Received: 22 December 2023 | Revised: 28 February 2024 | Accepted: 20 April 2024

IET Renewable Power Generation

DOI: 10.1049/rpg2.13132

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Wind speed probabilistic forecast based wind turbine selection and siting for urban environment

Shivangi Sachar[1] | Shubham Shubham[2,3] | Piotr Doerffer[4] | Anton Ianakiev[2] | Paweł Flaszyński[1]

[1]Institute of Fluid Flow Machinery, Polish Academy of Sciences, Gdansk, Poland

[2]Department of Civil Engineering, Nottingham Trent University, Nottingham, UK

[3]School of Aerospace, Transport and Manufacturing (SATM), Cranfield University, Bedford, UK

[4]Institute of Energy, Gdank University of Technology, Gdansk, Poland

Correspondence
Shubham Shubham, Department of Civil Engineering, Nottingham Trent University, Goldsmith Street, Nottingham NG1 5JS, UK.
Email: shubham.shubham@ntu.ac.uk

Funding information
H2020 Marie Skłodowska-Curie Actions, Grant/Award Number: 860101

Abstract

Wind energy being a free source of energy is becoming popular over the past decades and is being studied extensively. Integration of wind turbines is now being expanded to urban and offshore settings in contrast to the conventional wind farms in relatively open areas. The direct installation of wind turbines poses a potential risk, as it may result in financial losses in scenarios characterized by inadequate wind resource availability. Therefore, wind energy availability analysis in such urban environments is a necessity. This research paper presents an in-depth investigation conducted to predict the exploitable wind energy at four distinct locations within Nottingham, United Kingdom. Subsequently, the most suitable location, Clifton Campus at Nottingham Trent University, is identified where a comprehensive comparative analysis of power generation from eleven different wind turbine models is performed. The findings derived from this analysis suggest that the QR6 wind turbine emerges as the optimal choice for subsequent experimental investigations to be conducted in partnership with Nottingham Trent University. Furthermore, this study explores the selection of an appropriate probability density function for assessing wind potential considering seven different distributions namely, Gamma, Weibull, Rayleigh, Log-normal, Genextreme, Gumbel, and Normal. Ultimately, the Weibull probability distribution is selected, and various methodologies are employed to estimate its parameters, which are then ranked using statistical assessments.

1 | INTRODUCTION

In recent decades, global energy demand has surged due to population growth and rapid industrialization [1]. A large part of this energy comes from fossil fuels, which release significant amount of greenhouse gases causing major environmental changes including but not limited to global warming. Given the adverse impacts of climate change, there is a growing emphasis on renewable energy sources [2, 3]. Wind energy, being a clean, sustainable, and readily available source, has proved to be a promising alternative to perishable energy sources. This field is attracting a lot of research worldwide with the main focus on cost-effective methods and modified wind turbine designs to harness the power [4, 5]. Many projects have been initiated to promote the harnessing of energy using renewable resources. The paper in hand is in coordination with the project zEPHYR under Horizon 2020 which aims toward more efficient exploitation of on-shore and urban wind energy resources.

An important source of information when making the decision on the type of turbine and its installation location [6, 7], is the wind characteristic in the region. It provides information on the environmental conditions that the turbines will be exposed to, such as wind speed and turbulence [8]. This data is critical in designing turbines that can withstand harsh weather conditions, optimize energy production, minimize maintenance costs [9–11] and help predict their energy output. The total energy output of the wind turbine is influenced by various factors, some of them being site temperature, type of surface, wind speed, height of measurement device, air density etc. [12], apart from

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.
© 2024 The Author(s). *IET Renewable Power Generation* published by John Wiley & Sons Ltd on behalf of The Institution of Engineering and Technology.

the turbine design itself [13, 14]. Wind energy analysis also helps to evaluate the potential environmental impact of a wind energy project [15]. It takes into account factors such as noise pollution [16], visual impact, and the effects on local wildlife [17–19]. By studying these factors, experts can design projects that minimize their impact on the environment and local communities.

The wind energy potential in the city of Tehran, Iran was calculated by Keyhani et al. [20]. It was inferred that the wind potential of this area can be utilized for electrical and mechanical purposes that do not require direct connectivity to the power grid. The applications may include water pumping, battery charging, and local small-scale consumption. Faghani et al. [21] studied the wind data obtained from 35 different stations located in nine provinces of Iran. It was outlined that the spring and summer seasons combined gave good results in terms of wind potential, suitable for installing large-scale wind turbines, while for the second half, i.e. during the fall and winter seasons, the wind power density (WPD) drops substantially. Another analysis performed in the city of Zarrineh, Iran deduced that the location is more suitable for small-scale wind turbines for various applications [22].

Investigations carried out at a site in Iraq (Al Salman) by Mahmood et al. [23] indicated a mean WPD of 219 W/m^2, signifying that the site is suitable for wind energy exploitation by small wind turbines. Wind data was recorded for a period of 5 years between 2000 and 2005 in Turkey for the locations Çanakkale city centre and Bozcaada, an island in the Aegean Sea. It was concluded that Boczaada is a preferred location for large-scale electricity production [24].

Due to the fluctuating nature of wind patterns, which govern the energy output at any given location, it is imperative to find an optimal analysis technique. Over the years, many distributions have been developed to predict the probability density of wind. Studies demonstrated in [25] compare the Wakeby, Beta, Pert, generalized Pareto, Gamma, generalized Gamma function, and the Johnson SB distribution function. It was concluded that the Wakeby method outperformed the other functions used in the study, with a good agreement between the predicted and recorded data.

Some of the other distribution functions are the inverse Gaussian distribution, the generalized normal, the log-normal distribution, the three-parameter log-normal, the kappa, the normal two-variable distribution, the normal square root of the wind speed distribution, and hybrid distributions. Wind speed at the airport in Dolný Hričov was modelled using the lognormal, gamma and Weibull probability density distributions, with the Weibull prediction outperforming the others [26]. Through a comparative analysis of probability density distributions for the Mediterranean coast of Turkey over a 1-year period utilizing Rayleigh and Weibull predictions, it was determined that the Weibull model offered a better fit and superior probability density estimates for the entire duration of the study [27].

The kernel density estimation (KDE) is a relatively new distribution that is being employed in the field of wind potential analysis [28, 29]. The main disadvantage related to KDE is that it is primarily used for estimating the probability density function of a given data set based on its observed values. Therefore, it is not directly suitable for predictions. However, KDE may be used in conjunction with other models to make predictions about future data [30, 31]. It is also worth noting that there are other methods, such as machine learning algorithms and memory networks, that can be used to model wind speed distributions and make predictions about future wind speeds [32, 33]. These methods can be more flexible and better suited for capturing complex patterns and relationships in the data but may require more data and computational resources to implement and are out of the scope of the research presented in this paper. The Weibull distribution function has been chosen and discussed in detail in this paper. The factors which contribute to the selection of this distribution function include its ability to estimate its skewness satisfactorily, the velocity and the cubed velocity follow the same Weibull distribution, and the wind speed frequency distribution allows for simple estimation of the total WPD and its standard deviation [34].

In recent years, an increased interest by researchers has been observed in the wind power availability in Urban areas. The increasing number of high-rise buildings to meet the needs of the growing population, have proved to be quite attractive in the study of wind turbine deployment in such areas. The wind patterns observed in an urban setting are quite unpredictable and more turbulent. The heterogeneous terrain makes the studies more complex, especially when the uncertainty of changing city architectural plans is taken into consideration. This calls for special attention to study the local winds. The analysis done by Juan et al. [35] demonstrates the change in dimensionless power density when the width, height, and distance between the buildings are varied. A detailed illustration on how the wind velocity pattern fluctuates due to changes in the relative height of adjacent buildings is also presented in this paper. Thus, from this study it can be inferred that it is not only important to select the right city for optimal power production, but also the precise placement of the turbines when considering its installation in complex terrain urban settings.

Moreover, selecting appropriate input features (or predictors) is crucial for building accurate and effective wind speed forecasting models. The selection of features can significantly impact the model's performance. Some of the input features that can be used in prediction models include meteorological variables (temperature, pressure, and humidity), geographical features (latitude, longitude, and elevation), time of the day, historical wind speed data, wind direction, frontal system and clouds, topographical features etc. The selection of these variables depends on the type of data available and the probabilistic model used. Due to the highly fluctuating nature of these variables, the wind patterns can vary to a large extent. Prediction is thus required for each of these predictors which is quite complicated. An in-depth study about the uncertainty models used for predicting the input-cloud cover can be found in [36]. Also, due to the uncertainty of wind power generation, the generation capacity and probability distribution of wind power are affected. Research presented in [37, 38] provides a good evaluation of the topic. The comprehensive estimation

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

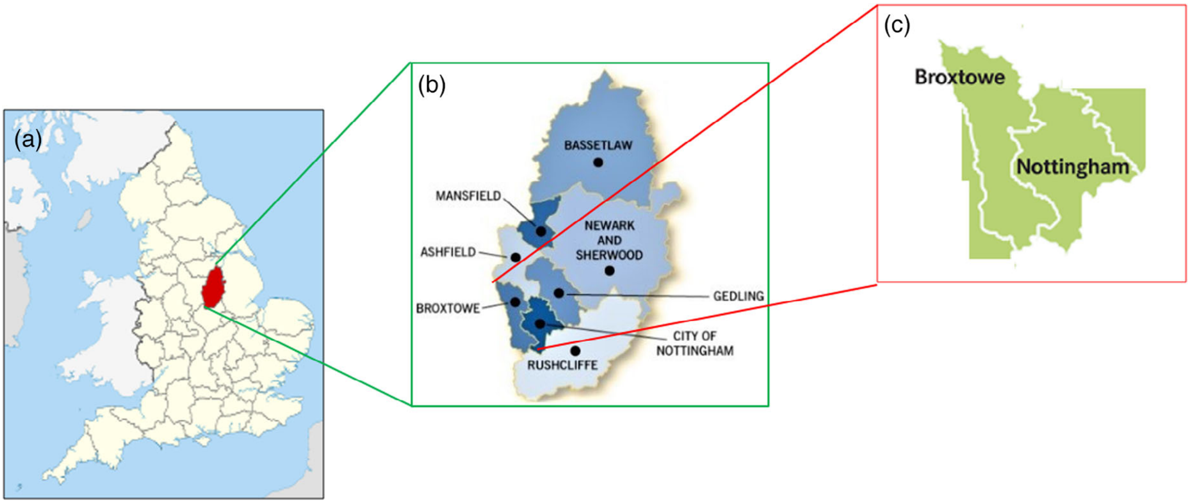


FIGURE 1 Area of study: (a) Nottinghamshire in black, (b) areas in Nottinghamshire, (c) areas under consideration.

of all predictors poses a considerable complexity, demanding in-depth research. The current article, however, does not extensively explore this intricate subject. Instead, it centers its focus on examining the impact of varying wind speed and terrain on wind energy potential, ultimately influencing the selection and siting of wind turbines.

