LiDAR technology for wind energy potential assessment: demonstration and validation at a site around Lake Erie

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Abstract: Wind energy potential assessment is crucial for proper wind farm siting. Typically, this involves installation of tall and costly meteorological masts with anemometers. New technology such as Light Detection and Ranging (LiDAR) is an alternative mobile technology that serves such purpose. This paper describes the principle of LiDAR technology and presents case studies of its applications to evaluate the energy output potentials at the site near Lake Erie in northern Cleveland, Ohio, USA. A ZephIR[®] LiDAR system is used to monitor one-year of vertical wind data profile (at 30m and 70m height) from May 2011 to April 2012, from which the wind statistics are determined. These include the monthly average of wind speed, turbulence intensity, Weibull shape and scale factor, wind compass rose, and wind power density, etc. The wind speed data is used to evaluate the wind power capacity factors for prototype wind turbines that are subsequently installed in 2012. The data of power output by the turbines between 2013 and 2015 is used to compare with those predicted based on wind speed model derived from LiDAR measurement. The results show that the estimated wind turbine's capacity factor from LiDAR data is satisfactory after excluding the maintenance days. This research demonstrates the potential of LiDAR technology as a cost effective way in providing reliable evaluation of wind energy potential.

Keywords: Wind energy, LiDAR, wind speed, Weibull distribution, capacity factor

1. Introduction

The desire to reduce greenhouse gas (GHG) emissions and the increasing demand for energy promote the development of renewable energy. Wind energy is one of the most important forms of renewable energy due to its eco-friendliness, cost-effectiveness, sustainability, and worldwide availability. Because wind energy currently has the most favorable ratio of investment cost to productivity among the different types of renewable energy technologies [1], wind energy installation capacity in the world has increased from 23,900 MW to 486,749MW (or 20 times) from 2001 to 2016 [2]; and this number is expected to increase at an even faster pace in the next few decades. In European countries such as Spain and Denmark, wind energy already contributes 22.8% and 37.6% respectively to the annual electricity demand according to the 2016 Spanish Electricity System preliminary report [3] and the Danish wind industry association [4]. According to the U.S. Department of Energy's (DOE) report, wind energy will supply the U.S. with 10% of the country's electricity by 2020, 20% by 2030, and 35% by 2050 [5]. Meanwhile, there is a growing interest in developing offshore wind energy, where the wind is normally

stronger and more uniform than onshore wind [6, 7]. Coastal wind sources in the United States are abundant and is a potential energy source [8]. The U.S. began to build its first commercial offshore wind farm, Block Island Wind Farm, in 2015 and it has been started to produce electricity in December 2016.

Although there are significant advantages of using wind energy, there are also disadvantages. For instance, wind energy is not suitable for all regions. It needs to be built at locations with higher wind speed in order to get high-energy output performance. Seeking a suitable location is the first and most important step when planning to build a wind farm. By means of site-specific wind measurements, the wind farm owner must decide both the size and type of wind turbine to be used. Finding a suitable location requires a detailed and often costly analysis of local wind conditions [9]. Extensive research [10-15] has been done to evaluate wind power potential in many countries in the last few decades and significant progress has been accomplished. Boudia and Guerri [16] investigated the wind energy potential at the coastline of Algeria using WAsP software and meteorological data from measurement stations, which helped to come up with the minimum wind energy price based on accurate wind resources assessment; Ohunakin [17] presents a statistical analysis of wind characteristics of five locations collected from the meteorological stations in Nigeria and evaluated the wind resources; Keyhani [18] uses eleven years' wind speed measurement data from the meteorological department to identify the wind energy potential in Tehran; Bilir et al. [19] evaluate wind energy potential in Ankara, Turkey based on wind speed data collected between June 2012 and June 2013 by a measurement station installed at the Atilim University campus. However, these researches required large amounts of data from meteorological stations, which cannot be reliably used at locations far away from meteorological stations. Traditionally, tall and costly meteorological masts are installed with cup and sonic anemometers at the proposed site. The cost for such towers over 60m is substantial [20]. An 80-meter lattice tower costs more than \$85,000 over a two-year life cycle. The cost includes: the price of the tower; concrete foundation and other construction costs; erection of the tower; FAA permit application and processing (required for towers over 60 meters); site acquisition; local building and other permits; removing the tower at the end [21]. The total cost is more expensive than using a LiDAR system. Additionally, onshore wind LiDAR measurements typically deliver a \$400,000 increase in the value of a project through more accurate Annual Energy Prediction (AEP) when compared to an 80 m met mast on a 20 MW onshore wind farm [22].

