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How can we create a map of the near-ground wind resource for a potential development site?

W.-G. Früh[1], A. Elliott[2] and K. Velayutham [2]

[1] Institute of Mechanical, Process and Energy Engineering, Heriot-Watt University, Edinburgh EH14 4AS, UK

[2] Katrick Technologies, 10 Montrose St, Glasgow G1 1RE, UK

Abstract. To overcome the challenges to make small-scale wind energy projects cost-effective and a useful contribution to energy consumption both, further small-scale turbine development is needed to maximise capture of the near-ground resource which is characterised by low mean wind speeds and high turbulence intensity, and a robust site evaluation and installation methodology to ensure placing devices in the best places and to have a reliable and realistic estimation of devices to be installed in those places. This paper focusses on the second requirement and develops a framework which combines some local wind speed measurements, readily available wind resource databases, and flow modelling in conjunction with device performance characteristics to create maps of potential electricity production over an identified development site. This approach can be viewed as a version of standard wind farm development approaches but scaled down in time and cost investment to be appropriate to the economics of small wind energy schemes.

Key words. Urban wind energy, wind resource metrics, wind resource mapping, Measure-Correlate-Predict (MCP).

1. Introduction

In contrast to utility-scale wind turbines, smaller devices with a rated capacity of up to a few of kilowatt have to operate in a much more challenging context. Their size, with a wind capture length scale of a few metres as most, makes them compatible to be deployed in relatively built up areas, from the urban environment to commercial and industrial estates. However, there the wind resource is characterised by a much lower average wind speed, much higher turbulence intensity, and spatially much more varied over a small area compared to megawatt wind turbines with rotor diameters in excess of 80 m. These facts led to the collapse in the market for building integrated turbines around the turn of the millennium after an early optimism and rapid growth in the 1990s [1]

What the analysis of [1] may not have fully appreciated is that it is not only the lower wind resource but also the variability in the wind direction which exacerbated the problems [2]. As a result, recovery of the small-wind technology and market has not converged on a standard technology unlike the emergence of the three-bladed upwind horizontal-axis wind turbine as the preferred choice for all wind energy converters larger than about 10 kW. Since about 2010, interest in smaller wind turbines has resurged with many technologies explored [3] which still leaves the challenge to match the best technology option to a given wind resource [4], which might be achieved through a morphological analysis [5].

Having identified a potential area of interest, the detailed wind resources can vary over distances as little as a metre or two and it is crucially important to be able to build up a detailed map of the wind resource in that area with a resolution of the size of the device or better to ensure that turbines are located in the best positions. Quantities to be mapped include as a minimum a mean wind speed rose together with a turbulence intensity profile as well as the variation of the wind direction at short time scales.

The key investment decision will ultimately be driven by the projected electricity production. Therefore, the mapping of the wind resource must continue from mapping the wind characteristics to a mapping of the potential electricity production. In a way, what is needed is a product like the Global Wind Atlas [6] but for a single development site such as a commercial or industrial estate. At the same time, such a process cannot involve the time-consuming resource analysis routinely completed for wind farms, as the economics of anticipated return from small wind turbine do not justify a costly resource assessment.

A. Aim and Objectives

This paper proposes a method to construct such a local wind resource map by combining a relatively short local wind measurement campaign with available regional wind climate data and some computational fluid dynamics (CFD) modelling. Major objectives to meet in the process are to

1. Determine guidelines for a minimum but sufficient number of locations for anemometers in the area

together with requirements for how long a location should be monitored,
2. Derive a complete set of metrics to capture the potential electricity production,
3. Identify a mapping between the local short-term measurements and any available regional data base,
4. Derive guidelines for the detail which must be resolved in the CFD models and how to plan a minimum yet sufficient set of model configurations to estimate the potential electricity production reliably, and finally
5. Define a coherent and clear overarching analysis pipeline for the preceding objectives.

Meeting all these objectives is far beyond the scope of this paper which begins by sketching out an initial proposed overarching analysis pipeline and then presents some results for the 2nd and 3rd objectives.