The main objectives of this article can be summarised as follows:

Primary objective:

- Leverage a large, geographically diverse dataset for assessing the feasibility of wind energy generation through wind turbine installation at optimal locations.
- Focus on exploring wind power production potential in various urban settings, including countryside, cities, and villages, considering variations in building structures, materials, and population densities.

Probability density distributions:

- Conduct an in-depth study of probability density distributions for wind energy potential assessment at specific locations.
- Apply seven different distributions (Gamma, Weibull, Rayleigh, Log-normal, Genextreme, Gumbel, Normal) to the data to identify the most fitting probability density function.

Parameter estimation:

- Select the Weibull probability density distribution as the most suitable, based on goodness of fit evaluation.
- Calculate probability density parameters using four estimation methods (STDM, MLM, MOM, PDM).

Location and application-specific nature:

- Demonstrate the location and application-specific nature of identifying an optimal wind speed distribution model.
- Evaluate goodness of fit using various statistical tools to compare errors and enhance the accuracy and reliability of statistical analyses.

Key goals:

- Identify the most suitable location for wind turbine installation.
- Determine the optimal wind turbine type for energy production.
- Conduct further experimental investigation, considering aspects such as power output, efficiency, and noise levels, both in absolute terms and as perceived by humans.

Campaign extension:

- Propose extending the campaign by installing additional wind turbines to harness untapped potential for energy generation in urban environments.

2 | DATA COLLECTION AND ANALYSIS

For the purpose of this study, the city of Nottingham in the county of Nottinghamshire, East midlands, England was chosen (Figure 1). Data was collected from five weather stations positioned at the locations as shown in Figure 2:

- Watnall - A village in the borough of Bouxton in Nottinghamshire.
- Bulwell - A market town in the City of Nottingham.
- Chaucer building - Campus of Nottingham Trent University (NTU) in the main city.
- Clifton campus - The campus of NTU in a suburban village in the city of Nottingham.
- Sutton Bonnington - A village and civil parish lying along the valley of the River Soar in the Borough of Rushcliffe, South-West Nottinghamshire.

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

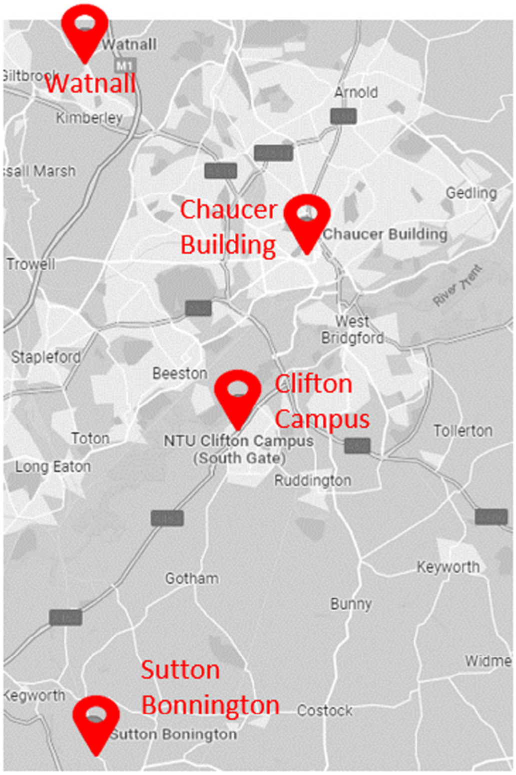


FIGURE 2 Locations studied in Nottingham.

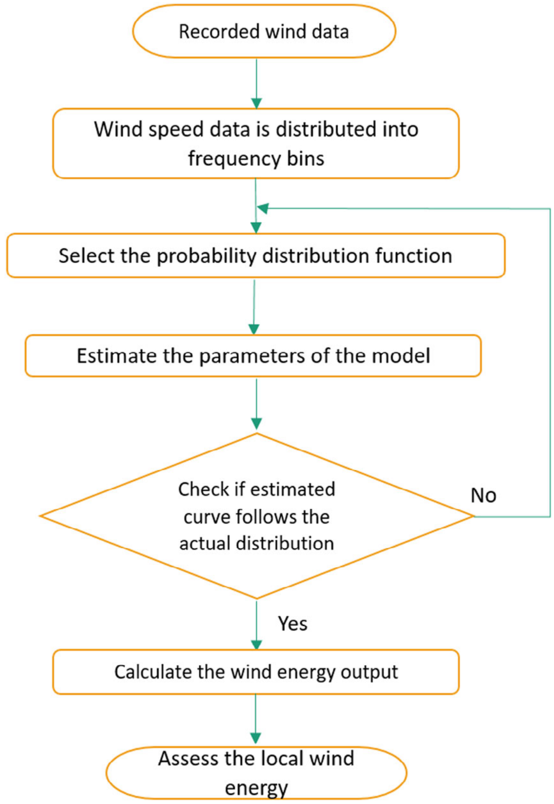


FIGURE 3 Algorithm followed for wind analysis.

The flow chart as shown in Figure 3 details the algorithm followed to perform the analysis of the measured wind. As mentioned in the prior sections, it is essential to select a suitable probability density function calculation model to analyse the wind energy production. This is achieved by comparing the estimated curves to the actual wind speed distribution. If this condition is not satisfied, the data is fed to another set of equations and the prediction model is changed until the results from the two are comparable.

2.1 | Wind power density and energy density

The wind power density (WPD) as calculated from the Weibull parameters can be given as 1.

$$\mathrm{WPD}(v) = \frac{1}{2}\rho c^3 \Gamma\left(1 + \frac{3}{k}\right) \tag{1}$$

and the WPD (average) of the recorded wind sample can be presented as:

$$\mathrm{WPD}(v) = \frac{1}{2}\rho \bar{v}^3 \tag{2}$$

The value of air density ρ is assumed to be 1.225 kg/m^3 and $\bar{v}$ is the mean velocity of the sample for the purpose of the calculations included in this paper. The wind energy density (WED) can be calculated by multiplying the WPD with the time over which the data has been sampled. EPD is generally expressed in the terms of kWh/m^2/year.

2.2 | Weibull distribution

The probability density function (PDF, $f(v)$) and the cumulative distribution functions of the Weibull distribution are as follows [39]:

$$f(v) = \left(\frac{k}{c}\right) \cdot \left(\frac{v}{c}\right)^{k-1} \cdot \exp\left(-\left(\frac{v}{c}\right)^k\right) \tag{3}$$

$$F(v) = 1 - \exp\left(-\left(\frac{v}{c}\right)^k\right) \tag{4}$$

where $f(v)$ is the probability to observe the wind velocity v at an instant. The Weibull paramaters include a dimensionless shape factor **'k'** and a scale factor(m/s) **'c'**. The shape factor provides information regarding the strength of the wind, whilst the scale factor details the range over which the frequencies of wind recorded have been scattered.

A number of methods are available to calculate the Weibull distribution parameters [40]. Over the years, studies have proved that certain methods are more accurate in some conditions, whilst giving a large difference between the recorded wind frequencies and the distribution for other cases. [41] investigated six different methods for predicting the Weibull parameters. It was found out that the change in topographical setting did not

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

affect the precision of the different estimation techniques used, but a direct effect was observed with increasing complexities of the terrain, resulting in heightened disagreement between the measured and the estimated sample distribution. The study of prevalent wind direction performed by plotting a wind rose has also proved to be an important factor in planning the location of the wind turbines.

Wind power analysis done in Bangladesh [42] was performed by using GM, EM, and PDM to estimate Weibull parameters along with the Rayleigh distribution function. It was concluded that GM produced comparatively more accurate values of the Weibull parameters, EM and PDM followed next, while the results from the Rayleigh distribution function were found to be most erroneous. The WPD in the centre of Iran was analysed using the Standard Deviation Method, EM and PDM at heights ranging from 10 and 100 m [21]. The results illustrated that PDM is the best method among the three for the prediction of k and c. The research performed by Mohammadi and Mostafaeipour [22] yielded that for the Zarrineh region in Iran, PDM gave more accurate results in contrast to STDM at a height of 10 m. The methods used to extend the study presented include the GM, STDM, MOM, PDM, MLE.

2.2.1 | Standard deviation method (STDM)

This method has been used extensively for predicting the Weibull parameters [43–45] and can be calculated by Equations (5) and (6).

$$k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086} \tag{5}$$

$$c = \frac{\bar{v}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{6}$$

where σ is the standard deviation and $\bar{v}$ is the mean velocity of the sample. The gamma function, Γ can be calculated using Equation (7)

$$\Gamma(x) = \int_0^{\alpha} y^{x-1}.e^{-y}\mathrm{d}y \tag{7}$$

where $y = (\frac{v}{c})^k$ and $\frac{v}{c} = y^{x-1}; x = 1 + \frac{1}{k}$

2.2.2 | Method of moment (MOM)

The method of moments was put forward by a British statistician Karl Pearson in the early 19th century and involves the calculation of the probability distribution parameters [46] and was introduced in the field of wind pattern study by Justus and Mikhail in the later half of the 19th century [47]. The Weibull parameters can be calculated by using Equations (8) and (9).

$$k = \left(\frac{0.9874}{\frac{\sigma}{\bar{v}}}\right)^{1.0983} \tag{8}$$

$$\bar{v} = c\Gamma\left(1 + \frac{1}{k}\right) \tag{9}$$

2.2.3 | Power density method (PDM)

A prior calculation of the energy pattern factor (E_{pf}) is required for the prediction of Weibull parameters by this method. This factor can be defined as the ratio of the total available wind power and the power calculated by taking the cube of mean wind speed [40, 48].