Another disadvantage of the traditional method is that the meteorological mast can only measure wind speed up to 80m in heights due to the limit of typical mast height. However, modern wind turbines' hub heights could reach as much as 150m above the ground level. Empirical equations such as the power law or the logarithmic law wind shear model are used to convert the wind speed measured at 10m or 30m heights to those at target heights. In Kwon's study [23], the author evaluated the wind energy potential at Kwangyang Bay on the southern coast of the Korean Peninsula using the Power Law to transform wind speed at 10m heights' to the wind speed at prototype wind turbine hub heights. They found that the uncertainty of wind velocity variation according to the change of heights is caused by the ambiguity of surface roughness at the site. Mostafaeipour [24] has investigated the wind energy resource in Kerman, Iran by using

14 years (1991-2004) of mean wind data at 10m heights from the local airport weather station. The author obtained wind speed data at other elevations by using the power law model. Durisic and Mikulovic [25] have discussed the wind energy resource in the South Banat region of Serbia based on wind data collected at 10m, 40m, 50m, and 60m from a 60m tube anemometer mast installed on the site. They also used the Power Law to calculate vertical wind speed profile. The accuracy of using the power law and the logarithmic law, however, depend highly on the wind shear coefficient and the roughness length chosen for the site. The wind shear coefficient and the roughness length varies within a large range even for the same type of terrain [26]. Accordingly, this could cause uncertainties in wind resource data, leading to large errors in the energy output evaluation.

LiDAR is a ground-based remote sensing instrument with many advantages: it is cheaper than building a metrological mast; it can measure wind data up to 200 meters above ground level; it is a ground-based instrument and is easy to remove; minimum human dependence as most of the processes are automatic down. The development of LiDAR technology offers easier, convenient, accurate, and continuous operation instruments to measure wind profiles near the ground. In Foussekis's study [27], the author compared the onshore wind speed measurement of the ZephIR LiDAR and classical cup anemometers installed on a 100 m height meteorological mast and the ZephIR LiDAR showed excellent correlation between LiDAR and the cup anemometer. Pena et al. [28] evaluated the mean wind speed using the ZephIR LiDAR and compared with cup anemometers from different masts for an offshore wind farm. The LiDAR performed good wind profiling at heights up to 160m. Kim et al. [29] had compared the ground-based LiDAR and met mast wind measurements for wind resource assessment over various terrain conditions and found LiDAR error rates for the measurement sites ranged approximately between 2% and 6%. Hung et al. [30] had tested accuracy and reliability of using floating LiDAR Omer [31] improved the modeling of the boundary layer wind field in a complex terrain and validated using Doppler LiDAR observations. Kumer et al. [32] had studied a methodology for assessing turbulent kinetic energy (TKE) from profiling wind LiDAR measurements, they retrieved a good TKE estimate with respect to sonic anemometer measurements. As described above, the studies on LiDAR measurements validation have been carried out continuously. However, most of the study has been validating LiDAR with met mast anemometer but not any study has been down to validate with real wind turbine's power output capacity. In this research, a LiDAR system is used to evaluate wind energy potential at an onshore site near Lake Erie at Cleveland, northeast of the United States. Wind speed data at 10-minutes' intervals at the proposed hub heights (30m and 70m) over a one-year period from May 2011 to April 2012 are analyzed. Characteristics of the wind, i.e., the mean wind speed, Weibull scale factor, Weibull shape factor, the wind rose, power density etc. are evaluated using monitoring data to determine the potential for wind power generation at the location. Two commercial wind turbines were constructed at the monitoring locations in 2012 and have provided electric power to the grid. Three years' power capacity data from 2013 to 2015 was recorded and compared with the prediction results with monitored wind speed data. Consequently, the accuracy of the LiDAR predictions of wind energy potential is evaluated. Suggestions and guidelines are provided to the wind energy industry on the potential of LiDAR for the wind energy resource assessment. The advantages of onsite wind

measurement by LiDAR and its application for long-term wind energy product prediction deserves further adoption by the wind energy industry.

