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Low-Cost Wind Resource Assessment for Small-Scale Turbine Installations Using Site Pre-Screening and Short-Term Wind Measurements

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A two-stage approach to low-cost wind resource assessment for small-scale wind installations

has been investigated in terms of its ability to screen for non-viable sites and to provide

accurate wind power predictions at promising locations. The approach was implemented as a

case study at ten UK locations where domestic-scale turbines were previously installed. In stage

one, sites were pre-screened using a boundary layer scaling model to predict the mean wind

power density, including estimated uncertainties, and these predictions were compared to a

minimum viability criterion. Using this procedure, five of the seven non-viable sites were

correctly identified without direct onsite wind measurements and none of the viable sites were

excluded. In stage two, more detailed analysis was carried out using three months onsite wind

measurements combined with measure-correlate-predict (MCP) approaches. Using this

process, the remaining two non-viable sites were identified and the available wind power density

at the three viable sites was accurately predicted. The effect of seasonal variability on the MCP

predicted wind resource was considered and the implications for financial projections were

highlighted. The study provides a framework for low-cost wind resource assessment in cases

where long-term onsite measurements may be too costly or impractical.

1   Introduction

Small-scale wind energy is a renewable energy technology with exciting prospects as we move towards a low carbon energy future. In order to achieve widespread deployment however, it is vital to develop tools capable of predicting the wind resource quickly, cheaply and accurately [1]. These tools will ensure that turbines are installed in locations which maximize the financial and environmental benefit and will allow customers to choose between competing low carbon technologies with confidence.

The need for suitable wind resource assessment tools has been highlighted by several studies. In 2008, Encraft along with a number of partners carried out a UK study of 26 building mounted small wind turbines, known as the Warwick Wind Trials [2], to investigate turbine performance in a variety of locations. The study highlighted the challenge of accurately predicting the potential wind resource using simple methods such as the NOABL (numerical objective analysis of boundary layer) [3] wind speed database. Among the study's conclusions were that more work was needed in creating robust methods for predicting mean wind speeds and wind speed distributions, particularly in urban areas [2]. Following the Warwick Wind Trials, in 2009 the Energy Saving Trust (EST, a UK foundation working in partnership with government and business) [4], completed a larger field trial of domestic-scale wind turbines. The field trial monitored the performance of 57 small-scale (0.4 – 6 kW) pole and building mounted wind turbines in a variety of locations throughout the UK over a one year period with the aim of assessing turbine performance at a variety of sites. While the results showed a promising potential for small turbines installed at appropriate locations, a large number of the monitored sites revealed wind speeds and turbine performance that were significantly lower than expected [5, 6].

In the large-scale wind industry, wind resource assessment is well established and typically involves the use of onsite anemometry to collect wind data over a period of 1-3 years [7]. These

data are used to make reliable predictions of the long-term wind energy resource as required by financial investors. In the small-scale wind industry these timescales are often impractical and the impact of such a measurement campaign on the total investment cost may be prohibitively high. In the absence of long-term onsite measurements, indirect methods must be used.

Indirect approaches may be broadly divided into modelling or data-led techniques. Simple modelling techniques, such as boundary layer scaling models, can be particularly efficient since after development and validation, onsite wind speed measurements are generally not required in order to make predictions. However, since uncertainties exist at each stage of the modelling process [8], the final predictions may not reach the accuracy required by investors [9]. In contrast, data-led techniques which involve direct wind speed measurements at the site of interest may result in more accurate resource predictions but they are more costly and time consuming to implement. One way of leveraging the advantages of both of these approaches is through the deployment of simple modelling techniques to screen sites for suitability followed by more detailed assessment of promising locations using short-term onsite wind speed measurements.

To investigate the feasibility of such an approach we have performed a case study of a subset of the installations involved in the EST field trial. Since each of these sites represents a location that was deemed suitable for the installation of a small-scale wind turbine, they provide an ideal opportunity to investigate the implementation of wind resource assessment tools in realistic scenarios. The case study is focused exclusively on assessing the wind resource at each site, as measured by onsite anemometry, and investigating the degree to which this may be predicted using a combined modelling and data-led approach.

The work addresses the following issues: (I) Investigation of the appropriateness of a boundary layer scaling model within a decision making context at real turbine sites for the purpose of

identifying locations worthy of further investigation. Specifically, we address the question as to whether, given the inherent uncertainties of such approaches, they can be of sufficient accuracy to screen sites based on a viability criterion. (II) Quantification of the propagated errors in the predicted wind resource arising from uncertainties in the model input parameters and identification of the relative importance of these uncertainties using a global sensitivity analysis. (III) Estimation of the added value, in terms of the accuracy of the predicted wind resource, of implementing a very short-term onsite measurement campaign at promising sites to supplement the modelling approach.

2 Methodology

The two-stage approach to wind resource assessment proposed in this study, following the recommendations from previous work [9, 10], can be summarised as follows:

(I) **Site pre-screening:** a boundary layer scaling model is applied at a potential wind turbine site to predict the mean wind speed at the proposed hub height of the turbine. The wind speed is used to derive a predicted mean wind power density and an associated uncertainty and this is compared against a predefined minimum viable value. If the predicted value is below this minimum, the site is deemed non-viable and excluded from further analysis.

