Journal of
Fundamentals of Renewable Energy
and Applications

BA et al., J Fundam Renewable Energy Appl 2017, 7:2
DOI: 10.4172/2090-4541.1000226

Review Article | Open Access

Small Wind Power Energy Output Prediction in a Complex Zone upon Five Years Experimental Data

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Abstract

In this paper, we investigate the performance of a micro-wind turbine in a complex through the power output prediction. The purpose is to show that due to long time period and very subtle onsite measurements the ideal position for the wind turbine can be determined considering experimental data under real conditions. More precisely, from well measured data (wind speed), the power output at one particular location can be approximated by the Weibull function. The considered model is tested and validated at an urban landscape location in Metz city, France, where anemometry is positioned at adjacent to the turbine and the instrumentation is specific to its surrounding location including record wind turbine data thanks to real time wireless communications. Technical data including wind speed and output power were analyzed and reported allowing to provide a reliable estimation of the wind energy potential in an urban location upon five years experimental data.

Keywords: Wind energy; Weibull distribution function; Wind speed; Urban wind powers

Introduction

Small and micro-wind turbines are designed to work in an urban environment and can meet the electricity needs of individual homes, farms, small businesses and villages or small communities which can be as small as 0.2 kW. Therefore, several micro-wind installations were carried out and demonstrate benefits and possibility of producing an adequate amount of power required to a rural area even at lower wind speed with most cost effective way [1-7]. Micro-wind turbines can play a very important role in urban electrification schemes in mini-grid applications and off-grid application for rural applications and even be complement to solar photovoltaic systems in off-grid systems or mini-grids. Architects are now incorporating wind turbines in their new build designs.

Major countries in the European Union (EU) have developed strategies to promote the growth of RES-E but French renewable output has lagged that of neighbor countries. The recent France's energy transition bill is encouraging householders to use micro renewable generation through financial incentives. Sitting urban wind power needs preliminary resources assessment such as wind characteristics and wind profile, topography of the terrain with respect to the roughness class and near-by obstacles. These parameters of a specific location are essentials for power output prediction and estimation to reduce payback time on capital investment. However, most research works used numerical models to predict power output of urban micro wind power.

Some researchers have ascertain the potential of building mounted turbines by providing the on-site measured data for design and assessment of micro-wind turbines installed in building blocks [8-13]. Similarly, the specific technology and design issues in the use of wind energy in buildings have been described by Mertens [14]. In considering where these technologies are likely to be installed, little is known of the wind resource in these environments and due to the very rough and heterogeneous landscapes, turbines close to the urban surface will experience site-specific [15]. Consequently, the wind fields undergo significant changes in urban areas compared to rural areas due to the channeling effect of the urban buildings. Therefore, most research works used numerical models needed to predict power output of urban micro wind power and assess this particular effect. Hence, some researchers have employed computational fluid dynamic modeling to indicate that turbines installed in urban environments are subject to wind particular effect. These works demonstrates the significance of turbine position and mounting height facing the building, such that small changes in location can have dramatic effects on the power generated. Accordingly, these installations appear to underperform when compared to installations in wind field undergo or rural environments.

Another approach is based on an appreciation/ quantification of how turbulence affects the productivity of a wind turbine which are required for the installation locations [16]. However, such analysis requires intensive computation resources and validation of results is very difficult to achieve owing to the requirement of the turbulence intensity modelization. Therefore, a genetic algorithms to wind farm performance evaluation and optimization for wind turbine placement has been applied [17,18]. Furthermore, an algorithm simulating the power output from the wind turbine based on wind average speed, the electrical load and the power curve has been developed [13]. A numerical wind speed data to estimate energy yields as well as analysis of financial payback periods under various scenarios applicable to micro-wind devices and the urban environment has been considered in Bahaj et al. [13]. Wind distribution functions and power evaluation models for optimization of wind farm configurations by genetic algorithms have been used in Wan et al. [19].

The goal of this paper is to investigate the performance of a micro-wind turbine in a complex urban area and show that due to long time period and very subtle onsite measurements the ideal position for the

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Received January 18, 2017; **Accepted** February 13, 2017; **Published** February 15, 2017

Citation: Ba MM, Harry R, Tanougast C (2017) Small Wind Power Energy Output Prediction in a Complex Zone upon Five Years Experimental Data. J Fundam Renewable Energy Appl 7: 226. doi:10.4172/20904541.1000226

wind turbine can be determined. The originality of our study is that the model arising from the well mounting turbines in such urban areas may provide the energy output prediction and estimation of payback time on capital investment.

In contrast with previous works, this paper focuses on the decision pertaining to installation so that optimal performance can be achieved considering the hub height with respect to proximity/influence of adjacent buildings/obstructions. Our predicting turbine productivity in the urban environment based on evaluation of roughness coefficient and Weibull distribution.