2. Methodology and Technical Background

2.1. Weibull distribution

The wind speed data observed from various studies with different observation methods usually have widely different parameters and cannot be used to compare the wind power potential directly. Therefore, a general wind distribution is needed to represent wind energy characteristics. The two most common distributions are the Weibull and the Rayleigh functions, where the Rayleigh distribution is a subset of the Weibull distribution [33]. In recent years, the Weibull distribution has been commonly used, accepted, and recommended in literature to express the wind speed frequency distribution [34] as it gives a better fit for measured monthly probability density distributions than other statistical functions [35, 36]. The density function of the Weibull distribution in its simplest form is [37, 38]:

$$f(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k} \quad (1)$$

where $f(v)$ is the probability density function, also refer to as pdf; v is wind speed (m/s); c is the scale factor (m/s) and k is the shape factor. A higher value of c indicates a higher wind speed is higher and the value of k indicates the wind stability. There are several methods used to calculate the parameters of the Weibull wind speed distribution for wind energy analysis such as mean wind speed and standard deviation (MWS), the method of moments (MM), the power density method (PDM), the graphical method (GM), and the maximum likelihood method (ML) [33, 39, 40]. In this research, the Weibull distribution is fitted to the wind speed data using the maximum likelihood method MLM [33]. Then the shape factor and scale factor could be calculated as follows [41, 42]:

$$k = \left(\frac{\sum_{i=1}^N v_i^k \ln(v_i)}{\sum_{i=1}^N v_i^k} - \frac{\sum_{i=1}^N \ln(v_i)}{N} \right)^{-1} \quad (2)$$

$$c = \left(\frac{1}{N} \sum_{i=1}^N v_i^k \right)^{1/k} \quad (3)$$

where v_i is the average wind speed in time step i and N is total the number of nonzero wind speed data points.

2.2. Wind power density

The power of wind could be estimated according to the well-known equation [26]:

$$P(v) = \frac{1}{2} \rho A v^3 \quad (4)$$

in which $P(v)$ is the wind power (W); ρ is the density of air (typically 1.225 kg/m^3); A is the rotor swept area, and v is the inflow wind speed.

To indicate the wind resources at a certain site, the wind power density (WPD), which describes how much kinetic energy from the wind per area can be transformed into energy production [43], is the most commonly used parameter. The WPD equation is shown as follows [28]:

$$p(v) = \int_0^\infty \frac{P(v)}{A} f(v) dv = \frac{1}{2} \rho c^3 \Gamma\left(\frac{k+3}{k}\right) \quad (5)$$

in which $p(v)$ is the wind power density (WPD) in W/m^2 , Γ is the gamma function which has a standard form of [35, 44]:

$$\Gamma(x) = \int_0^\infty e^{-u} u^{x-1} du \quad (6)$$

2.3. Turbulence intensity

The causes of wind speed turbulence are obstacles on the soil surface, roughness length of the terrain, and local dynamic variations of the air pressure and temperature [25]. There are many statistical descriptors of turbulence which may be useful, and the turbulence intensity is one of those parameters. Turbulence intensity (TI) is a measure of the overall level of wind turbulence [26]. It is a relative indicator of turbulence and not an absolute value [45]. Its formal equation is shown below [46]:

$$TI = \frac{\sigma_u}{\bar{u}} \quad (7)$$

in which TI is the turbulence intensity and σ_u is the standard deviation of the wind speed variations about the mean wind speed $\bar{u}$, usually defined over 10 min.

2.4. Capacity factor

The capacity factor is defined as the ratio of the average power output to the rated output power of the generator and is given as follows [26, 47]:

$$C_f = \frac{P_{ave}}{P_r} \times 100\% = \frac{\exp[-(v_c/c)^k] - \exp[-(v_r/c)^k]}{(v_r/c)^k - (v_c/c)^k} - \exp[-(v_f/c)^k] \quad (8)$$

in which P_{ave} is the average power output of the wind turbine (kW), P_r is the rated electrical power of the wind turbine (kW), v_c is the cut-in wind speed, v_f (m/s) is the cut-off wind speed, and v_r (m/s) is the rated wind speed respectively.

The capacity factor, which is a measure of the usefulness of using a certain wind turbine, is studied for the two selected wind turbines in this research.