2. Methodology

This section begins by introducing how the overarching analysis pipeline was conceived, followed by detailed derivation of the key wind resource metrics and concluded by describing the mapping tools based in established Measure-Correlate-Predict methods to incorporate regional wind climate databases into the analysis.

A. Analysis Pipeline

The analysis pipeline was designed around the required information, freely available yet quality-controlled resources, and tools which are established at least in principle. The required information is an estimate of the potential electricity production from a device placed in a location within the surveyed area together with a specification of the confidence interval in that estimate.

Available information is in the form of many decades of atmospheric re-analysis databases providing hourly measures of averaged wind speed and direction at 10 m and 100 m above ground and wind gusts at 10 m above ground alongside a long list of other atmospheric information. The two main providers of such information are the MERRA II dataset curated by NOAA [7] and the ERA5 reanalysis curated by Copernicus [8,9]. With that a long-term wind resource data base for the nearest grid points on a global grid with a quarter degree resolution. Alongside those, there might be other sources of data with similar quality.

Established tools to fill in the gaps at least in principle include Measure-Correlate-Predict methods [10], CFD modelling of flow around buildings or structures [5], and conversion from wind to power using manufacturers' performance curves. Backtracking from the required deliverable, research and development questions to be tackled are:
1. What are the necessary wind resource characteristics or metrics to cover the sensitivity of device to the highly variable near-ground wind conditions?
2. How many wind conditions need to be modelled in CFD to cover the wind characteristics with sufficient detail using the least amount of valuable time and resources?
3. How should the information from local measurements and databases be used to configure the CFD models?
4. How much detail is needed to be resolved in the CFD models?
5. How should those CFD results of selected wind conditions be combined for a reliable estimate?
6. Which MCP methods are suitable for this task?
7. How many and for how long should anemometers be deployed?
8. How many years of wind data from the database should be used.

Remembering the scope of this paper, research questions 1, 7, and 8 will be addressed here in more detail.

B. Data sources

For this study, two Campbell ultrasonic 2D anemometers were deployed for 105 days from the end of December 2022 until the end of March 2023. on a site near Edinburgh, one on a 2 m mast on the ground and the other on the top of a 6-storey car park as one of the tallest buildings on the site.

Two wind climate data bases were used, one from a nearby anemometer by the UK Meteorological Offices [11] and the other the already mentioned ERA5 data base [9]. The Met.Office database stored hourly averaged wind and gusts rounded to the nearest *knot* at the anemometer's height of 10 m above ground while ERA5 data set provides the wind velocities as cartesian u,v components in m/s as the gust as a wind speed also in m/s, all with a high precision.

An initial screening showed that the advantage of the Met.Office data being actual measurements nearby, the relationship between them and our anemometers was less clear than to the ERA5 data. One of the reasons might be the rounding but another reason might be that local conditions around the Met.Office anemometer introduced its own bias while the ERA5 data base is not sensitive to small local features.

C. Wind resource metrics

Given that the near-ground wind resource is characterised by a much higher turbulence intensity and directional variability of the wind, four resource metrics are proposed: the mean wind speed and wind direction, as the exact correlates of the available climatology data, augmented by a measure of the turbulence intensity and by how much the wind direction changes within the hour.

While anemometers can usually record one wind speed and direction every second or even 4 samples per second, the most detail available from databases are averaged wind speeds at two levels, once per hour together with a measure of gusts observed in that hour. The aim of this analysis is to explore to what degree the information about the wind shear and gusts in the databases can be linked to the observed turbulence intensity from the anemometers.

To do this, two methods of calculating a turbulence intensity for an hour from the anemometers were used since the standard definition of turbulence intensity

$$\boldsymbol{TI} = \frac{\textbf{st.dev}\,(u(t))_{t\in T}}{\textbf{mean}\,(u(t))_{t\in T}} \tag{1}$$

is usually based around an averaging window of $T = 10$ minutes. Here we explored using the full hour as the averaging window as well as averaging over the six 10-minute values of *TI* within an hour and using the maximum of those six values.