$$E_{pf} = \frac{\frac{1}{n}\sum_{i=1}^{n} v_i^3}{\left(\frac{1}{n}\sum_{i=1}^{n} v_i\right)^3} = \frac{\overline{v^3}}{(\bar{v})^3} = \frac{\Gamma\left(1+\frac{3}{k}\right)}{\Gamma^3\left(1+\frac{1}{k}\right)} \tag{10}$$

The E_{pf} calculated using the above equations is then used to calculate the Weibull parameters as illustrated in Equations (11) and (12).

$$k = 1 + \frac{3.69}{E_{pf}^2} \tag{11}$$

$$c = \frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{12}$$

2.2.4 | Maximum likelihood estimation (MLE) or maximum likelihood method (MLM)

MLE is one of the most extensively used Weibull distribution estimation technique. The estimation of the parameters is carried out by maximizing the likelihood function, resulting in their most probable evaluation. The likelihood estimation function was proposed by Fisher [49] and extended for application in wind data analysis by Stevens and Smulders [50]. The Weibull distribution is represented as Equation (13). Performing further evaluation of this equation results in Equation (14). Therefore, finding the most likely value of k, an iteration needs to be performed by considering an initial value of the shape factor.

$$L(v_i, k, c) = \prod_{i=1}^{n}\left\{\left(\frac{k}{c}\right)\left(\frac{v_i}{c}\right)^{k-1}\exp\left[-\left(\frac{v_i}{c}\right)^k\right]\right\} \tag{13}$$

$$k = \left[\frac{\sum_{i-1}^{n} v_i^k \ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i-1}^{n}\ln(v_i)}{n}\right]^{-1} \tag{14}$$

$$c = \left(\frac{1}{N}\sum_{i=1}^{N} v_i^k\right)^{1/k} \tag{15}$$

where v_i is the wind speed at an instant i.

This method can be further extended to modified maximum likelihood method (MMLM). This method is similar to MLE

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

RIGHTSLINK

with the addition that the observed data is arranged according to the wind speed bins. The frequency of each bin formed within a specific range of wind speeds, corresponds to its probability [51].

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k \ln(v_i) f(v_i)}{\sum_{i=1}^{n} v_i^k f(v_i)} - \frac{\sum_{i=1}^{n} \ln(v_i) f(v_i)}{f(v \geq 0)} \right]^{-1},$$

$$c = \left[\frac{1}{f(v \geq 0)} \sum_{i=1}^{n} v_i^k f(v_i) \right]^{1/k} \tag{16}$$

2.3 | Wind speed at height

An additional important factor to be taken into account when performing the wind analysis is the height at which the wind velocities have been recorded. This needs to be adjusted according to a reasonable height at which the wind turbine needs to be mounted. Equations (18)–(22) can be used to calculate the Weibull parameter values, the energy and power density values for a desired height. The power law given by Equation (17) is used to extrapolate the wind velocity recorded at height 'Z' to the height of interest 'Z_h' (hub height) [52]. The surface roughness given by α can be calculated according to the conditions mentioned in [53].

$$V = V_h \left(\frac{Z}{Z_h} \right)^{\alpha} \tag{17}$$

$$k_b = \frac{k}{\left[1 - 0.0881 \ln \left(\frac{z_b}{z_{ref}} \right) \right]} \tag{18}$$

$$c_b = c \left(\frac{z_b}{z_{ref}} \right)^{n} \tag{19}$$

$$v_b = c_b \Gamma \left(1 + \frac{1}{k_b} \right) \tag{20}$$

$$\bar{P}_b = \frac{1}{2} \rho \bar{v}_b^3 = \frac{1}{2} \rho \bar{v}_b^3 \frac{\Gamma\left(1 + \frac{3}{k_b}\right)}{\Gamma^3\left(1 + \frac{3}{k_b}\right)} = \frac{1}{2} \rho c_b^3 \Gamma \left(1 + \frac{3}{k_b} \right) \tag{21}$$

$$E_D = \frac{1}{2} \rho c_b^3 \Gamma \left(1 + \frac{3}{k_b} \right) T \tag{22}$$

In the above equations, the Weibull parameters at a height 'b' are described as k_b and c_b. The velocity is given by v_b, average power density as $\bar{P}_b$, duration of measurement 'T' and the energy density as E_D.

2.4 | Statistical tools for wind distribution evaluation

Several statistical tools are available to calculate the error between data sets [40]. By comparing different statistical tools for comparison of errors, we can gain a more complete understanding of the strengths and limitations of each tool and make more informed decisions about which tool to use in a given context. This can help to ensure that the analysis is accurate and meaningful, and can help to avoid potential pitfalls or misinterpretations that can arise from using a single tool in isolation. Details of the methods used for calculating the errors between the predicted function and observed data set for the cases under consideration are presented in this section.

Mean absolute percentage error

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{X_{pre} - X_{obs}}{X_{obs}} \right| \times 100 \tag{23}$$

Root mean square error

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \left(X_{obs} - X_{pre} \right)^2}{N}} \tag{24}$$

Variance error (R^2)

$$R^2 = \frac{\left(\sum_{i=1}^{n} \left(X_{obs} - \overline{X_{obs}} \right) \times \left(X_{pre} - \overline{X_{pre}} \right) \right)^2}{\sum_{i=1}^{n} \left(X_{obs} - \overline{X_{obs}} \right)^2 \times \sum_{i=1}^{n} \left(X_{pre} - \overline{X_{pre}} \right)^2} \tag{25}$$

Chi square error (χ^2)

$$\chi^2 = \frac{\sum_{i=1}^{N} \left(X_{obs} - X_{pre} \right)^2}{X_{pre}} \tag{26}$$

where N = no. of observations,
X_{pre} = predicted values from the probability distribution
X_{obs} = observed values from the data set
$\overline{X_{pre}}$ = mean of the predicted values from the probability distribution
$\overline{X_{obs}}$ = mean of the observed values from the probability distribution.

MAPE gives the mean absolute value between the predicted terms from the Weibull distribution and the values calculated from the collected data sample. RMSE is essentially the standard deviation of the predicted errors. The predicted errors (residual) signify how far the data points are from the regression curve. It can also be explained as how spread the data is about the best fitting line [54]. R^2 illustrates the fraction of variance of the true value recorded by the regression model, in contrast to the residuals as in the case of RMSE. A value of R^2 close to 1 is considered preferable to determine the goodness of the fit [55]. Even though this model is simple to use, it cannot completely take into account the effect of the theoretical distribution, thus, it is recommended to use it in conjunction with other methods [56].χ^2 is another test used to determine the closeness of the predicted data to the observed data. This is a non-parametric tool, i.e. it is distribution-free and can be used to compare groups with different sample sizes. In addition, this

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

TABLE 1 Small industrial wind turbines - suitable for urban environments.

Company	Model	Diameter	Tower height (m)	Blade length (m)	Swept area (m^2)	Rated power (kW)	Cut-in speed (m/s)	Type
WEPOWER	Falcon 3.4 kW	3	5.5	3.6	10.8	3.4	2.7	VAWT
	Falcon 5.5 kW	4	5.5	4.6	18.4	5.5	2.7	VAWT
	Falcon 12 kW	6	5.5	6.2	37.2	12	2.7	VAWT
Kliux energies	Zebra plus	3.4	6	3.05	10.37	4.9	2.5	VAWT
Interwin	Maia S	3.3	6-12(folding)	1.65	8.5	1.8	2.8	HAWT
	Maia M	3.7	6-12(folding)	1.85	10.8	2.3	2.5	HAWT
	Maia L	4.7	6-12(folding)	2.35	17.4	3.3	2.3	HAWT
Quite Revolution	QR 6	3.1	6-18(folding)	5.1	15.81	7	1.5	VAWT
Delft University of Technology (TUD)	Turby	1.99	6-7.5(folding)	3	5.97	3	4	VAWT
Aventa	AV-7 LoWind	12.9	18	6.45	129	6.5	2	HAWT
FinnWind	Tuule 200	5	18	2.5	19.6		2–2.5	HAWT

study provides information about how each compared group affected the complete study, making it one of the significant tools [57].

2.5 | Selection of wind turbine

One of the major goals after analysing the optimal wind resource available is to check for the type of wind turbine to be installed. A variety of wind turbines are available in the market and can be selected based on the purpose of interest. Since this study is limited to urban environments, research was done on wind turbines to suit such conditions. Small wind turbines are designed to generate electricity for residential or small commercial use, and they are typically less than 100 feet in height. They are designed to operate at lower wind speeds and can be installed on rooftops or other small areas, making them ideal for urban environments. The small vertical axis wind turbines are generally preferred in an urban environment as they have a unique design that allows them to capture wind from any direction, which is particularly useful in urban environments where wind direction can change quickly and unpredictably due to buildings and other structures [58, 59]. They are also quieter than horizontal axis wind turbines, making them more acceptable to the neighbourhood [60, 61]. These can also be installed closer to the ground, making them a good option for rooftops and small urban spaces, also allowing for easy access to the equipment parts for maintenance. Thus, it can be inferred that a combination of both the above-mentioned types of rotors, i.e. a small VAWT is a good choice for the case study under consideration. VAWTs can again be classified as Darrieus and Savonius-type rotors. The Savonius type rotor is drag-based while the Darrieus WT is lift-based and offers a comparatively higher efficiency than the former.

A comparison of a few commercially available small wind turbines which are suitable for urban environments has been presented in Table 1. Power production analysis related to the selected locations for each of these turbines has been detailed in Section 4.

3 | RESULTS AND DISCUSSION

3.1 | Mean wind speed

The mean wind speeds of the locations under consideration have been shown in Table 2. The data set includes the mean values of wind measurements done over a period of 1 year using 10-min average. The mean wind speeds for two locations, i.e. Sutton Bonnington—a village in the countryside and Watnall a village close to the city with a higher number of buildings are shown over a period of 3 years (2018–2020). One clear observation from the two is that Sutton Bonnington has a higher value of average wind speed. This may be attributed to the fact that this village has relatively lower urbanization, thus less number of buildings.

Figure 4 shows the hourly variation of the wind speeds while Figure 5 demonstrates the average wind speed for each month. Looking into the details of the hourly wind speed averages, it can be seen that the wind speed has the least deviation for the year 2019 for both the locations. When the complete data set of the hourly variation over the 3 years is taken into consideration, the average mean wind speed in the case of Sutton–Bonnington is ranging between 3 and 3.6 m/s. While in the case of Watnall, this deviation ranges between 2.3 and 3.2 m/s. Another interesting factor in case of Watnall is the drop in wind speeds between 12 PM to 2 AM for all the years.