3. Description of the Technology and Study Site

3.1. ZephIR[®] LiDAR

Light Detection and Ranging (LiDAR) is a remote wind sensing technology capable of measuring three-dimensional relative wind velocity at multiple fixed distances from the optical transceiver [48]. The basic LiDAR principle relies on measuring the Doppler shift of radiation scattered by natural aerosols carried by the wind [49] such as water droplets, pollen, or dust. These aerosols will reflect the laser light and this light is measured in the LiDAR's photodetector and is known as backscatter. The analog signal is sampled at 100 MHz and converted at 200kHz to power spectra using a 256-point time domain FFT (Fast Fourier Transform) [50] in order to obtain an acceptable signal-to-noise ratio [28]. The accuracy of the LiDAR system has been tested against cup anemometer with wind speed correlations of 0.99 or better [51, 52]. This study is mainly based on a data set collected by laser-based ZephIR® wind LiDAR. The LiDAR consists of a continuous-wave laser with a cone angle of 30.6° to the zenith. The measurement of the radial velocities is by 1.55μm laser which is in the infrared range and will not harm human eyesight. The ZephIR® LiDAR can be rapidly deployed, configured, and redeployed with both onboard data storage system and wireless data transmissions systems. The ZephIR® LiDAR obtains approximately 150 line-of-sight measurements in 20 milliseconds and 3 seconds of data to derive horizontal and vertical wind speed components and wind direction. In any given azimuth direction, LiDAR measures the line of sight or radial velocity, V_{LOS} , which contains resolved components of the horizontal wind speed (u) and vertical wind speed (w) according to the following equation [28]:

$$V_{LOS} = abs[u \cos(\theta - \theta_d) \sin(\phi) + w \cos(\phi)] \quad (9)$$

in which θ is the instantaneous azimuth angle and θ_d is the wind direction. By assuming the flow is uniform throughout the entire measuring volume, u , w , and θ_d can be obtained using a non-linear least squares method. In this research, the wind speeds data at 30m and 70m were analyzed corresponding to the hub heights of the prototype wind turbine.

Fig. 1. ZephIR® wind LiDAR

3.2. Wind turbine prototype

Two commercial wind turbines Vestas® V-27 and Nordex® N-54 were built on the studied site in 2012 and have generated electricity to the grid ever since. Three years' (2013-2015) of wind energy power capacities from the monitored wind production data is used as a comparison basis to with the theoretical wind energy power capacity. d 1. Both wind turbines are three blades upwind horizontal wind turbines. The V-27 wind turbine has 30m hub heights with 3.5m/s cut-in wind speed and 26m/s cut-out wind speed. The N-54 wind turbine has much higher hub height which is 70m above the ground level. The cut-in wind speed and the cut-out wind speed of the N-54 wind turbine are 3m/s and 25m/s separately. Both of the wind turbines' rated wind speed is 14m/s. The wind turbines' power curves are shown in Fig. 2.

Fig. 2. Prototype wind turbine power curves

Table 1. Prototype wind turbine parameters [53]

Performance	Description	
Model	Vestas® N-27	Nordex® N-54
Manufacturer	Denmark	Germany
Rated Power	225kW	1MW
Number of blades	3	3
Rotor diameter	27 m	54 m
Cut-in wind speed	3.5 m/s	3 m/s
Cut-out wind speed	26 m/s	25 m/s

Rated wind speed	14 m/s	14 m/s
Hub height	30 m	70 m

4. Results and Analysis

4.1. Description of the measurement site

The state of Ohio is among the pioneers in promoting wind energy resources. According to the National Oceanic and Atmospheric Administration (NOAA), Ohio has great wind energy potential, especially near Lake Erie area. The target area of this research is about 4 miles away from the Lake Erie coastline and is located near a manufacturing plant in northeast Cleveland. The exact latitude and longitude of the location is 41°36'07.8" N, 81°29'48.7" W. The LiDAR system is positioned at an open terrain location with no obstacles. The topography of the site nearby could be described as a flat area with buildings under 10m high. Because the programmed heights of the LiDAR system were selected at 30m and 70m, which are the hub heights of the two wind turbine prototypes, no height conversion is needed in this research.