To both, align the average wind direction from the database, the averaging of the wind direction sampled every hour had to deal with the periodic nature of that variable. To do this, the prevailing wind sector was found by creating a histogram of wind directions in 30° bins. Having found this, the wind directions were unwrapped such that the discontinuity was in the wind sector opposite to the prevailing wind. If that opposite sector was between 0° and 180° (or the prevailing wind between 180° and 360°), 360° was added to all wind direction angles below that value. Conversely, if the prevailing wind direction was less than 180°, 360° was subtracted from all angles above its opposite:

$$\boldsymbol{\theta_p} = \textbf{mode}\left(\textbf{hist}(\boldsymbol{\theta}, \boldsymbol{bins} = \textbf{30°})\right) \tag{2}$$

followed by

$$\boldsymbol{\theta} = \begin{cases} \textbf{if } \boldsymbol{\theta_p} < \textbf{180°}: & \boldsymbol{\theta} - \textbf{360°} \quad \forall\, \boldsymbol{\theta} > \boldsymbol{\theta_p} + \textbf{180°} \\ \quad \boldsymbol{else} & \boldsymbol{\theta} + \textbf{360°} \quad \forall\, \boldsymbol{\theta} < \boldsymbol{\theta_p} - \textbf{180°} \end{cases} \tag{3}$$

Having moved the angle discontinuity to the opposite direction of the prevailing wind enables the reliable calculation of the mean wind direction. It also makes it possible to calculate its standard deviation to define a measure of the directional variability akin to the turbulence intensity for the wind speed. In contrast to wind speed, where the mean wind speed has a direct quantitative link to the resource, the wind direction has a qualitative influence. Therefore, it does not make sense to divide the standard deviation of the wind direction by its mean. Instead, the appropriate normalised measure is to rescale the standard deviation by the full compass, i.e., divide by 360°. This leads to the definition of a directional variability, *DV* of

$$\boldsymbol{DV} \equiv \frac{\textbf{st.dev}\,(\boldsymbol{\theta}(t))_{t\in T}}{\textbf{360°}} \tag{4}$$

D. Measure-Correlate-Predict (MCP)

The method to extend the local measurements into a long-term wind resource climate for the site is based on the standard Measure-Correlate-Predict (MCP) methods [9] with the extension from correlating mean wind speed and direction also measures of their variability. For this variability, one of the research tasks is to find the most suitable correlates to the direct variability measures given in equations (1) and (4). The two most obvious candidates from the ERA5 data set are the gusts as well as the wind shear and wind veer between the mean winds at 10 m and 100 m above ground. In the following, any of those options is referred to as $\boldsymbol{UV_{ERA}}$ for speed variability and for directional variability $\boldsymbol{DV_{ERA}}$. As already mentioned, those ERA5 measures are then compared against three possible reductions to hourly information: a) using the full hour for *T*, b) using the standard 10-min averaging and then average those across the hour, and c) using the maximum of the 10-minute turbulence intensity and directional variability.

After this, several MCP methods should be tested. For the scope of this paper, the binned linear regression is presented in detail, with pointers to more advanced methods to be explored in future work, in particular that based on multi-variate Principal Component Analysis [12].

The basic binned linear MCP method finds the best fit line to the subset of time-aligned mean wind speeds within a wind speed bin. The wind speed bins are determined from a visual inspection of the scatter plot of wind speed ratio,

$$\boldsymbol{q_{\langle u\rangle}} \equiv \frac{\langle \boldsymbol{u_{ane}}\rangle}{\boldsymbol{u_{ERA,10m}}} \tag{5}$$

With a similar inspection of the ratio of the

$$\boldsymbol{q_{\langle TI\rangle}} \equiv \frac{\boldsymbol{TI}}{\boldsymbol{UV_{ERA,}}} \text{ and } \boldsymbol{q_{\langle DV\rangle}} \equiv \frac{\boldsymbol{DV}}{\boldsymbol{DV_{ERA,}}} \tag{6}$$

3. The Analysis Pipeline

The proposed analysis pipeline is illustrated as a schematic in Figure 1. Once an interested developer has identified a location, the first step is a screening process which makes use of readily available long-term wind speed data bases. An example of this would be the hourly wind speed at 10 m above ground at the nearest grid point of the ERA5 or MERRA2 re-analysis database. That screening process can be based on a simple criterion that the annual mean wind speed for that data base exceeds a minimum threshold. The exact threshold will certainly depend on the device performance and may also need to reflect the distance of the location to the grid point and the nature of the landscape.