This paper presents a methodology to evaluate the real power output of a micro wind turbine based on experimental results under a long time period 2012 to 2016 thanks to very subtle onsite measurements to determine the ideal position for the wind turbine in an urban environment. More precisely, it is possible to define a reliable model for a particular complex zone. The originality of the considered method is to adapt the theoretical Weibull predictable model with the real experimental data production based only on the wind profile of the installation area.

The following Section 2 describes the GREEN platform and micro wind turbine as well as wind power parameters and data location. In this section, roughness coefficient is determined proofing that the experimental site correspond to a turbine urban sitting. Section 3 gives the wind real measurements of the considered location. The wind power output for the urban sitting is presented in the Section 4 which briefly describes the considered Weibull Model estimation and its application for the considered study case where the measurement power output performance during five years are detailed. The modeling wind speed and power output methodology for the case study is presented in the Section 5, where experimental data have been compared with simulation results to validate a micro wind turbine output power prediction model and proving the reliability micro wind power estimation in a specific urban sitting. Section 6 gives a discussion to justify the considered approach achieving the goal attempt. Finally, Section 7 draws appropriate conclusions.

Micro Wind Turbine Power Parameters and Location

Wind observation location

For our study, the experimental data are provided from the GREEN platform where several renewable energy technologies are implemented for modeling, managing and optimization of energy consumption. All technologies are monitored, including real weather conditions data are recorded and processed for prediction analysis (Figure 1). The platform GREEN is equipped with a residential Skystream three blades 2.6 kWatts horizontal axis wind turbine, which is at 12 m above the ground level. Installing a domestic micro wind turbine in France is usually subject to planning permission and total height must not exceed 12 m. The blades are constructed from two halves of compression molded fiberglass. The curve of the blade helps to more efficiently capture the energy in the wind and to reduce the sound of the blades as they move through the air. The turbine is a downwind design where the blades of the turbine are downstream from the nacelle, which is quieter and inherently better at finding the wind direction than upwind designs. The associated 3 blades Wind power Skystream in an urban area is represented in the Figure 2.

The inverter constantly monitors the turbine and the electrical connection to ensure that the electric energy generated by the turbine is synchronized with the frequency and voltage of the building's electrical system. Table 1 indicates the Skystrean technical specifications. The inverter actually draws about 5-7 Watts to operate the monitoring system. Consequently, the turbine will not generate electricity when the electrical grid to the building is down.

Wind speed is measured by a 3-cups rotor anemometer at the same height as the wind power. The anemometer is part of a meteorological weather station and wireless computer interface allows direct communication with the anemometer. It displays the current weather station data in a real-time report on the computer. Figure 3A presents the block diagram of the considered micro-wind turbine system while the Figure 3B gives a snapshot of the power output monitoring. Thus, a wireless wind monitors allows to save large quantities of data for download (2 Megabytes of internal memory) and use a ZigBee wireless link to computer for data acquisition. Indeed, the wind turbine has a built in 2.4 GHz wireless radio that sends performance data to a desktop computer in the GREEN platform monitoring with a wireless receiver. More precisely, the wireless wind monitor measures wind speed, direction data every minute and stores wind statistics once per minute. Figure 3B shows the Skyview software track the generation of the turbine displaying the data wind turbine in a defined sample time [20]. Thus, from data acquisition we can calculate histogram data.

The GREEN platform is located in building at the University of Lorraine, Metz, France. The investigation site location is given in the Table 2.

Figure 4 gives the climate of localization platform. More precisely, Figure 4A provides a map specifying isobaric and wind curves, temperature and nebulosity. Figure 4B gives the wind direction in percentage of the urban localization of the considered micro-wind

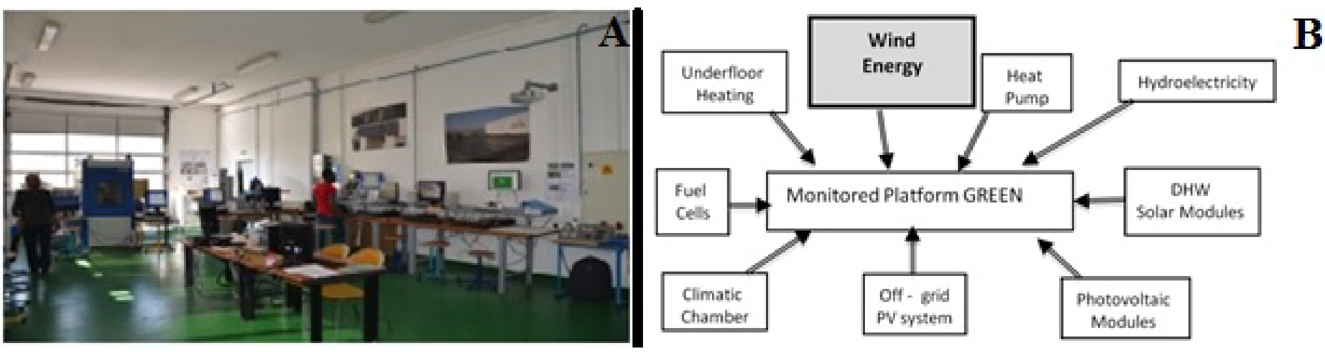

Figure 1: **A.** Monitoring room; **B.** Synoptic of the GREEN platform.