The monthly wind data represented as in Figure 5 shows a similar wind speed pattern for the two locations with a dip in the wind speeds from April to October. An amusing observation made in the case of the location Sutton–Bonnington is the sudden dip in the monthly wind speed average from 2018 to 2019–2020. As even a slight change in the surrounding of the meteorological mast, such as additions of building and

MOST WIEDZY Downloaded from mostwiedzy.pl

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 Weibull parameters calculated using different formulas.

Site	$\bar{v}$ (m/s)	σ	Parameters	STDM	MOM	PDM	MLE	Preferred method
Clifton Campus	3.764	2.125	k	2.156	2.141	2.092	2.173	MLE
			c	3.949	3.948	3.944	3.964	
Bulwell	4.759	2.490	k	2.008	2.020	1.979	2.022	MLE
			c	5.370	5.371	5.368	5.384	
Chaucer	1.334	2.125	k	1.679	1.665	1.474	1.73	PDM
			c	1.494	1.493	1.474	1.507	
Watnall	2.63	1.061	k	2.419	2.213	3.408	2.244	PDM
			c	2.966	2.97	2.927	2.984	
Sutton–Bonnington	3.266	1.800	k	1.908	1.896	2.104	1.848	PDM
			c	3.681	3.680	3.687	3.567	

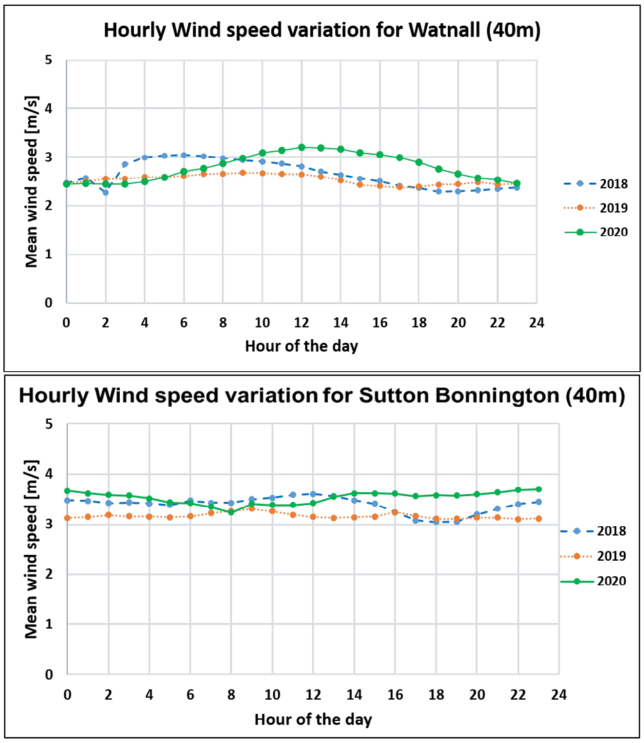


FIGURE 4 Hourly wind distribution for Sutton, Bonnington, and Watnall areas in Nottingham.

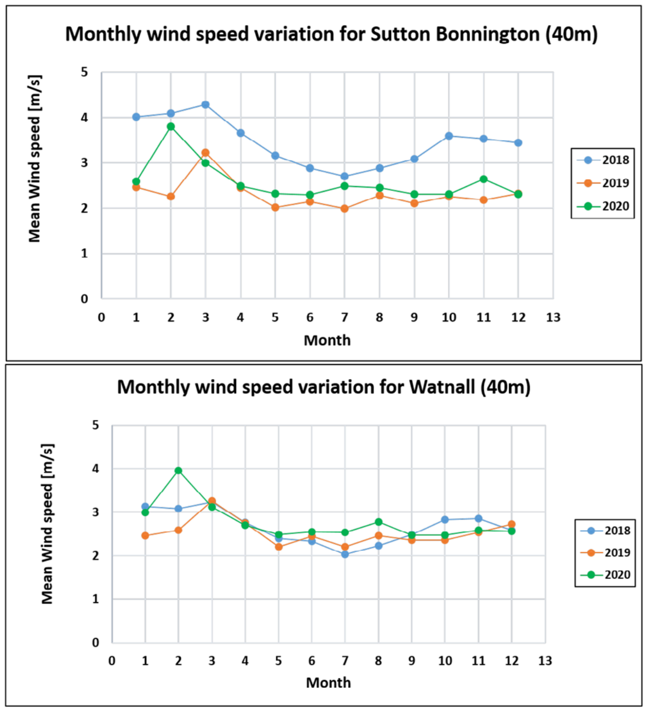


FIGURE 5 Monthly wind distribution for Sutton, Bonnington, and Watnall areas in Nottingham.

deforestation can lead to a change in the local wind patterns. This change can be linked to a variation in the topography of the surrounding area. The exact factors that influenced the wind speed distribution need to be studied in more detail. The lowest wind speeds were observed for the warm months from April to September.

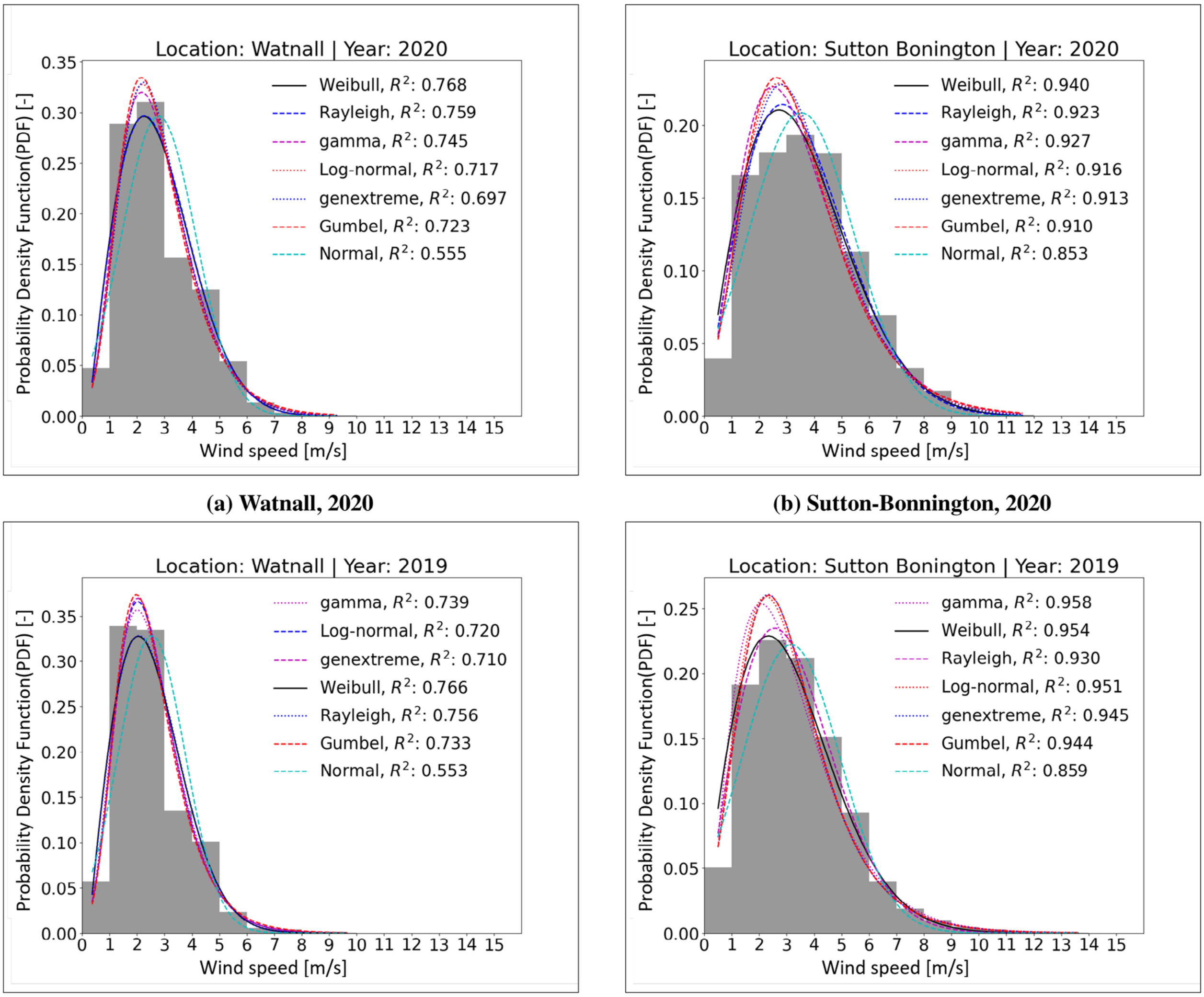
It is to be noted that all the calculations were performed by normalising the velocities at a height of 40 m using Equation (17). This height has been chosen as it is one of the most commonly used hub height when considering the installation of wind turbines. For the purpose of this study, the surface roughness (α) value has been assumed to be 0.27.

3.2 | Comparison of different probability distribution methods

Many different probability density estimations have been employed in various studies to statistically characterise the wind energy potential for a given data set. A detailed investigation was also performed in order to find a suitable distribution function under different conditions. Seven different distributions namely Gamma, Weibull, Rayleigh, Log-normal, Genextreme, Gumbel, and Normal were applied to the data in order to find the best probability density function for the wind potential assessment. The parameters for these distributions were calculated using MLE. Analysis was performed for two locations—Watnall and

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl



(a) Watnall, 2020 **(b) Sutton-Bonnington, 2020**

(c) Watnall, 2019 **(d) Sutton-Bonnington,2019**

FIGURE 6 Error analysis of Weibull parameters using different statistical tools for different locations and year 2019–2020.

Sutton–Bonnington, for three consecutive years (2018–2020). The plots showing the comparison of different distributions for a part of the data recorded over the years 2019 and 2020 are shown in Figure 6. R^2 is used as the goodness of fit criterion and its corresponding value to each of these distribution functions has also been detailed in the plot.

Overall, it was observed that Rayleigh, Weibull, and Gamma methods outperformed the other approaches for the different years and locations under consideration. It should also be noted here that Rayleigh distribution produced identical results to the Webull probability density distribution. This can be attributed to the fact that Rayleigh probability distribution function is a special case of Weibull distribution when the shape factor value is '2', as observed for the study presented. The exponential or Gaussian distribution can be defined by changing the value of the shape parameter to $k = 1$ and $k \geq 3$, respectively. The ability of Weibull distribution to incorporate these specific probability distribution instances, suitability to investigate very high wind speeds [62], and the capability to describe the data asymmetrically about a mean value, ease of analysis, make it a preferable choice for wind energy estimation as compared to the other distribution functions discussed in this paper.