If the location has successfully met the screening stage, the detailed analysis begins in two parallel work packages. The first is to install a small number of anemometers at the site, where 'small' is ideally two or three at carefully selected locations. If only one anemometer is available, that could be used to sample different locations, one after the other. If the selected wind energy device is able to capture significant parts of the turbulence, then the sampling rate should be high enough to resolve this part of the turbulence spectrum. The duration for which a location should be sufficient to cover a reasonable range of wind speeds and enough wind direction to cover those observed in the wind rose for the nearby data base.

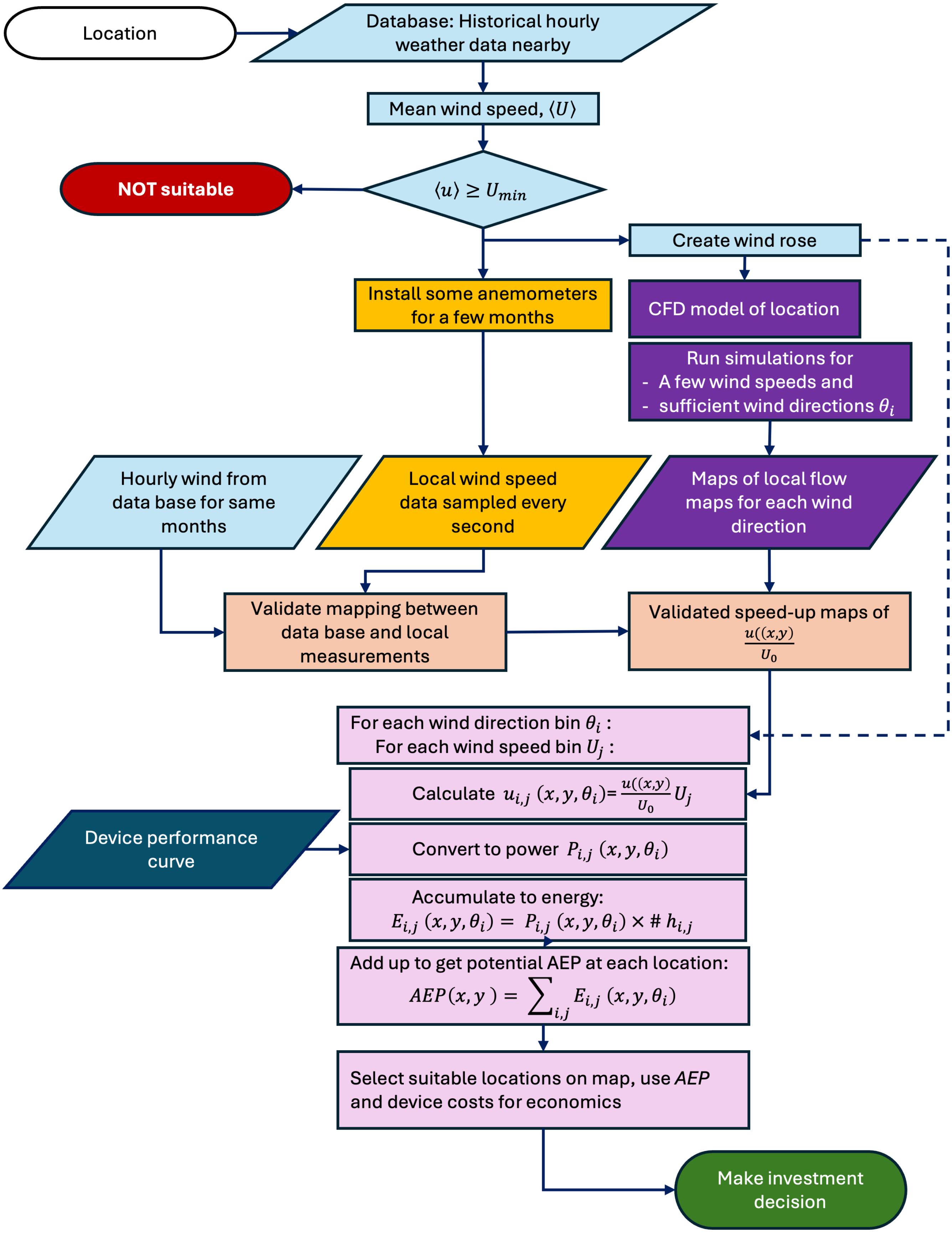

Fig.1. Schematic of the analysis pipeline.

Once the local wind speed data have been collected, it is possible to construct the relationship between the local wind conditions and those for the location of the data base by extracting the data base information covering the same time period as the measurement campaign at the location for the MCP analysis.

In parallel to measuring the wind speed and correlating it against the database, a CFD model of an area with the location in its centre, where the overall topography of the area should be resolved such that the mesh size in the core location is comparable to the capture area (or rotor) of the device, but that resolution can become coarse outside the core location. The development location also needs to represent any structures such as buildings with a similar resolution while structures further away can be represented by crude blocks. The distance from the side boundaries of the domain to the core location should be sufficient for any inlet or outlet condition effects have become insignificant in the core location.

In the setting of the boundary conditions, one key assumption allows us to reduce the number of simulations required while obtaining sufficient information: the key modifications of the local wind speed over the data base wind speed will be locational steering due to buildings and topography and localised speed-up or slow-down of the wind by the same topography. It is therefore important to cover a large number of wind directions but