4.2. Wind data analysis

The seasonal wind speed characteristics derived with theoretical methods using Eqs. (2-5) for both 30m and 70m are shown in Table 2. The table shows that the highest mean wind occurs in the winter season and the lowest mean wind speed occurs in the summer for both 30 m and 70 m heights. The mean wind speed of 30 m and 70 m heights in the winter are 5.44 m/s and 6.70 m/s respectively. It is clear that the mean wind speed increases with height as the mean wind speed of 70m heights is higher than the mean wind speed at 30m height during all seasons. At 30 m, the lowest Weibull scale factor of 4.29 m/s occurs in the summer and the highest value of 6.16 m/s occurs in the winter. The same trend can be found at 70 m. The Weibull shape factor k varies from 2.02 in the spring to 2.35 in the summer at 30 m and varies from 2.11 in the spring to 2.46 in the summer at 70 m. The relatively high value of k indicates that the variation of mean wind speed about the annual mean is small during the summer for both heights.

Table 2. Seasonal wind data characteristics

Site Location	Height (m)	Time	Mean Wind Speed (m/s)	S.D.	Weibull Shape Factor k	Weibull Scale Factor c (m/s)
41°36'07.8"N 81°29'48.7"W	30	Spring	4.77	2.51	2.02	5.40
		Summer	3.80	1.72	2.35	4.29
		Autumn	4.40	2.20	2.13	4.99
		Winter	5.44	2.60	2.24	6.16
	70	Spring	5.92	2.99	2.11	6.70

Summer	4.79	2.08	2.46	5.41
Autumn	5.60	2.65	2.25	6.33
Winter	6.70	3.11	2.3	7.58

The seasonal wind rose and the frequency histogram of seasonal wind speeds was plotted in Fig. 3-4 at both measured heights. The Weibull distribution and the frequency distributions of the wind speed matched very well at the monitoring site; therefore, the Weibull distribution factors could successfully be applied for the wind potential assessment and be used to calculate the annual production of the wind turbine prototype in this research. From the histogram shown in Fig. 3, we can see the most wind speed bins located between 2m/s and 5m/s during summer and autumn for the 30m height of the site. However, most of the wind speed bins increase to 4m/s to 7m/s during winter and spring. The wind speed distribution at 70m in Fig. 4 follows the same trend; the distribution falls between 3m/s and 5m/s in the summer and between 4m/s and 7m/s during winter.

The wind rose diagrams, which were constructed using the measurements of wind speeds and corresponding wind directions, provide useful information on the prevailing wind direction and availability of directional wind speed in different wind speed intervals [45]. The seasonal wind direction frequencies for both 30m and 70m heights have been plotted in Fig. 3-4 based on the mean wind speed data of one year (May 2011 to May 2012) in 10-minute time intervals. The effect of topography is obvious at the site as the dominant wind direction in the spring, summer, and autumn is from S for both heights. For the height of 30m, the percentage of wind speed from the south is 17% in the spring, 16% in the summer, and 13% in the autumn. The dominant wind directions in the winter, however, come from NE and ENE with a probability of 14% and 15% respectively. For the 70m, the probability of wind direction from S is 15% in the spring, 14% in the summer, and 12% in the autumn. The wind direction at the height of 70m is more dispersive. For instance, the second dominant wind directions from ENE, E, and ESE all reach 11% in the summer. And the second dominant wind directions from SW and SSW reach 10% in the autumn. The dominant wind directions in the winter also come from NE and ENE, which are 16% and 14% respectively.

a. Spring

b. Summer

c. Autumn

d. Winter

Fig. 3. 30m seasonal wind rose and wind speed distribution histogram from May 2011 to May 2012

a. Spring

b. Summer

c. Autumn

d. Winter

Fig. 4. 70m seasonal wind rose and wind speed distribution histogram from May 2011 to May 2012

4.3. Wind power density

The monthly variations of wind power density evaluated using Eq. (5) for both heights are shown in Fig. 5. The power densities show significant variations from season to season. Fig. 5 shows that the mean wind power density follows the same trend as seasonal mean wind speed which is lower during summer and higher during winter. The maximum wind power density of both heights occurs in January and they are 250W/m^2 and 455W/m^2 for 30m and 70m respectively. The minimum value happens in April and the values are 66 W/m^2 and 125 W/m^2 respectively. The figure also shows that the variation of the wind power density increases with height by comparing wind power density at 30m and 70m. The average wind power density at 30m and 70m are 115W/m^2 and 216W/m^2 respectively.