Moreover, the Weibull distribution is also more flexible when compared to the gamma distribution. Thus, the Weibull probability density function was finally selected for characterizing the wind energy potential of a given data set. It was further analysed to study the effect of the method used on predicting the shape and scale parameters of the distribution.

3.3 | Weibull distribution

Different methods used for the estimation of Weibull parameters are compared in Figure 7. The data represents the estimates calculated from a single day using 10 min average for the location Clifton campus. The best-fitting curve is given by STDM in this case. Since the sample considered for this plot is only for 1 day at a particular location, this result cannot be generalized and

MOST WIEDZY Downloaded from mostwiedzy.pl

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

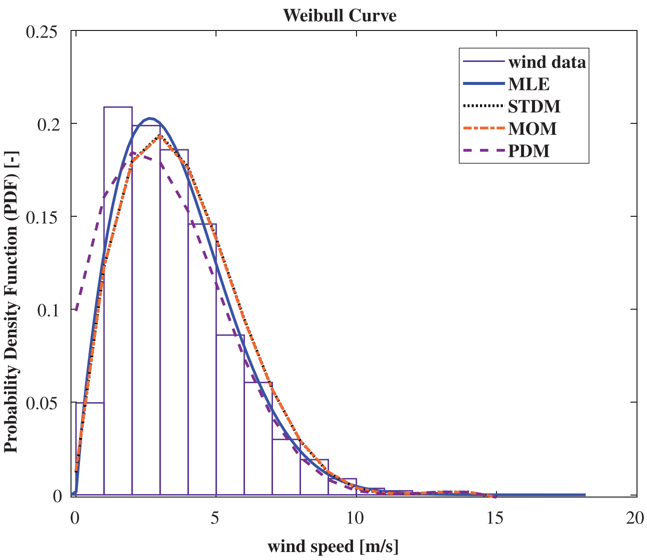


FIGURE 7 Weibull distribution estimation using different methods for calculating the parameters.

requires further detailed investigation. Thus, this plot illustrates why is it important to find the best-fitting curve in each of the cases under consideration for wind analysis.

Table 2 details the parameters measured using different Weibull methods for various locations in the Nottingham region. These measurements were taken for a period of 1 year from June 2020–2021. Plots in Figure 8 demonstrate the error analysis performed for the four methods STDM, MOM, PDM, and MLE. This goodness of fit check was implemented as explained in Section 2.4. The plot is characterized by groups of bars. Each of these groups depicts the method that was used to predict the Weibull distribution parameters (x-axis), while every bar represents the error measured using: R^2, Chi-square, RMSE, and MLE (as shown on four different y-axis). This comparison allows us to rank the methods that give the most accurate predictions of the Weibull parameters at the particular location. The method preferred for each of the locations is also highlighted in Table 2. Results obtained from the error analysis are consistent with the literature, that one single method is not sufficient to perform wind energy analysis at varying locations.

Following the Weibull distribution analysis for different locations during the same year, another study considering wind data collected from suburban locations consisting of different population densities and architectural features was performed. The variation between k and c is calculated for the years under consideration. It is observed that the shape factor is almost constant with a maximum variation of 4% in the case of Sutton–Bonnington and 1.3% in the case of Watnall (Figure 9).

The layout of buildings and their architectural designs influence the local wind energy. A concentration effect is generated because of spacing between building which is generally smaller than their height. This effect results in an increased wind velocity and thus the wind energy potential [63]. Higher number of buildings concentrated in an area for the location of Clifton Campus as compared to Sutton–Bonnington can thus

TABLE 3 Energy density production comparison of different locations in Nottingham.

Site	$\bar{v}$ (m/s)	Method	Energy density (kWh/m^2/year)
Clifton Campus	3.76	MLE	418
Sutton–Bonnington	3.27	MLE	354
Watnall	2.63	PDM	128
Chaucer Building	1.33	PDM	36

be accounted for the increased mean wind speed and the resulting power available for exploitation.

Figures 10a and 10b show the Weibull probability distribution over a period of 3 years 2018–2020, calculated using the maximum likelihood estimation for the locations Sutton Bonnington and Watnall respectively. This presents an interesting contrast of the wind patterns between a less populated and fielded area and a countryside that is comparatively more architecturally developed than the prior. In the case of Sutton–Bonnington, maximum velocities in the range of 16m/s are observed with a maximum frequency of 0.23. In the case of Watnall, the maximum velocity is restricted to 12 m/s, but a higher frequency of the order 0.33 is attained.

3.4 | Wind power density and energy

The energy density for the locations under consideration, over a period of 1 year are as observed in Table 3. It is observed that Clifton campus gave the highest value of energy density, found by using the maximum likelihood estimation and the least results were given by the Chaucer building using the power density method. This is directly related to the low wind speed recorded at this location. MLE nad PDM were found to be suitable for predicting the Weibull distribution parameters for the different locations under consideration.

While the values corresponding to the suburban and the village location for the years 2018–2020 are as shown in Table 4. It should be noted that the location Bulwell was excluded from further analysis due to contradictions with local laws. MLE was found suitable for four out of six cases as described in the table, while STDM proved to be the most useful method for only two cases. Sutton–Bonnington can be concluded as a good option when considering the wind energy availability over the 3 years under consideration. It can be inferred that MLE is the preferred method for most of the cases under consideration.

4 | WIND TURBINE SELECTION

The next step of the study was to compare commercially available small wind turbines for installation in the optimal locations obtained. Results obtained in Table 3 suggest that the Clifton campus and Sutton–Bonnington are the most suitable locations. As the average wind velocity at both locations is ≈ 3.5 m/s,

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

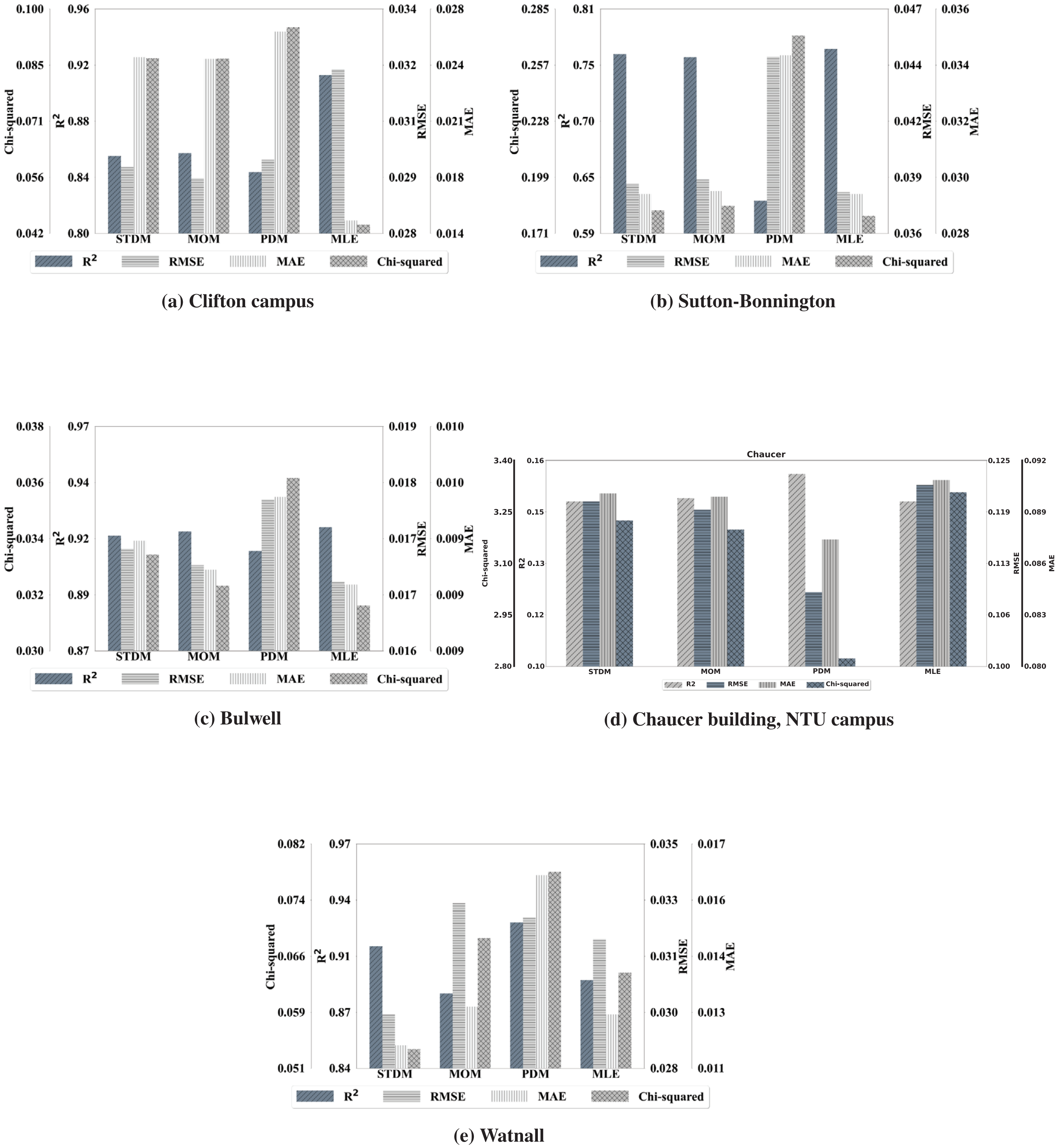


FIGURE 8 Error analysis of Weibull parameters using different statistical tools.

the wind turbines with a maximum cut-in speed of 3 m/s were selected for maximum wind energy conversion (refer Table 1). However, due to Governmental regulations and permissions from the local authorities, the Clifton campus was selected as the final place for WT installation. In addition, the installation of the turbine on the university campus offers a valuable opportunity for practical investigations across diverse fields, including medicine, engineering, and social sciences, and will promote the use of sustainable energy practices while inspiring and motivating students to participate actively in this emerging field. The results of this study may be leveraged to implement wind turbines at various locations on the campus, further promoting the utilization of green energy in everyday activities.