Figure 2: The 3 blades wind power skystream of the GREEN platform.

Technical Specifications	
Rated capacity	2.4 KW
Rotor diameter	3.72 m
Swept area	10.87 m²
Rated speed	50-330 rpm
Cut-in Wind speed	3.5 m/s
Rate Wind speed	13 m/s

Table 1: Skystream technical specifications.

turbine which mainly directed to south-west. Figure 4C details the real measured wind direction of the used micro-wind turbine for our experimental which is in concordance to local wind forecast where the maximal wind field is at the direction East and South-East with 5.5 m/s.

Wind power function

A micro-wind turbine is characterized by the wind power function which gives the power output, in kilowatts (W), for a given wind speed V given in m/s. The wind turbine converts wind power into mechanical power. The mechanical power generated by the wind turbine at the shaft is given by the Equation 1 [21].

$$P(W) = \frac{1}{2} C_p \rho S V^3 \qquad (1)$$

Where ρ is the air density which depends on altitude, air pressure and temperature. C_p is the wind-turbine power coefficient (dimensionless), S is the swept area of the rotor blades (in m²) and V is the wind speed (in m/s). Figure 5 shows the measured power curve for the Skystream of the experimental GREEN platform site for an experimental day. It can be noted that the cut in speed is below the value indicated in the technical specifications as mentioned in the Table 1.

Micro-wind turbine coefficient

The output power from the wind is given by the Equation 1, where the typical value of mean air density (ρ) used in this work is 1.22 kg/m³. From the Equation 1, it can be concluded that each parameter has an effect on the output power. C_p is the wind-turbine power coefficient. The theoretical maximum power efficiency of any design of wind turbine is 0.59 (i.e., no more than 59% of the energy carried by the wind can be extracted by a wind turbine). This is also called the Betz Limit. Wind turbines cannot operate at this maximum limit. The C_p value is unique to each turbine type and is a function of wind speed applying to operating turbine. For this experimental GREEN platform site, we determined the power coefficient from measurements as represented in the Figure 6 which gives the C_p value given as C_p=0.34.

Roughness coefficient

The roughness coefficient depends on the variability of wind speed at the site due the height above the ground and the rough- ness of the terrain which is a function of the wind direction. Several researchers have investigated wind speed profiles at different turbine heights and various expressions have been established to determine wind profiles while estimating the increase in wind speed with height [22]. In this study, we assumed the change in speed is less pronounced and we simply used the power law exponent relation [9] which is given by the following Equation 2.

$$\frac{V_0(h_0)}{V_0(h_0)} = \left(\frac{h_0}{h_1}\right)^{\alpha} \qquad (2)$$

Where $V_0(h_0)$ (m/s) and $V_1(h_1)$ (m/s) are the measured mean wind speeds at the reference height h_0 (m) and new height h_1 (m) at which the wind speed is predicted, respectively. α is the roughness coefficient. From Equation 2, the roughness coefficient is given as follows:

$$\alpha = \frac{\ln V_0(h_0) - \ln V_1(h_1)}{\ln(h_0) - \ln(h_1)} \qquad (3)$$

Table 3 indicates some roughness's for different types of topography.

The roughness coefficient for this experimental site is determined using reference height (h_1) and the corresponding mean wind speed (V_1) data from the military airport only 5 km away from the Green platform. The other values are measured from the investigation site given in the Table 4.

The roughness coefficient calculated from Equation 3. Therefore, we obtain α=0,389 ≈ 0.4. As indicated in the Table 3 and showing in the Figure 2, the used micro-wind turbine is close to trees and buildings. Indeed, the considered micro-wind turbine of the Green platform is situated in an urban zone.

Urban Zone Versus Rural Zone

The output power of a wind turbine is strongly influenced by the mean wind speed to which it is subjected. In urban areas, the effect of buildings, tall trees, may not only reduce the mean wind speed but may also increase the standard deviation of the wind fluctuations. The experimental site as indicated in section 3 is an urban case. In the Table 5, we determine the daily, monthly mean speed for the five years period (2012, 2013, 2014, 2015 and 2016) and the corresponding standard deviation. Figure 7 represents monthly mean speed of the five years analysis. The bar charts illustration shows good monthly similarity.

The standard deviation σ is determined by using the Equation 4 [23].