it is sufficient to sample a small number of wind speeds since the speed-up or speed-down can be to a good approximation represented as the wind speed ratio introduced in equation (5). While it would be possible to obtain a first estimate of that ratio from a single reference wind speed, replicating the simulations with a selected ‘low’, ‘medium’ and ‘high’ reference wind speed will also provide information about the confidence interval in that process, which would be a necessary tool in the final decision making when the financial risk is to be evaluated.

The wind directions and the chosen wind speeds are based on the wind rose obtained earlier from the data base, which also gives the prevalence of each resolved wind speed-direction bin.

Having completed the flow simulations, the correlation between the data base conditions and the local site conditions is used to create corresponding velocity ratio maps for the area matching each wind speed-direction bin covered in the wind rose. Using the device’s performance characteristics, the wind speed for the wind speed bin U_j and the velocity ratio map can be used to create maps of equivalent power output. These can then be accumulated to energy production for the frequency (number of hours) of that wind speed-direction bin is observed in the wind rose.

The final step in the formal site analysis is the summation of the energy contribution from each wind speed-direction bin to a map of possible Annual Energy Production, *AEP*. This will then be the basis for the decision maker as to how to proceed, in terms of how many devices to install and, most importantly, where to install them to maximise the benefits.

4. Results

In line with the flow of the schematic in Figure 1, the results are presented such that the climatology from the ERA5 data set near the location is presented, followed a description of the anemometer data, and concluded by their correlation

A. *Long-term reference data*

The long-term record of the ERA5 grid point gave a mean wind speed of 4.22 m/s at 10 m above ground and a wind rose as shown in Figure 2a, with a clear prevailing wind direction from the Southwest.

a) b)

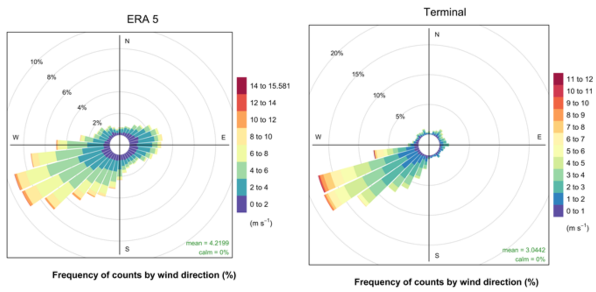

Fig.2. Wind roses, a) for the long-term ERA5 climatology, b) for the local anemometer.