Figure 11 shows the average electrical power produced (kW) for the duration of wind data available. The top-performing wind turbines in the order of power produced are Falcon- 12kW,

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

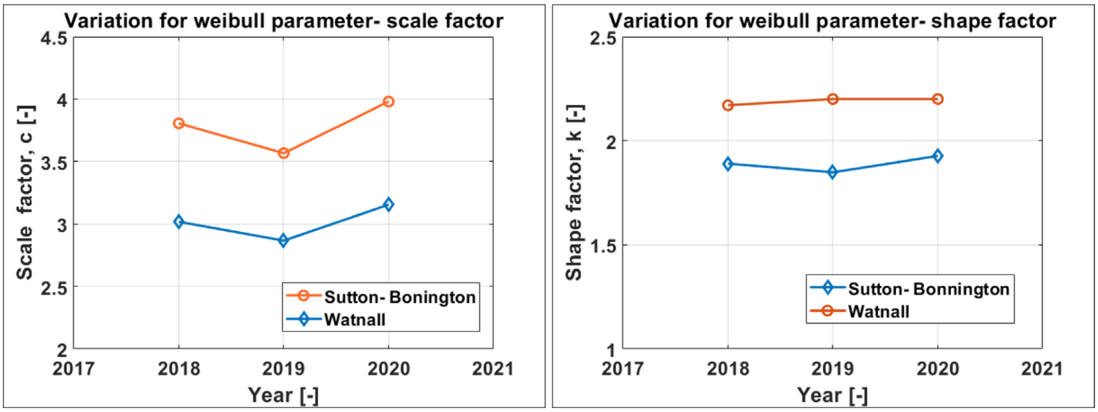


FIGURE 9 Shape and scale parameters variation over the years under consideration.

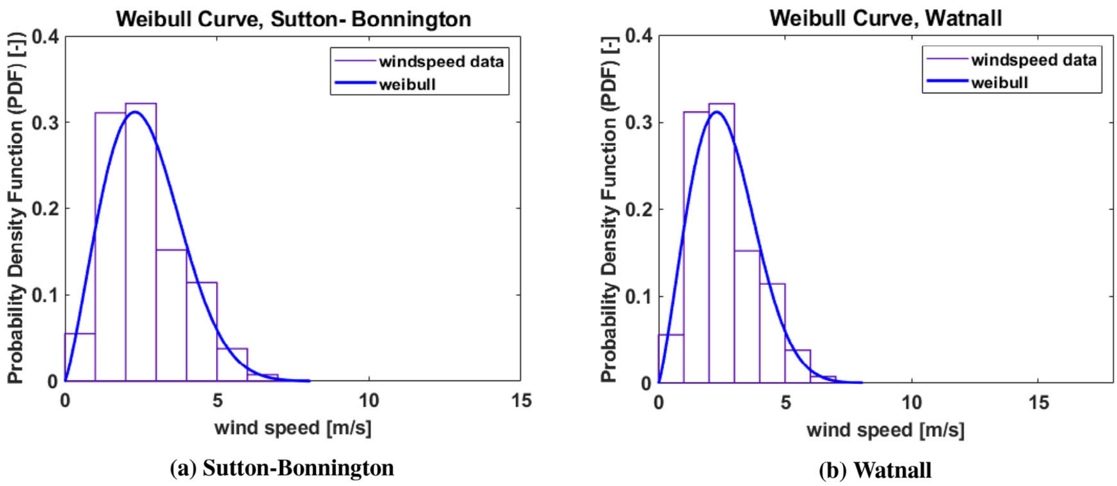


FIGURE 10 Weibull distribution plots.

TABLE 4 Power production comparison over 3 years.

Site	Year	Method	Power density(W/m^2)	Energy density (kWh/m^2/year)
Watnall	2018	MLE	20.68	181.14
	2019	STDM	17.27	151.28
	2020	MLE	23.16	204.47
Sutton Bonnington	2018	STDM	47.80	418.76
	2019	MLE	40.45	354.31
	2020	MLE	53.47	468.37

AV7-Lo wind, and QR6. AV7-Lowind WT performs the best due to a very large diameter (12.8 m), resulting in a swept area of 129 m^2, which is about ten times that of QR6 and thus generates very high power. Due to the practical restriction and sizing constraints of the location selected, this wind turbine was discarded. Next, the comparison between QR6 and Falcon-12 kW demonstrated that although the latter produced a higher average power than the former, by ≈1 kW, it was characterised by a higher cut in velocity and two times the diameter.

Finally, QR6 wind turbine was selected for the current study and a collaboration was established with the company Quiet Revolution to evaluate the performance of their commercial VAWT model, QR6 [64]. This particular model possesses a compact and easy integration design, incorporating an aesthetically pleasing swept blade (helical shape) configuration with a unique blade tip designed to minimize noise. Additionally, the blade structure exhibits excellent aero-elastic characteristics, enabling it to harness turbulent wind conditions and

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

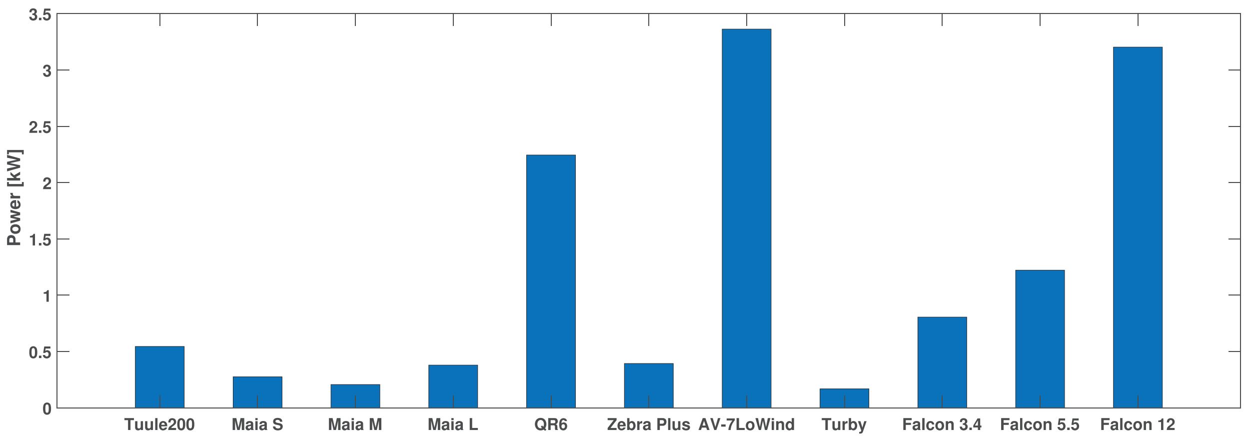


FIGURE 11 Variation of electrical power for various commercially available wind turbines suitable for installation in an urban environment.

mitigate vibration. The QR6 model commences operation at wind speeds as low as 1.5 m/s and includes safety cutoff features for wind speeds exceeding 20 m/s. The turbine comprises power regulation mechanisms that initiate an automatic shutdown in the event of an emergency and is designed for a life expectancy of over 30 years. The device is also equipped with an industrial programmable logic controller and is configurable to conform to grid codes in different regions worldwide. These attributes make the QR6 model a highly attractive option for installation at the designated site.

Experiments related to the noise production and efficiency of the wind turbine in real-case scenarios will also be conducted, as well as social studies related to public perception and potential effects on human health.

5 | CONCLUSION

This study includes an in-depth comparison of different probability density functions available to perform wind energy assessment. Seven different distributions namely Gamma, Weibull, Rayleigh, Log-normal, Genextreme, Gumbel, and Normal are applied to the data in order to find the best probability density function for the wind potential assessment. The method with the best fitting is then selected and the probability density parameters are then calculated using another four methods. This research study has concluded that the Weibull distribution is a useful approach for characterizing the wind speed distribution at four distinct sites, encompassing a village, countryside, and university campus within a city. These findings hold relevance for comprehending the potential wind resource in selected urban locations. This study additionally examines the influence of population, building density, and variations in geometry on the available wind energy density. Finally, a comparison of eleven commercially available small wind turbines has been performed to select a WT which is apt for the selected site. It is noteworthy that while the location with the highest available energy may be identified, it may not always prove to be the most optimal location due to other considerations such as noise production, turbine size and type, public perception, governmental regulations, and related factors.

Some of the specific observations and inferences from this study include:

- Comparison between different probability density function demonstrates that Weibull is the best choice for wind energy analysis when compared to different distributions namely Gamma, Weibull, Rayleigh, Log-normal, Genextreme, Gumbel and Normal according to based on the goodness of fit.
- It has been noted that the site with the highest total power density for any comparison data demonstrates the maximum average wind speed and the lowest value of k. This is in agreement with literature as found in [34].
- The Clifton campus of Nottingham Trent University has the highest wind energy production.
- HAWTS seem to be more suitable for installation in the countryside due to the higher range of attainable wind velocities and available installation area.
- Small VAWTS are more suitable to be installed in the city due to their ability to perform with low wind speeds and the requirement of small starting torque. They also perform well in a restricted space as compared to their horizontal counterpart. Moreover, the vertical configurations of wind turbines are omnidirectional and can achieve higher efficiency even under turbulent conditions [65]. These characteristics make VAWTs an excellent choice for urban settings.
- A comparison of multiple wind turbines for average power production per annum suggests that the wind turbine QR6 from Quite Revolution Ltd presents an optimal trade-off between power production, size, operational wind speed and noise production.
- The power density method and maximum likelihood estimation gave the best fitting curves for the probability density functions, for the considered locations.
- Shape and scale factor variation can be used to predict the future wind probability distribution within an error of 4% as observed for the study compared over different years.

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

Thus, it can be concluded that the selected locations are not suitable for large-scale wind energy production, however, small-scale wind energy can be produced. Extensive numerical studies have also been performed to compare different wind turbines and their respective configurations [66, 67]. Considering the results obtained from the mathematical analysis, it has been decided to install a Darrieus-type vertical axis wind turbine in the Clifton campus of Nottingham Trent University, UK. The objective is to perform an experimental investigation to validate the predictions made through the probability density estimations.

The present study underscores the significance of statistical analysis methods such as Weibull estimation in the context of wind energy applications. By testing the QR6 VAWT, this study confirms its suitability for use in urban environments while identifying opportunities for further refinement and exploration. As the wind energy sector continues to expand, these findings provide critical insights into how wind speed data can be evaluated and leveraged to facilitate the advancement of economically viable and environmentally sustainable wind energy initiatives, particularly in urban settings where wind resources are available.