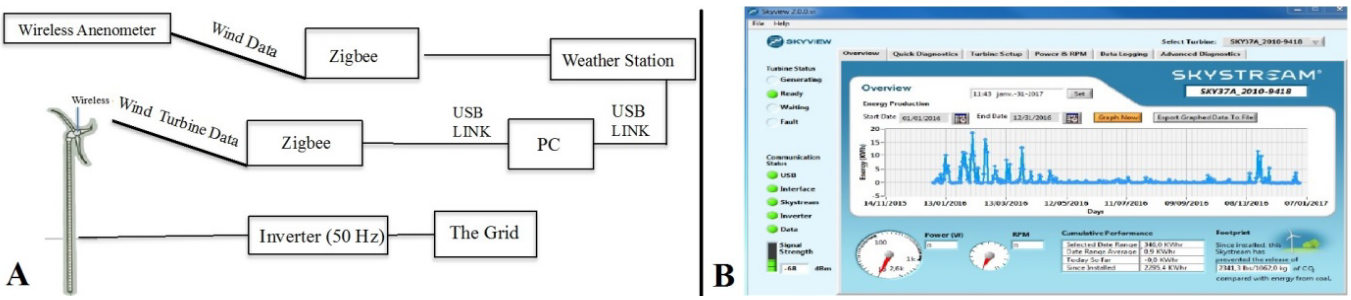

Figure 3: **A.** Block diagram of the micro-wind turbine system. **B.** Displaying real time power output and round per minute (RPM).

Location	Latitude	Longitude	Elevation
Metz	49°05'N	6°13'E	182 m above sea level

Table 2: GPS coordinates of the GREEN platform.

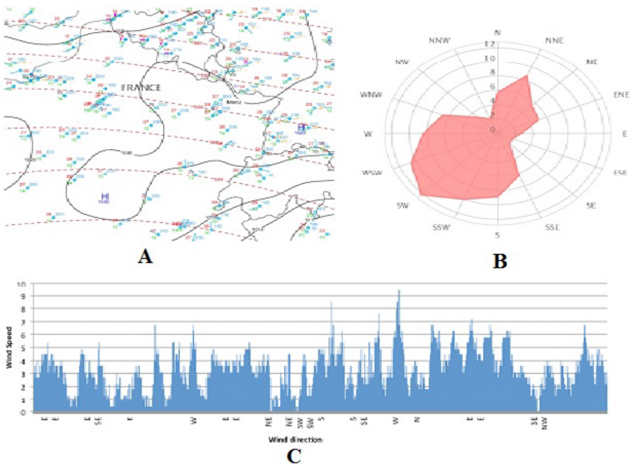

Figure 4: A. France climate map; **B.** Wind direction in percentage of the urban localization test site; **C.** Wind direction of the GREEN platform experimental zone.

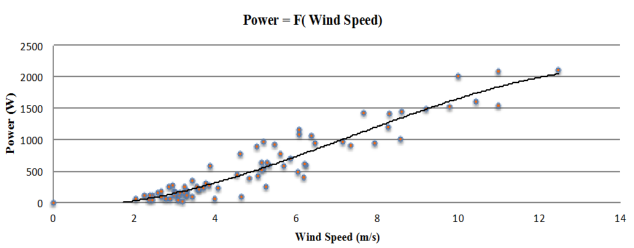

Figure 5: Power output as a function wind speed for an experimental day.

$$\sigma = \left[\frac{1}{N-1} \sum_{i=1}^{n} \left(V - \overline{V} \right)^2 \right]^{\frac{1}{2}} \tag{4}$$

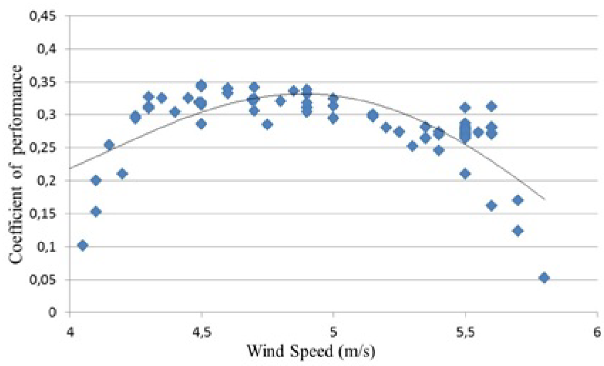

Figure 6: Coefficient of performance as a function wind speed.

Wind Shear Coefficients	
α	Description
0.1	Perfectly smooth
0.2	Flat grassland or low
0.3	Trees or hills, bulding in area
0.4	Close to trees or buildings
0.5	Very close to trees or buldings
0.6	Surrounded by tall trees or buldings

Table 3: Some roughness coefficients.

Reference values	h_1=192 m	V_1=5 m/s
Predicted values	h_0=12 m	V_0=1.7 m/s

Table 4: Experimental data of wind speed versus height.