B. *Local wind speed data*

Figure 3 shows a 10-minute segment of wind speeds sampled by the anemometer every second. That particular segment had a mean wind speed of around 3 m/s and a turbulence intensity of over 40 %. The entire measurement period had a mean wind speed of 3.04 m/s and a wind rose in shape similar to that from ERA5 as shown in Fig. 2b.

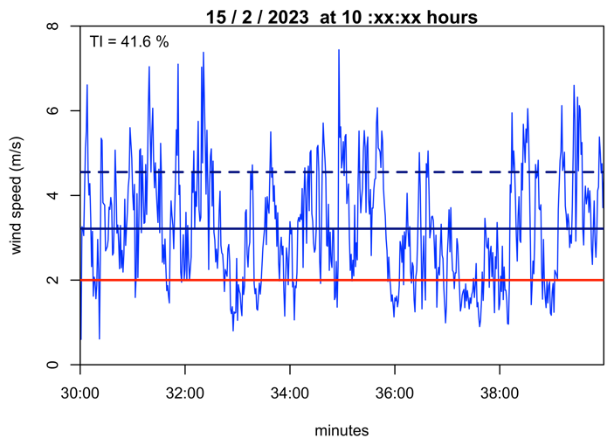

Fig.3. 10-minute segment of wind speeds recorded at a sampling rate of 1 Hz. Solid dark blue line: 10-min mean; solid red line: assumed cut-in wind speed of device; dashed blue line: assumed rated wind speed of device.

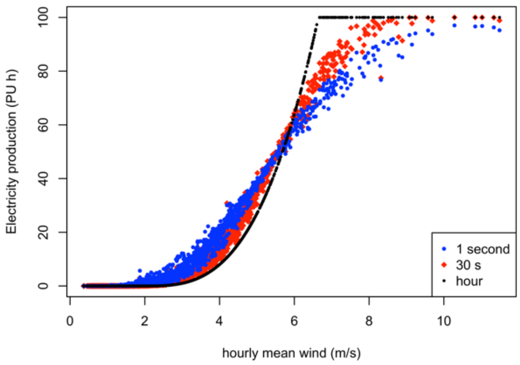

Fig.4. Device performance curve. Black line: reference performance curve; red dots: effective performance with a device response time of 30 s; blue dots: effective performance with a device response time of 1 s.

C. *Device performance metrics*

To estimate the effect of the high turbulence on a device's power output, a simple model was assumed which took a standard wind turbine performance curve, shown as the black curve in Fig. 4, where the cut-in wind speed and the rated wind speed are indicated as the solid red line and dashed blue line Fig. 3. It was then assumed that the inertia of the rotor and power train results in a device response time. Fluctuations faster than the response time are not noticed by the power train but fluctuations slower than that are those of the standard performance time. The resulting effective power output at a resolved wind speed is therefore applying to a moving-window averaged wind speed with a window length of the response time. The effect of this averaging on the power output is illustrated by the red and blue dots for response times of 1 s and 30 s, respectively. This clearly shows that extracting the intrinsic turbulence at speeds above the rated wind speed can be detrimental but results in significantly higher output at slower wind speed.

D. *Site – database correlation.*

To demonstrate first, how long the local measurement campaign should be, the ERA5 data updated during the measurement period were correlated against the historical ERA5 record. As the wind direction distribution is the most important factor in how the local wind is affected by its surrounding, Fig. 6 shows the correlation of the accumulated wind direction distribution with the history as the correlation coefficient against for how many days the anemometer was gathering data.