NOMENCLATURE

VAWT	Vertical axis wind turbine
HAWT	Horizontal axis wind turbine
PDM	Power density method
MOM	Method of moments
STDM	Standard deviation method
MLM	Maximum likelihood method
MLE	Maximum likelihood estimation
MAPE	Mean average p ercentage error
RMSE	Root mean square error
R^2	Variance error
KDE	Kernel density estimation
WPD	Wind power density
WED	Wind energy density
PDF	Probability density function
CDF	Cumulative density function
V_{avg}	Average velocity(m/s)
$\bar{v}$	Mean velocity(m/s)
χ^2	Chi-square error
E_{pf}	Energy pattern factor
EM	Emperical method
k	Weibull shape factor/parameter
c	Weibull scale factor/parameter
Γ	Gamma function
X_{pre}	Predicted values from the probability distribution
N	No. of observations
X_{obs}	Observed values from the data set
$\overline{X_{pre}}$	Mean of the predicted values from the probability distribution
$\overline{X_{obs}}$	Mean of the observed values from the probability distribution
σ	Standard deviation
NTU	Nottingham Trent University
$f(v)$	Probability of wind velocity at an instant
v_i	Wind speed at an instant i (m/s)
Z	Height at which velocity is recorded
Z_h	Hub height or height of interest
ρ	Air density
k_h	Shape factor at height 'h'
c_h	Scale factor at height 'h'
E_D	Energy density
$\overline{P_h}$	Average power density at height 'h'
SWT	Savonius wind turbine
T	Duration of measurement
m	metres
s	second

AUTHOR CONTRIBUTIONS

Shivangi Sachar: Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing—original draft. **Shubham Shubham**: Conceptualization; data curation; resources; validation; writing—review and editing. **Piotr Doerffer**: Conceptualization; project administration; resources; supervision; writing—review and editing. **Anton Ianakiev**: Conceptualization; funding acquisition; project administration; resources; supervision; writing—review and editing. **Paweł Flaszyński**: Conceptualization; funding acquisition; project administration; resources; supervision; writing—review and editing.

ACKNOWLEDGEMENTS

The project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 860101 – zEPHYR and has been supported by CI TASK (Gdansk, Poland).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Zenodo at: https://doi.org/10.5281/zenodo.8297571

ORCID

Shivangi Sachar https://orcid.org/0000-0002-4130-1040
Shubham Shubham https://orcid.org/0000-0003-1941-8469
Anton Ianakiev https://orcid.org/0000-0002-1413-8110

REFERENCES

1. Pagnani, D., Kocewiak, Ł., Hjerrild, J., Blaabjerg, F., Bak, C.L.: Integrating black start capabilities into offshore wind farms by grid-forming batteries. IET Renewable Power Gener. 17(14), 3523–3535 (2023). https://doi.org/10.1049/rpg2.12667
2. Rogers, T., Ashtine, M., Koon, R.K., Atherley Ikechi, M.: Onshore wind energy potential for small island developing states: findings and recommendations from Barbados. Energy Sustainable Dev. 52, 116–127 (2019). https://doi.org/10.1016/j.esd.2019.08.002
3. García Caballero, E., Appendini, C.M., Figueroa Espinoza, B., Allende Arandía, M.E., Magar, V., Gross, M.S.: Wind energy potential assessment

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

for mexico's yucatecan shelf. Energy Sustainable Dev. 74, 415–429 (2023). https://doi.org/10.1016/j.esd.2023.04.016
4. Eltayesh, A., Castellani, F., Natili, F., Burlando, M., Khedr, A.: Aerodynamic upgrades of a Darrieus vertical axis small wind turbine. Energy Sustainable Dev. 73, 126–143 (2023). https://doi.org/10.1016/j.esd.2023.01.018
5. Enevoldsen, P., Xydis, G.: Examining the trends of 35 years growth of key wind turbine components. Energy Sustainable Dev. 50, 18–26 (2019). https://doi.org/10.1016/j.esd.2019.02.003
6. Iyappan, L., Kasinatha Pandian, P.: Geoprocessing model for identifying potential wind farm locations. IET Renewable Power Gener. 10(9), 1287–1297 (2016). https://doi.org/10.1049/iet-rpg.2015.0187
7. Naik, K., Ianakiev, A., Galadanci, A.S., Cucca, G., Sun, M., et al.: Evaluating the potential of wind and solar energy in achieving zero energy ratings in residential homes: a Nottingham case study. Smart Energy 13(1), 100129 (2023). https://doi.org/10.1016/j.segy.2023.100129
8. Li, M., Shen, Y., Yao, J., Ye, D., Fan, J., Simmonds, I.: An assessment of observed wind speed and wind power density over China for 1980–2021. Wind Energy 25(12), 2052–2070 (2022). https://doi.org/10.1002/we.2783
9. Justus, C., Hargraves, W., Yalcin, A.: Nationwide assessment of potential output from wind-powered generators. J. Appl. Meteorol. 15(7), 673–678 (1976). https://www.jstor.org/stable/26177565
10. Byrne, R., Hewitt, N.J., Griffiths, P., MacArtain, P.: Observed site obstacle impacts on the energy performance of a large scale urban wind turbine using an electrical energy rose. Energy for Sustainable Dev. 43, 23–37 (2018). https://doi.org/10.1016/j.esd.2017.12.002
11. Cooney, C., Byrne, R., Lyons, W., O'Rourke, F.: Performance characterisation of a commercial-scale wind turbine operating in an urban environment, using real data. Energy Sustainable Dev. 36, 44–54 (2017). https://doi.org/10.1016/j.esd.2016.11.001
12. Capps, S.B., Hall, A., Hughes, M.: Sensitivity of Southern California wind energy to turbine characteristics. Wind Energy 17(1), 141–159 (2014). https://dx.doi.org/10.1002/we.1570
13. Ramprakash, T.T., Shubham, S., Ianakiev, A.: Effect of blade shape on aerodynamic and aeroacoustic characteristics of vertical axis wind turbines using mid-fidelity and high-fidelity methods. In: AIAA SciTech Forum. American Institute of Aeronautics and Astronautics, Washington, D.C. (2024)
14. Shubham, S., Avallone, F., Brandetti, L., Wright, N., Ianakiev, A.: Effect of struts and central tower on aerodynamics and aeroacoustics of vertical axis wind turbines using mid-fidelity and high-fidelity methods. In: AIAA SciTech Forum, pp. 1–25. American Institute of Aeronautics and Astronautics, Washington, D.C. (2024)
15. Saidur, R., Rahim, N.A., Islam, M.R., Solangi, K.H.: Environmental impact of wind energy. Renewable Sustainable Energy Rev. 15(5), 2423–2430 (2011). https://doi.org/10.1016/j.rser.2011.02.024
16. Xu, Z., Wei, J., Zhang, S., Liu, Z., Chen, X., Yan, Q., Guo, J.: A state-of-the-art review of the vibration and noise of wind turbine drivetrains. Sustainable Energy Technol. Assess. 48, 101629 (2021). https://doi.org/10.1016/j.seta.2021.101629
17. Maclaurin, G., Hein, C., Williams, T., Roberts, O., Lantz, E., Buster, G., Lopez, A.: National-Scale Impacts on Wind Energy Production under Curtailment Scenarios to Minimize Bat Fatalities. National Renewable Energy Laboratory, Golden, CO (2022)
18. Ferreira, P., Lima, F., Ribeiro, F., Vieira, F.: A mixed-method approach for the assessment of local community perception towards wind farms. Sustainable Energy Technol. Assess. 33, 44–52 (2019). https://doi.org/10.1016/j.seta.2019.02.004
19. Byrne, R., MacArtain, P.: The 15-year operational experiences of an 850 kw peri-urban wind turbine: lessons learned from a behind-the-meter installation in ireland. Energy Sustainable Dev. 70, 342–360 (2022). https://doi.org/10.1016/j.esd.2022.08.011
20. Keyhani, A., Ghasemi Varnamkhasti, M., Khanali, M., Abbaszadeh, R.: An assessment of wind energy potential as a power generation source in the capital of Iran, Tehran. Energy 35(1), 188–201 (2010). https://doi.org/10.1016/j.energy.2009.09.009
21. Faghani, G.R., Ashrafi, Z.N., Sedaghat, A.: Extrapolating wind data at high altitudes with high precision methods for accurate evaluation of wind power density, case study: center of iran. Energy Convers. Manage. 157, 317–338 (2018). https://doi.org/10.1016/j.enconman.2017.12.029
22. Mohammadi, K., Mostafaeipour, A.: Using different methods for comprehensive study of wind turbine utilization in Zarrineh, Iran. Energy Convers. Manage. 65, 463–470 (2013). https://doi.org/10.1016/j.enconman.2012.09.004
23. Mahmood, F.H., Resen, A.K., Khamees, A.B.: Wind characteristic analysis based on weibull distribution of Al-Salman site, Iraq. Energy Rep. 6, 79–87 (2020)
24. Celik, A.N.: Review of turkey's current energy status: a case study for wind energy potential of Çanakkale province. Renewable Sustainable Energy Rev. 15(6), 2743–2749 (2011). https://doi.org/10.1016/j.rser.2011.03.017
25. Nedaei, M., Assareh, E., Walsh, P.R.: A comprehensive evaluation of the wind resource characteristics to investigate the short term penetration of regional wind power based on different probability statistical methods. Renewable Energy 128, 362–374 (2018). https://doi.org/10.1016/j.renene.2018.05.077
26. Pobočíková, I., Sedliačková, Z., Michalková, M.: Application of four probability distributions for wind speed modeling. Proc. Eng. 192, 713–718 (2017). https://doi.org/10.1016/j.proeng.2017.06.123
27. Celik, A.N.: A statistical analysis of wind power density based on the Weibull and rayleigh models at the southern region of turkey. Renewable Energy 29(4), 593–604 (2004). https://doi.org/10.1016/j.renene.2003.07.002
28. Lee, G., Ding, Y., Xie, L., Genton, M.G.: A kernel plus method for quantifying wind turbine performance upgrades. Wind Energy 18(7), 1207–1219 (2015). https://doi.org/10.1002/we.1755
29. Wang, Z., Wang, W., Liu, C., Wang, B., Feng, S.: Short-term probabilistic forecasting for regional wind power using distance-weighted kernel density estimation. IET Renewable Power Gener. 12(15), 1725–1732 (2018). https://doi.org/10.1049/iet-rpg.2018.5282
30. Chen, P., Li, C., Zhang, X.: Degradation trend prediction of pumped storage unit based on a novel performance degradation index and GRU-attention model. Sustainable Energy Technol. Assess. 54, 102807 (2022). https://doi.org/10.3390/en15020605
31. Han, Q., Meng, F., Hu, T., Chu, F.: Non-parametric hybrid models for wind speed forecasting. Energy Convers. Manage. 148, 554–568 (2017). https://doi.org/10.1016/j.enconman.2017.06.021
32. Qi, M., Gao, H., Wang, L., Xiang, Y., Lv, L., Liu, J.: Wind power interval forecasting based on adaptive decomposition and probabilistic regularised extreme learning machine. IET Renewable Power Gener. 14(16), 3181–3191 (2020). https://doi.org/10.1049/iet-rpg.2020.0315
33. Kou, P., Wang, C., Liang, D., Cheng, S., Gao, L.: Deep learning approach for wind speed forecasts at turbine locations in a wind farm. IET Renewable Power Gener. 14(13), 2416–2428 (2020). https://doi.org/10.1049/ietrpg.2019.1333
34. Hennessey, J.P.: Some aspects of wind power statistics. J. Appl. Meteorol. Climatol. 16(2), 119–128 (1977). https://doi.org/10.1175/1520-0450(1977)016⟨0119:SAOWPS⟩2.0.CO;2
35. Juan, Y.H., Rezaeiha, A., Montazeri, H., Blocken, B., Wen, C.Y., Yang, A.S.: Cfd assessment of wind energy potential for generic high-rise buildings in close proximity: Impact of building arrangement and height. Appl. Energy 321, 119328 (2022). https://doi.org/10.1016/j.apenergy.2022.119328
36. Lin, F., Zhang, Y., Wang, J.: Recent advances in intra-hour solar forecasting: a review of ground-based sky image methods. Int. J. Forecast. 39(1), 244–265 (2023). https://doi.org/10.1016/j.iforecast.2021.11.002
37. Zhang, Z., Zhou, M., Wu, Z., Liu, S., Guo, Z., Li, G.: A frequency security constrained scheduling approach considering wind farm providing frequency support and reserve. IEEE Trans. Sustainable Energy 13(2), 1086–1100 (2022). https://doi.org/10.1109/TSTE.2022.3150965
38. Chen, Y., Zhang, Z., Chen, H., Zheng, H.: Robust UC model based on multi-band uncertainty set considering the temporal correlation of wind/load prediction errors. IET Gener. Transm. Distrib. 14(2), 180–190 (2020). https://doi.org/10.1049/iet-gtd.2019.1439
39. Weibull, W.: A statistical distribution function of wide applicability. J. Appl. Mech. 18(3), 293–297 (1951)