$\overline{V}$ is the mean wind speed (m/s), N is the number of wind speed data. The calculated values of the standard deviation of the five years are given as follows:

$$\sigma_{2012}=0.4137\ (m/s) \tag{5A}$$

$$\sigma_{2013}=0.3494\ (m/s) \tag{5B}$$

$$\sigma_{2014}=0.3826\ (m/s) \tag{5C}$$

$$\sigma_{2015}=0.3254\ (m/s) \tag{5D}$$

$$\sigma_{2016}=0.4568\ (m/s) \tag{5E}$$

As the standard deviation of the wind speed fluctuations relative to

Month	2012	2013	2014	2015	2016
January	2.10	1.83	1.93	2.17	2.01
February	1.40	1.42	1.32	1.87	1.90
March	1.42	1.20	1.47	2.08	2.07
April	2.05	2.19	1.38	1.61	1.63
May	1.56	1.24	1.75	1.49	1.32
June	1.33	1.35	1.44	1.54	1.08
July	1.41	1.49	1.17	1.62	1.07
August	1.30	1.05	1.24	1.40	1.03
September	1.29	1.31	1.01	1.60	0.87
October	1.40	1.55	0.92	1.00	1.30
November	1.03	1.87	1.09	2.02	1.65
December	2.44	1.96	2.20	1.59	0.79
Mean speed (m/s)	1.56	1.54	1.41	1.67	1.39
σ (m/s)	0.4137	0.3494	0.3826	0.3254	0.4568

Table 5: Yearly mean wind speed.

Year	2012	2013	2014	2015	2016
Month	Power (W)				
January	84.83	74.89	61.56	95.27	80.24
February	48.84	44.21	35.67	53.90	50.91
March	45.64	24.44	42.87	37.81	71.2
April	90.94	82.13	80.23	95.81	92.67
May	31.15	22.71	34.66	30.73	21.78
June	30.95	23.75	46.34	27.98	18.56
July	40.22	5.63	40.29	27.16	16.45
August	28.15	20.22	42.53	28.32	15.34
September	30.19	25.13	32.31	20.38	10.12
October	58.80	21.32	40.77	22.18	55.67
November	65.18	72.19	16.24	50.98	76.23
December	187.13	110.28	125.97	166.6	67.78

Table 6: Five years monthly mean power.

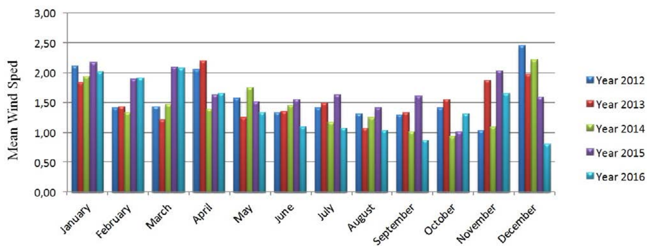

Figure 7: Five years representation of monthly mean wind speed.

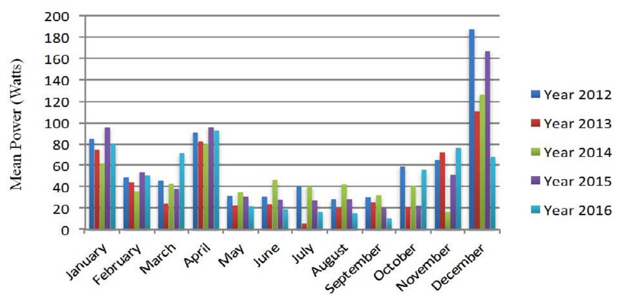

Figure 8: Bar charts of monthly mean power.

the mean wind speed in rural areas is likely to be reasonably constant. The standard deviations from Equation (5A) and Equation (5E) reflect a more rural area than urban area for the GREEN platform experimental site. The mean standard deviation upon the five years is 0.3855. As the urban environment not only influences the mean wind speed, it also affects the standard deviation and consequently the mean power output. In the Table 6, we determined the monthly mean power output for the five experimental years.

Figure 8 gives comparison of five years power output. We can see close similarity of the monthly power output for different years confirming a rural zone profile for an urban installation. Indeed, this is due to a long time period and very subtle onsite measurements to determine the ideal position for the wind turbine. The mean power output from a wind turbine as a function of mean wind speeds, is determined by a probability density distribution. The Weibull function is commonly used for fitting measured wind speed probability distribution. This point is discussed in the next section.