Fig. 5. Monthly variation of Wind power density

4.4. Turbulence intensity

The monthly turbulence intensity (TI) at two different heights can be calculated as follows using Eq. (7). In this research, the TI values were calculated only using wind speed above 4 m/s in 10 minutes' intervals and the results are shown in Fig. 6. In general, wind speed at 70m height has a higher value of TI than wind speed at 30m height. Lower values of TI happen during summer time in June and July for both heights with the lowest value reaches 19.40% and 24.29% for 30m and 70m respectively. Both heights have higher value during spring which reaches the highest value reaches 31.26% and 35.25% for 30m and 70m respectively. It can be concluded that the data recorded region is characterized by a high level of wind turbulence with annual average TI at 27.10% for 30m and 30.60% for 70m.

Fig. 6. Monthly variation of turbulence intensity

4.5. Capacity factor

The former discussed two commercial wind turbines Vestas® V-27 and Nordex® N-54 are selected to calculate the theoretical energy output in this sector. The theoretical seasonal capacity factors are calculated according to Eq. (8) and the results are shown in Table 3. The capacity factors are computed using the monitoring one-year wind speed data at both 30m and 70m heights and power curves of the two prototype wind turbines. The range of the capacity factor for V-27 wind turbine varies from 5.37% in the summer to 17.89% in the winter. The overall trend of the capacity factor is lower during summer and higher during winter. The similar trend is observed from the capacity factor of the N-54 wind turbine at the height of 70m. The capacity factors of the N-54 wind turbine are higher than V-27 as expected as the wind speed at 70m is higher than that at 30m as shown in section 4.2. The annual theoretical average capacity factors of the two wind turbines are 12.36% and 16.68% respectively.

Table 3. Seasonal theoretical capacity factors of the two wind turbine prototypes

Season	V-27 Capacity Factor (%)	N-54 Capacity Factor (%)
Winter	17.89	24.45
Spring	13.17	18.45
Summer	5.37	8.67
Autumn	13.00	15.16
Average	12.36	16.68

Table 4-5 shows the actually seasonal capacity factors of the two wind turbines from 2013 to 2015 recorded by the meters installed in the two wind turbines. The tables also show the operation days of the two wind turbines which excludes the maintenance and service days. The data for summer and autumn of 2013 was missing because some technical issues happened in the meter's data acquisition system. The issues were solved in the October of 2013 and the meter functions properly afterward. For the V-27 wind turbine, the operational days varies from 60 days to 82 days for each season. As expected, the capacity factor of the V-27 wind turbine is higher during winter and lower during summer because of the wind pattern observed in section 4.2. The capacity factors of the V-27 wind turbine vary from 3.23 in the summer of 2015 to 16.46% in the winter of 2013. The difference between theoretical capacity factors and the real capacity factors are also shown in the Tables. The negative value means the real capacity factors are lower than the theoretical capacity factors. So the real capacity factors are overall smaller than the theoretical capacity factors.

For the N-54 wind turbine, the actual capacity factors vary from 3.50% in the summer of 2013 to 16.87% in the winter of 2014. The difference between a theoretical capacity factor and monitoring capacity factor reaches 9.93% in the spring of 2015. Table 4-5 illustrate that the maintenance and service days take a significant amount of time for both wind turbines. Part of the reason might because these two wind turbines are all used wind turbines which served 10 to 20 years.

Table 4. V-27 wind turbine seasonal operation days and capacity factors

Year	Season	Days of operation	Capacity Factor (%)	Compare with theoretical Capacity Factor (%)
2013	Winter	62	10.89	-7.00
	Spring	68	9.31	-3.86
	Summer	N.A.	N.A.	N.A.
	Autumn	N.A.	N.A.	N.A.
2014	Winter	82	16.46	-1.43
	Spring	74	10.37	-2.80
	Summer	61	3.83	-1.54
	Autumn	60	9.19	-3.81
2015	Winter	74	11.68	-6.21
	Spring	65	7.68	-5.49
	Summer	59	3.23	-2.14
	Autumn	71	10.89	-2.11

Table 5. N-54 wind turbine seasonal operation days and capacity factors

Year	Season	Days of operation	Capacity Factor (%)	Compare with theoretical Capacity Factor (%)
2013	Winter	71	15.41	-9.04
	Spring	72	12.69	-5.76
	Summer	50	3.50	-5.17
	Autumn	73	11.01	-4.15
2014	Winter	65	14.59	-9.86
	Spring	67	11.25	-7.20
	Summer	69	6.39	-2.28
	Autumn	52	13.37	-1.79
2015	Winter	73	16.87	-7.58
	Spring	54	8.51	-9.93
	Summer	66	5.01	-3.66
	Autumn	48	6.97	-8.19

