionless shape parameter of the Weibull distribution, and s is its scale parameter, whose dimension is the same as that of v (m/s). The Weibull parameters can be estimated in a straightforward way for each selected site, see Section 4.1 for details.

Now, it is essential to note that the rated wind speed at which *CF* is maximal does not necessarily coincide with the one for which C_p is also maximal, and vice-versa. This can be illustrated by the plot of *CF* and C_p against the normalized rated wind speed (V_r/s), as depicted in Fig. 1. The mathematical expressions underpinning *CF* and C_p can be found in Sections 4.4 Capacity factor (CF) and average output wind power density of the wind turbine, 4.5 Power coefficient (C, respectively. In Fig. 1, the normalized rated wind speed has been varied from 0.1 to 4 with a step size of 0.05, while k has been varied from 1.0 to 3.4 with a step size of 0.4.

Fig. 1 shows that the plots for the *CF* and C_p have peaks at different values of V_r/s for the same value of k. This implies that at a maximal *CF*, C_p is relatively low, which indicates that the conversion efficiency of the available wind potential into useful energy is lower. Conversely, at a maximal C_p, *CF* is relatively low, which indicates that the cost of the wind turbine generator equipment is higher, since it is being used for less time. Thus, it is necessary to find the V_r/s which optimizes a function of *CF* and C_p that is related to the output wind power density, and optimizing this function ensures a higher energy production for a longer duration. Variations in the wind speeds at any location are obvious. Therefore, Kwon [31] recommended conducting an uncertainty analysis to assess the wind energy potential. Unlike most of the European countries, major parts of the world are facing variable climatic changes throughout the year [30], which significantly govern the wind regime available at a given site. Analyzing wind data annually may lead to erroneous estimations of the wind power potential (WPP). However, to assess the economic viability of the WPP, it is important to characterize the wind speeds correctly [39]. Therefore, to correctly estimate the WPP, consideration of hourly mean wind speed data month-wise is of paramount importance [14,42].

Fig. 2 depicts the plots of the monthly mean wind speed data for three stations, namely Trivandrum, Ahmedabad, and Calcutta of India, which were taken as reference stations to carry out the research work, showing the seasonal behavior from the monthly average of the wind speed data. The figure shows that higher monthly mean wind speeds occur during the months between May and July, and lower monthly mean wind speeds occur during the months between October and January for all three stations. Indian climatology is the windiest during the southwest monsoon season, i.e., during the months between May

and September. During this season, the probability of higher wind speeds is much greater. Moreover, the winter season in India is during the months between October and January, which has an increased probability of low wind speeds. Therefore, the turbines are rarely operating during this season.
To evaluate $V_{r,opt}$, Janagmshetti and Rau [26] proposed a turbine performance index (*TPI*) based on optimizing *CF* and C_p, and they suggested a formula to estimate the speed parameters of the turbine, i.e., V_c, V_r, and V_f. This *TPI* was then used by Abul'Wafa [1] to perform a research in Egypt. Yeh and Wang [51] proposed yet another *TPI*. However, these approaches are applicable only for regions or countries where the wind climate is rather stable throughout the year or where data analyses were performed on an annual basis for power generation. It is well known that wind is an intermittent form of energy and cannot have the same behavior throughout the year. The annual estimation of wind resources leads to fallacious judgment about the input power; hence, monthly analysis of the wind speed data is of utmost importance, as we have explained in the previous section. Consequently, previously suggested *TPI*'s are deemed inapplicable in the cases where monthly analysis of the wind speed data is quite essential. As already mentioned, several other research papers suffer from the shortcoming of neglecting the importance of C_p.

In this work, a novel *TPI*, which we call Month-based Turbine Performance Index (*MTPI*), has been proposed that (i) considers both *CF* and C_p, (ii) considers monthly averages of the wind speed data, and (iii) enables an estimation of the optimum speed parameters of the wind turbine for a given site that, in turn, yields high-energy output. Moreover, this work also enables the determination of the most likely direction for the installation of wind farms based on wind behavior, so that the most probable zone for the installation of the wind farm can be predicted at the planning stages.

The paper is organized as follows. In Section 2 we introduce our new month-based turbine performance index. Section 3 describes the geographical conditions and the periods in which our data were collected. Mathematical details such as the estimation of the Weibull parameters, extrapolation of the estimates to other heights, and the expressions for *CF* and C_p are provided in Section 4. The wind data are analyzed in Section 5, where we also show the power of our new performance index in the determination of the optimum rated wind speed. We conclude the paper with final remarks in Section 6, and the Appendix presents a more mathematical calculation underpinning the determination of the capacity factor, *CF*.

Section snippets

Our new proposal: Month-based Turbine Performance Index (*MTPI*)

The expression of the output wind power density corresponds to $\overline{WPD}_{output} = \frac{1}{2} \times \rho \times CF \times C_p \times \eta_{mech} \times \eta_{ele} \times V_r^3$, see Section 4.4 for its derivation. Here, ρ=1.225 kg/m^3 is the wind density, η_{mech} is the mechanical efficiency of the system, η_{ele} is the electrical efficiency of the system, and the latter two quantities are generally provided by the manufacturer. Therefore, theoretically it is difficult to calculate $\overline{WPD}_{output}$ depending on these turbine characteristics. This explains why one cannot use simply …

Geographical conditions and observation period

The Indian Meteorological Department (IMD), Pune, recorded long-term hourly mean wind speeds in km/h at a height of 10 m above the ground level with a Dyne Pressure Tube Anemograph (DPTA). The observation period for which the wind speed data are available varies from station to station. In the present study, the wind data of Trivandrum, Ahmedabad, and Calcutta stations have been selected as reference datasets from three distinct regions in India. These metropolises were selected because they…

Estimation of Weibull parameters

Several distinct methods to estimate the parameters of the Weibull distribution have been proposed in the literature. In a recent work, Gugliani et al. [23] have proposed a new procedure, called Modified Energy Pattern Factor (MEPF) method, and shown its superiority over conventional methods such as the maximum likelihood method, modified maximum likelihood method, method of moments, least squares method, power density method, and the energy pattern factor method. This comparison was based on…

Results and discussion

In this study, the optimum speed parameters of wind turbines have been determined for the three stations Trivandrum, Ahmedabad, and Calcutta using the new *MTPI* to yield a high-energy output for longer durations. Different commercially available wind turbines with varying hub heights have been assessed to verify the applicability of the proposed approach.

In India, the majority of the strong wind comes along with the onset of the southwest monsoon. Trivandrum and Ahmedabad are situated in the…

Conclusions

The optimum wind turbine parameters have been identified in this study for fluctuating wind climates in the Indian subcontinent using a novel Month-based Turbine Performance Index (*MTPI*). The proposed *MTPI* considers the hourly mean wind speed data month-wise and enables evaluating the optimum rated turbine speed for a given site. The following conclusions have been drawn from our study at the three sites of Trivandrum, Ahmedabad, and Calcutta:

1. The Indian subcontinent experiences a wide variation …

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.…

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