Weibull Function and Wind Speed

The most commonly observed distribution providing small errors in the calculating of densities and better experimental matching is the Weibull [24,25] probability distribution function (pdf) which is given by the three-parameter Weibull distribution as given by the Equation 6.

$$F(T)=\frac{k}{\eta}\cdot\left(\frac{T-\gamma}{\eta}\right)^{k-1}\exp-\left(\frac{T-\gamma}{\eta}\right)^{k} \quad (6)$$

Where, $F(T) \geq 0$, $T \geq 0$ or k, $\gamma > 0$, $\eta > 0$,

$-\infty<\gamma<\infty$ and:

- k is the shape parameter, also known as the Weibull slope
- η is the scale parameter
- γ is the location parameter

Frequently, the location parameter is not used and the value for this parameter can be set to zero. When this is the case, the pdf equation reduces to that of the two-parameter Weibull distribution given by the Equation 7 as follows:

$$F(T)=\frac{k}{\eta}\cdot\left(\frac{T}{\eta}\right)^{k-1}\exp-\left(\frac{T}{\eta}\right)^{k} \quad (7)$$

Usually, when climate has no zero values and then keep the wind turbine on run, the location parameter must be determined. Frequently, the location parameter is not used when the data base of the mean climate have very low or zeros measured values. Thereby, the location parameter may be set to zero. In our case study, measurement shows that the wind speed is too low or null during at least 850 h/year and then under the cut-in wind speed lower than 3.5 m/s, see the Table 1 to set micro wind turbine on. Consequently, in our modeling the location parameter is set to zero. Therefore, the pdf equation reduces to that of the two parameters Weibull distribution given by the Equation 8.

$$F(V)=\frac{k}{A}\left(\frac{V}{A}\right)^{k-1}\exp\left(-\left(\frac{V}{A}\right)^{k}\right) \quad (8)$$

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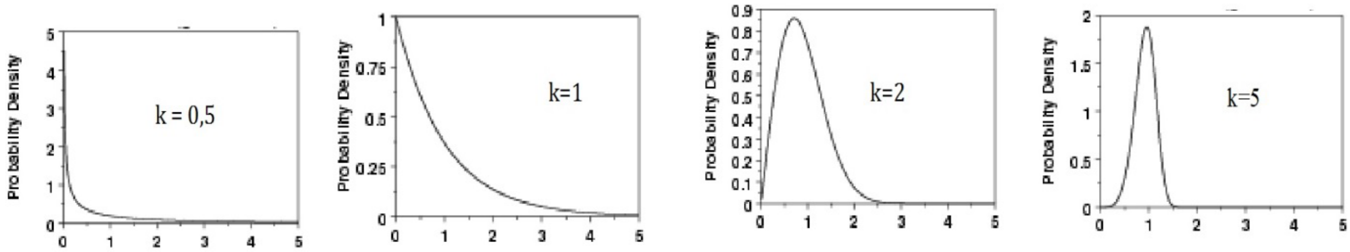

Figure 9: Weibull curves for some k values.

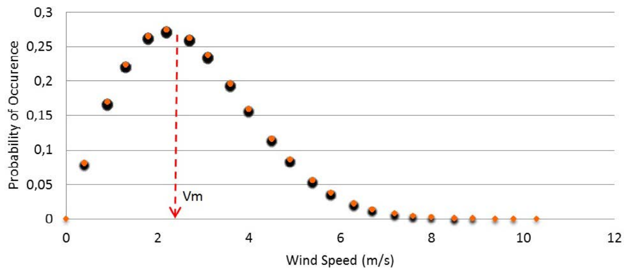

Figure 10: Probability of occurrence as a function of wind speed for a particular day.

- where, η=A=Weibull scale parameter in (m/s),
- k is s the unitless shape parameter,
- T=V=wind speed (m/s).

Figure 9 gives a representation of pdf for different k values while keeping η constant. There are several methods that are used for estimating the Weibull parameters A and k, depending on which wind statistics are available. We used the mean wind speed and standard deviation (σ) method as suggested in Hussein et al. [26]. Thus, the calculated value of k specifying the GREEN platform conditions can be obtained by using the mean wind speed and the standard deviation as follows by the Equation 9.

$$k = \left(\frac{\sigma}{\overline{V}}\right)^{-1.0983} \tag{9}$$

Thereby, considering the measured mean wind speed (Table 5) and the mean standard deviation during the year 2015, the calculated value of k is 2.37. The resulting equation is transformed into Equation 10.

$$F(V) = \frac{2.37}{A}\left(\frac{V}{A}\right)^{1.37}\exp\left(-\left(\frac{V}{A}\right)^{2.37}\right) \tag{10}$$

Figure 10 is an example of the experimental image of the probability density distribution calculated from the Weibull function, for a particular day. The particular wind speed V_m is nearly 2.5 m/s and probability of occurrence is more that 25%.

Using the Weibull statistical method for evaluation of local wind probabilities for five consecutive years (2012, 2013, 2014, 2015 and 2016) of the GREEN platform, wind power site are represented in Figure 11. The curve shape is similar to the Figure 9 with k=2. From this figure, the comparison between the probability distribution function calculated from the Weibull function and the wind speed distribution based on data for the studied urban location, indicates that the most probable and corresponding wind speed upon 5 years are close and lies between 1.3 and 1.4 m/s.