4.6. Capacity factor comparison

In sector 4.5, the actual capacity factors of the two wind turbines show a significant difference between the theoretical capacity factors. However, the normal operation days also vary significantly from season to season. This part of the research aims to evaluate if the difference between theoretical energy output and actual energy output was because of the maintenance and service days. The theoretical capacity factors, recorded data capacity factors, and capacity factors only consider operation days (except maintenance and service days) are compared in this section and the results are shown in Fig. 7-8. The negative value means the real energy output was higher than the theoretical energy output and the positive value means lower. Table 4-5 illustrate that both wind turbines have higher energy output than theoretical in the autumn of 2015. This might because the wind speed in the autumn of 2015 is higher than the wind speed in the autumn of the data monitoring year.

From Fig. 7, it can be seen from the plot that the theoretical capacity factor line is higher than the capacity factor derived from recorded data. Further observation showed that the capacity factor only considers operation days is overall closer to the theoretical capacity factor except in the winter of 2014. The difference average between the theoretical capacity factors and actual data capacity factors is 3.58%, however, the difference between the theoretical capacity factors and capacity factors only considering operation days is only 0.57%.

The N-54 wind turbine follows the same trend as shown in Fig. 8. It depicts that the theoretical capacity factors are much higher than the recorded data capacity factors but very similar to the capacity factors only consider operation days. The results indicate that average difference between the theoretical capacity factors and recorded data capacity factors is 6.22%. However,

the difference between the theoretical capacity factors and capacity factors only considering operation days is only 0.31%.

From the discussion, it can be concluded that the accuracy of predicting the long-term wind energy output using LiDAR data is acceptable if the wind turbine maintenance and service days are taken into consideration. This demonstrates the reliability of LiDAR for accurate wind energy assessment.

Fig. 7. Capacity factors of V-27 wind turbine calculated with LiDAR-measured wind speed data versus monitored electricity output (with or without excluding the maintenance days)

Fig. 8. Capacity factors of N-54 wind turbine calculated with LiDAR-measured wind speed data versus monitored electricity output (with or without excluding the maintenance days)

5. Conclusions

Evaluation of wind characteristics is the first step when planning to build a wind farm. The traditional way of using tall meteorological masts with cup anemometers is costly and not necessarily covers the designed hub height. Besides, the wind speeds measured at a different height need to be converted to target hub height using empirical equations that can introduce another layer of uncertainty. As LiDAR technology developed rapidly in the past decades, some of the researches have been down to compare the wind resources assessment using LiDAR technology and met mast. However, most of these previous research only compares the monitoring wind data but not integrate the data to estimate the wind energy output capacity of the wind turbine and compare with the actual service turbines. This study evaluated the implementation potential of LiDAR system for onsite wind resource assessment. This mobile instrument can simultaneously measure the wind speed and wind direction for multiple locations up to 150 m of height above ground level. The monitored wind speed profile data over a one-year period at 10-minute time intervals is used to determine the characteristics of the wind. The wind energy production predicted from field measured wind speed data by LiDAR is used to compare with the theoretical wind energy output with the actual wind energy output of two utility-scale wind turbines over a three-year period. Major conclusions include:

- Analyses of the wind data demonstrate strong seasonal variabilities in the wind speed. Wind energy potential in the winter is higher than that in the summer at both 30 m and 70 m elevations. The results also indicate that the wind direction at the height of 70 m is more dispersive than that at 30 m.
- Wind speed at 70 m height has a higher value of TI than wind speed at 30 m height and the test site is characterized by a high level of wind turbulence with annual average TI at 27.10% for 30 m and 30.60% for 70 m.
- The differences in the theoretical capacity factors estimated from wind data collected by LiDAR versus those of actual in-service wind turbines is typically less than 9.93%.
- The predicted wind energy output by use of LiDAR monitored wind speed data together with the manufacturer power curves agree well with the monitored actual energy production, after considering the downtime due to maintenance. The average difference between theoretical capacity factors and real capacity factors are 0.57% and 0.31% for V-27 and N-54 wind turbines respectively.

Overall, the results from this study indicate that LiDAR provides a reliable measurement of wind speed under field conditions. It provides a cost-effective way for field assessment of wind energy production potentials for wind turbine and wind farm siting purpose.

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