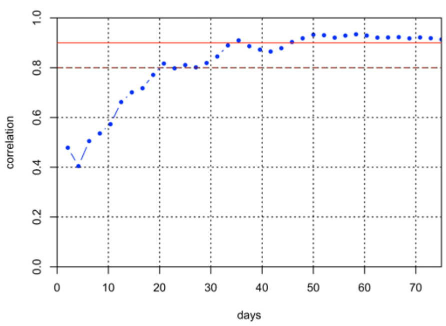

Fig.7. Correlation coefficient of the wind directions captured against measurement duration.

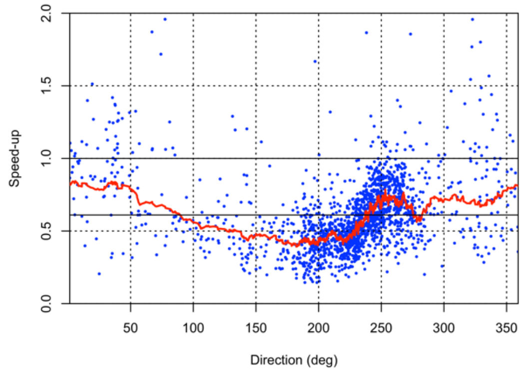

Fig.7. Scatterplot of the local speed-up against those from the ERA5 wind direction. Red line: speed-up averaged over direction.

This shows that for this particular location and time of year, the correlation has exceeded a level of 0.9 consistently after about 50 days.

A simple linear regression of the anemometer wind speeds averaged over an hour to be time-aligned with the ERA5 wind speeds for the same period gave an underlying best fit of

$$\boldsymbol{u} = (\mathbf{0.620} \pm \mathbf{0.011})\, \boldsymbol{u_{ERA}} - (\mathbf{0.13} \pm \mathbf{0.06}) \quad (7)$$

with an $r^2 = 0.65$, showing significant scatter especially in the crucial intermediate and most frequent range. Analysing the variation of the local wind over the ERA5 wind by wind direction gave a clear systematic behaviour illustrating the strong steering effect of the local topography and built environment. This is shown in Fig. 7, confirming the initial assumption of using the wind direction to decide the length of the measurement campaign.

As the turbulence intensity clearly affects the device's performance, a proxy for this has to be identified in the ERA5 data set. Prime candidates for the initial exploration were the wind shear between the 10 m and 100 m winds as well as the wind gust at 10 m. Surprisingly none of them showed a clear correlation. Instead, the best correlation was with the local mean wind speed.

5. Discussion and Conclusions

The work presented so far, has outlined a rational framework for optimally placing small wind energy devices in an identified development area as well as providing a method to estimate the energy productivity and economic benefits in a reliable manner.

At this stage, the work has demonstrated that short local measurement campaign of wind speeds at selected locations is essential to link available resource data reliably to the location. To return to the research question 7 posed in Section 2.A, even a measurement period of less than two months might be sufficient, which is very much within reach of interested developers. However, the minimum period will depend on the local climate conditions as well as the time of year. Here, we have demonstrated a simple criterion to judge if the anemometer has gathered sufficient data.

From a power production perspective, it has been demonstrated that the productivity of a deployed device will depend strongly on the local turbulence levels as well as its own conversion process and control strategy. The analysis has shown that standard measure-correlate-predict methods can work well but only as long as they include the wind direction in the analysis.

However, simple correlations between database features and local turbulence measures have not yet been successful and it appears that the local turbulence characteristics are more determined by local features rather than wider atmospheric conditions. There is certainly a need for further work on this aspect. Given the observations, it is likely that some machine learning process could yield much better results than inposed function fitting. Given the intrinsic dynamics governing wind, including synoptic geostrophic winds at the larger scales and localised factors at the site, a recommendation would be to choose a 'pattern-fitting-and finding' method, such as Random Forest or Gradient Boost methods, over empirical fitting of a transfer function, such as artificial neural nets.

In addition to these specific further work packages to address the questions raised in the analysis, the general further work will need to focus on the most effective method to carry out the flow modelling.

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