Mean speed over each period of Figure 11 is nearly the same and defined as the total area under the curve F (V) - V integrated between

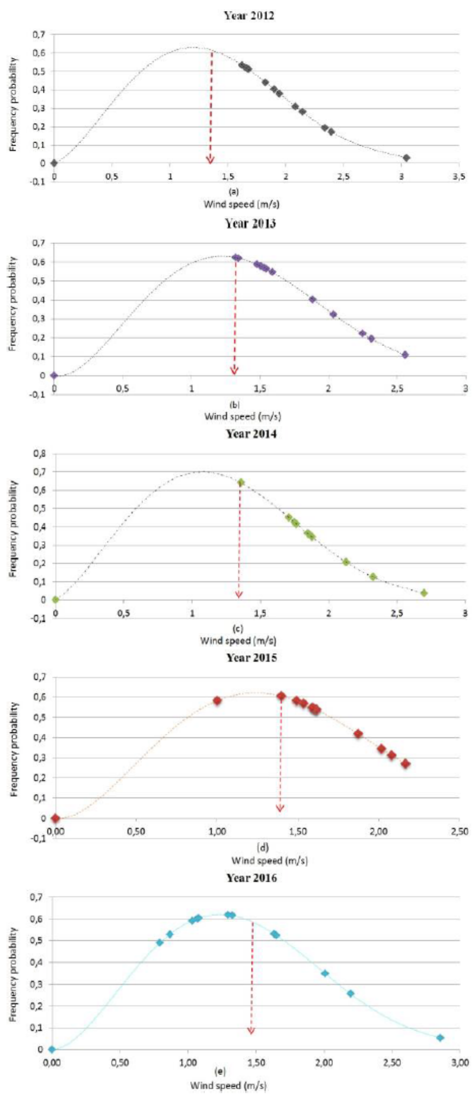

Figure 11: Weibull function versus wind speed upon 5 years.

windless days (V=0 m/s) to a very windy day (V=∝ m/s) divided by the total number of hours in the year which is nearly the same for each year as deduced from the Figure 11. The annual mean speed [27] is therefore the weighted average speed and is given by Equation 10:

$$V_{mean} = \frac{1}{H}\int_0^{\infty} F(V).\ V\ dV \qquad (11)$$

H is the number of operating hours and in this work, H=3600 h per year for this particular site. The integral expression of V_{mean} of Equation 11 can be approximated to the Gamma function as expressed by the Equation 12:

$$V_{mean} = A\cdot\Gamma\left(1+\frac{1}{k}\right) \qquad (12)$$

where Γ is the Gamma function which is obtained from the Equation 13:

$$\Gamma\left(X\right) = \int_0^{\infty} \exp\left(-t\right)\ t^{X-1}\ dt \qquad (13)$$

Table 7 indicates the experimental site results for the four years experimental data. Each resulting mean speed from the Table 7 is a similar trend to the area under the corresponding curve of the Figure 11.

Weibull Function and Power Output

Power output

Output power from the wind is proportional to various parameters as given section 2.2. The primary parameter is wind speed, where the output power is proportional to the cube of the speed and the speed varies with height according to power law exponent relation. We should state all effected parameters on the power output and concentrated on how to find the average annual wind speed by using Weibull probability distribution. From this average annual wind speed, we can determine the expected output power as discussed later. The output power from the wind is given by the Equation 14 [28]:

$$P_{out} = \frac{1}{2}\rho S C_P V_{rmc}^3 \qquad (14)$$

Where V_{rmc} is the root mean cube speed given as follows by the Equation 15:

$$V_{rmc}^3 = A^3\cdot\Gamma\left(1+\frac{3}{k}\right) \qquad (15)$$

Replacing the Equation 15 into the Equation 14, we deduce the following expression:

$$P_{out} = \frac{1}{2}\rho S C_P A^3\Gamma\left(1+\frac{3}{k}\right) \qquad (16)$$

The monthly calculated energy output using the Weibull-data, $E_{Weibull}$ (kWh) is given by the Equation 17 as follows:

$$E_{Weibull}\ \left(kWh\right) = \sum_i^n P_{i,output}\ F_i\left(V\right)\cdot T_i \qquad (17)$$

Where Ti is the number of hours of wind power operation and the number of days in a particular month. Figure 12 shows the relationship between Weibull function and mean power output upon 5 years measured data. The most yearly probable output for this site lies in the range of 45 W to 70 W and for an operating time of 5300 hours per year. The estimating output per year lies between 240 kWh and 371 kWh.

Year	k	A (m/s)	V_{mean} (m/s)
2012	2.37	2.03	3.59
2013	2.37	1.54	2.72
2014	2.37	1.41	2.50
2015	2.37	1.67	2.81
2016	2.37	1.48	2.62

Table 7: Mean speed from experimental data.