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

MOST WIEDZY Downloaded from mostwiedzy.pl

40. Kaplan, Y.A.: Determination of the best Weibull methods for wind power assessment in the southern region of Turkey. IET Renewable Power Gener. 11(1), 175–182 (2017). https://doi.org/10.1049/iet-rpg.2016.0206
41. Kang, S., Khanjari, A., You, S., Lee, J.H.: Comparison of different statistical methods used to estimate Weibull parameters for wind speed contribution in nearby an offshore site, republic of korea. Energy Rep. 7, 7358–7373 (2021). https://doi.org/10.1016/j.egyr.2021.10.078
42. Islam, K., Dussadee, N., Chaichana, T.: An approach to determine the weibull parameters and wind power analysis of Saint Martin's Island, Bangladesh. MATEC Web Conf. 70, 09004 (2016). https://doi.org/10.1051/matecconf/20167009004
43. Katinas, V., Marčiukaitis, M., Gecevičius, G., Markevičius, A.: Statistical analysis of wind characteristics based on Weibull methods for estimation of power generation in Lithuania. Renewable Energy 113, 190–201 (2017). https://doi.org/10.1016/j.renene.2017.05.071
44. Azad, A.K., Rasul, M.G., Yusaf, T.: Statistical diagnosis of the best Weibull methods for wind power assessment for agricultural applications. Energies 7(5), 3056–3085 (2014). https://doi.org/10.3390/en7053056
45. Shaban, A.H., Resen, A.K., Bassil, N.: Weibull parameters evaluation by different methods for windmills farms. Energy Rep. 6, 188–199 (2020). https://doi.org/10.1016/j.egyr.2019.10.037
46. Pearson, K.: Method of moments and method of maximum likelihood. Biometrika 28(1/2), 34–59 (1936). https://doi.org/10.2307/2334123
47. Justus, C.G., Mikhail, A.: Height variation of wind speed and wind distributions statistics. Geophys. Res. Lett. 3(5), 261–264 (1976). https://doi.org/10.1029/GL003i005p00261
48. Akdağ, S.A., Dinler, A.: A new method to estimate Weibull parameters for wind energy applications. Energy Convers. Manage. 50(7), 1761–1766 (2009). https://doi.org/10.1016/j.enconman.2009.03.020
49. Fisher, R.A.: Frequency distribution of the values of the correlation coefficient in samples from an indefinitely large population. Biometrika 10(4), 507–521 (1915). https://doi.org/10.2307/2331838
50. Stevens, M., Smulders, P.: The estimation of the parameters of the Weibull wind speed distribution for wind energy utilization purposes. Wind Eng. 132–145 (1979). https://www.jstor.org/stable/43749134
51. Chang, T.P.: Performance comparison of six numerical methods in estimating Weibull parameters for wind energy application. Appl. Energy 88(1), 272–282 (2011). https://doi.org/10.1016/j.apenergy.2010.06.018
52. Islam, M.R., Saidur, R., Rahim, N.A.: Assessment of wind energy potentiality at Kudat and Labuan, Malaysia using Weibull distribution function. Energy 36(2), 985–992 (2011). https://doi.org/10.1016/j.energy.2010.12.011
53. QBlade - next generation wind turbine simulation. https://qblade.org/ (2022). Accessed 2023
54. RMSE: root mean square error. https://www.statisticshowto.com/probability-and-statistics/regression-analysis/rmse-root-mean-square-error/ (2021). Accessed 2023
55. Kantar, Y.M., Usta, I.: Analysis of the upper-truncated Weibull distribution for wind speed. Energy Convers. Manage. 96, 81–88 (2015). https://doi.org/10.1016/j.enconman.2015.02.063
56. Hossain, J., Sharma, S., Kishore, V.: Multi-peak Gaussian fit applicability to wind speed distribution. Renewable Sustainable Energy Rev. 34, 483–490 (2014). https://doi.org/10.1016/j.rser.2014.03.026
57. McHugh, M.: The chi-square test of independence. Biochem. Med. 23, 143–9 (2013). https://doi.org/10.11613/BM.2013.018
58. Shahizare, B., Nik Ghazali, N., Chong, W., Tabatabaeikia, S., Izadyar, N., Esmaeilzadeh, A.: Novel investigation of the different omni-direction-guide-vane angles effects on the urban vertical axis wind turbine output power via three-dimensional numerical simulation. Energy Convers. Manage. 117, 206–217 (2016). https://doi.org/10.1016/j.enconman.2016.03.034
59. Kumar, R., Raahemifar, K., Fung, A.S.: A critical review of vertical axis wind turbines for urban applications. Renewable Sustainable Energy Rev. 89, 281–291 (2018). https://doi.org/10.1016/j.rser.2018.03.033
60. Eriksson, S., Bernhoff, H., Leijon, M.: Evaluation of different turbine concepts for wind power. Renewable Sustainable Energy Rev. 12(5), 1419–1434 (2008). https://doi.org/10.1016/j.rser.2006.05.017
61. Shubham, S., Wright, N., Avallone, F., Ianakiev, A.: Aerodynamic and aeroacoustic investigation of vertical axis wind turbines with different number of blades using mid-fidelity and high-fidelity methods. In: AIAA AVIATION 2023 Forum, p. 3642. American Institute of Aeronautics and Astronautics, Washington, D.C. (2023). https://doi.org/10.2514/6.2023-3642
62. Rohatgi, J., Araújo, A., Primo, A.R.: Extreme wind speeds and their prediction for wind turbines. Wind Eng. 37(6), 595–603 (2013). https://doi.org/10.1260/0309-524X.37.6.595
63. Blocken, B., Carmeliet, J., Stathopoulos, T.: CFD evaluation of wind speed conditions in passages between parallel buildings–effect of wall-function roughness modifications for the atmospheric boundary layer flow. J. Wind Eng. Ind. Aerodyn. 95(9), 941–962 (2007). https://doi.org/10.1016/j.jweia.2007.01.013
64. QuiteRevolution: Vertical axis wind turbines the QR6 helical VAWT. https://www.quietrevolution.com/products/ (2020). Accessed 2023
65. Rezaeiha, A., Montazeri, H., Blocken, B.: On the accuracy of turbulence models for CFD simulations of vertical axis wind turbines. Energy 180, 838–857 (2019). https://doi.org/10.1016/j.energy.2019.05.053
66. Shubham, S., Naik, K., Sachar, S., Ianakiev, A.: Performance analysis of low Reynolds number vertical axis wind turbines using low-fidelity and mid-fidelity methods and wind conditions in the city of Nottingham. Energy 279, 127904 (2023). https://doi.org/10.1016/j.energy.2023.127904
67. Shubham, S., Wright, N., Ianakiev, A.: Application of richardson extrapolation method to aerodynamic and aeroacoustic characteristics of low Reynolds number vertical axis wind turbines. In: 28th AIAA/CEAS Aeroacoustics 2022 Conference, p. 3022. American Institute of Aeronautics and Astronautics, Washington, D.C. (2022)

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Sachar, S., Shubham, S., Doerffer, P., Ianakiev, A., Flaszyński, P.: Wind speed probabilistic forecast based wind turbine selection and siting for urban environment. IET Renew. Power Gener. 1–16 (2024). https://doi.org/10.1049/rpg2.13132

MOST WIEDZY Downloaded from mostwiedzy.pl

17521424, 0, Downloaded from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.13132 by Institution Of Fluid Flow Machinery, Wiley Online Library on [04/11/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License