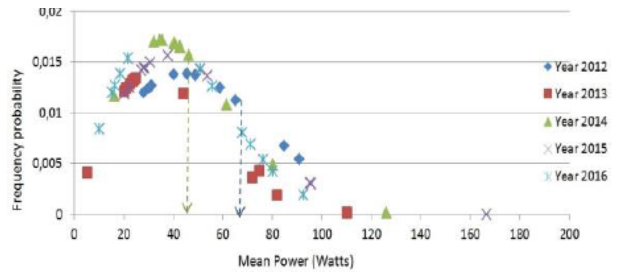

Figure 12: Weibull representation of 5 years power output.

Year	k	A (m/s)	Energy (kWh) (Weibull)	Measured Energy (kWh)
2012	2.37	2.03	372.77	279.83
2013	2.37	1.54	329.92	346.94
2014	2.37	1.41	311.36	297.14
2015	2.37	1.67	348.12	361.16
2016	2.37	1.48	314.16	295.17

Table 8: Comparing 5 years energy output.

Table 8 gives the five years of energy calculated from Weibull function and measured ones. The measured energy is the raw data recorded using data loggers. We deduce that the Weibull-representative energy outputs is nearly of good agreement with the recorded data energy outputs from the experimental platform site. The root mean square error (RMSE) between the estimated Weibull distribution from mean wind and the Weibull distribution from measured power is given in the Table 9. We calculated the RMSE for 2014 corresponding to the middle year between 2012 until 2016.

The results of measurements and power calculation shows a strong correlation with low RMSE value of around 0.5%, obtained from the Weibull model and the measured energy data can be found using the Equation 18 [25]:

$$Error\,(\%) = \left|\frac{E_{(Weibull)} - E_{(Measured)}}{E_{(Measured)}}\right| \qquad (18)$$

Table 10 gives the errors for the five years between 2012 until 2016. We observe from this table that for year 2012, we obtained a higher error rate due to mainly some lost wireless zigbee communication occured over experimental measurements and leading the lack of data during the data acquisition. Also few days between the 20th and 31st are missing for December 2016 due to technical problem.

Discussion

To investigate the potential performance of micro-wind turbines, we have considered a real well-studied siting case of a micro wind turbine in complex urban areas. We used the quality of wind speed assessment and Weibull probability density function for describing the measured wind speed frequency distribution upon five years real experimental data. Our goal is to provide the energy output prediction of specific locate urban places for possible installation sites of a wind

Year 2014	
Calculated Weibull value (Mean wind)	**Weibull distribution value (Measured power)**
0.011299	0.010805
0.004239	0.017171
0.015104	0.016452
0.015541	0.004874
0.012982	0.017167
0.015253	0.015709
0.015957	0.01685
0.015916	0.016512
0.015616	0.017045
0.015137	0.016786
0.015863	0.01171
0.008608	0.000175
RMS	0.005738

Table 9: RMSE between the estimated Weibull distribution from mean wind and Weibull distribution from measured power for the year 2014.

Year	Error (%)
2012	0.2493
2013	0.0516
2014	0.0457
2015	0.0434
2016	0.0551

Table 10: Errors for the 5 years.

turbine and which are essential before any installation or modeling of the expected energy in urban configurations. To meet our goal, our approach performs an initial investigation which is required to know the wind speed and turbulence characteristics at the corresponding turbine height for specific location before installing micro wind turbine in an urban site. In summary, from real experimental results and although siting micro wind turbines in an urban environment is not generally considered as finest locations, we can deduce when local climate conditions can be taken into consideration to deduce good locations generating useful amounts of electricity at a reasonable cost and can be a worthwhile investment.

Conclusion

The paper investigates the potential performance of micro-wind turbines in complex urban areas upon five years real experimental data. The main contribution is to provide a pragmatic approach providing the energy output prediction and estimation of payback time on capital investment. More precisely, our study is to provide the ideal position for the wind turbine allowing optimal performance can be achieved in function of the hub height with respect to proximity/influence of adjacent buildings/obstructions in the urban zones through very subtle onsite measurements.

In our approach, we used the quality of wind speed assessment and Weibull probability density function for describing the measured wind speed frequency distribution. The root mean cube speed is useful in quickly estimating the annual energy potential of the site. Thereby, by considering the proposed modeling with real conditions only depending of the speed and wind direction statistics, we can estimate the power production potential for a specific micro wind turbine installation in a particular urban area site. The originality of our study upon many years data is to provide the energy output prediction and estimation of payback time on capital investment can be determined. The consequently, our approach allows to know the potential wind speed which can be exploited as an installing micro wind turbine in a complex urban site.

Acknowledgments

The authors wish to acknowledge the GREEN platform industrial partners. The work described in this paper has been supported by UEM French local electricity company and also funded by the Tous Chercheurs project of the Bettencourt Foundation.

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