(II) **Detailed analysis:** For sites passing the pre-screening stage, short-term (3 months) onsite measurements are used along with MCP analysis to make a more precise prediction of the available wind resource and to identify any remaining non-viable sites. In practice, short-term onsite measurements may be obtained using a mobile meteorological mast or portable LiDAR (light detection and ranging) equipment depending on the number of sites to be assessed [11].

Using this approach, the additional time and investment required for onsite measurements are not wasted on sites which are clearly non-viable and are instead concentrated on sites that have already been identified as having a good potential. The success of this approach is investigated by comparing predictions made at stages I and II with onsite wind data obtained over a 12 month period at the selected UK sites.

The following sections outline each stage of the process in more detail. Firstly, the meteorological measurements and the geographical locations of the sites are described. Next, details are given of the boundary layer scaling model and MCP approaches used to make wind resource predictions, including specific factors related to short onsite measurement periods. Finally, a viability criterion for use in the site pre-screening stage is developed.

2.1 Meteorological measurements

This study utilises wind data collected during the EST field trial of domestic-scale wind turbines mentioned previously. For the duration of the field trial, five minute averages of wind speed (resolution 1 ms^{-1}) and wind direction (resolution 1º) were collected at each turbine location using ultrasonic anemometers located at a height close to that of the turbine hub [5]. Following the completion of the field trial, these data were transferred to the UK trade body RenewableUK for the purpose of further dissemination to the research community. Data for the current study were obtained directly from this source.

In order to fully investigate the wind resource assessment approaches, ideally wind data covering a number of years are used to account for both seasonal and inter-annual variations. However, given the relative infancy of the small-scale wind industry, long-term wind data from small turbine installations are not widely available. In the absence of long-term wind data, measurements covering a full year with a relatively strict data coverage criterion are desirable. In the current case study, a criterion of greater than 95% data coverage over a full 12 month

period was used in order to properly account for seasonal variability. Of the 57 fully monitored sites in the field trial, only 10 sites (referred to here as target sites) were found to achieve this criterion. While this represents a relatively small sample, the 10 sites were located in a range of terrains (urban, sub-urban, rural and coastal) and at a variety of heights above ground level (5-12 m). Hence they are a useful starting point in investigating general trends associated with the application of resource assessment tools to real-world, small-scale wind turbine sites.

To implement the MCP approaches, concurrent measurements from nearby reference sites are required. Reference sites were selected from the UK Meteorological Office (Met Office) anemometer network [12] on the basis of their proximity to the target sites and the openness of the terrain, as judged by satellite images. In cases of pairings with coastal target sites, preference was given to coastal reference sites. The Met Office reference site data used in this work consisted of hourly averages of wind speed (resolution 1 knot = 0.51 ms^{-1}) and direction (resolution 10º) recorded at a height of 10 m above ground level and averaged over a complete hour. Due to the different averaging periods for the Met Office reference and EST target sites, the EST observations were processed to obtain hourly averages of wind speed and direction. These data were time-aligned with the hourly Met Office observations resulting in concurrent data sets for each reference and target site pair, covering the period April 2008 – March 2009. The geographical locations of the target and reference sites are shown in Figure 1 and further details are given in Table 1.

Figure 1: Approximate geographical locations of meteorological monitoring sites. Circles represent target sites (T) and stars represent reference sites (Rf).

Target sites				Reference sites		
Site	Terrain	$\bar{u}_{obs}$(ms^{-1})	h(m)	Site	Terrain	d(km)
T1	Coastal	1.8	7.7	Rf1	Coastal	43
T2	Rural	4.9	8.0	Rf2	Rural	36
T3	Rural	2.4	9.8	Rf3	Semi-rural	15
T4	Coastal	3.6	5.0	Rf4	Coastal	8
T5	Sub-urban	2.2	11.3	Rf4	Coastal	20
T6	Urban	2.5	9.0	Rf5	Semi-rural	31
T7	Coastal	3.0	7.7	Rf6	Coastal	3
T8	Rural	4.3	7.0	Rf7	Rural	72
T9	Rural	4.6	7.0	Rf7	Rural	59
T10	Urban	2.3	12.0	Rf8	Coastal	50

Table 1: Summary of meteorological monitoring sites. $\bar{u}_{obs}$ is the observed mean wind speed as obtained from onsite wind speed measurements over a 12 month period, h is the target site anemometer height above ground level and d is the separation between the target and reference sites.

2.2 Boundary layer scaling model

The modelling approach used in this work is based on a semi-empirical (SE) model first developed by the UK Met Office, which uses the principles of boundary layer meteorology to predict the spatially averaged mean wind speed without the need for direct meteorological measurements [8]. The model is also conceptually similar to that applied by Heath *et al.* [13] to investigate the potential energy output from a hypothetical micro-wind turbine installation in London. While the study by Heath *et al.* also investigated the detailed effects of building scale wind flows in urban areas using computational fluid dynamics, the SE methodology considers only the spatially averaged flow and is applicable to a variety of terrain types. The SE model was previously the subject of a detailed study [9] that evaluated its real-world performance and suggested modifications to improve the accuracy of its predictions. In this work, we have implemented the model along with the modifications recommended in reference [9]. Since a detailed description of the model is available elsewhere [8, 9], here we present only a summary of the pertinent steps.

For wind flows close to the Earth's surface, under neutral stability conditions and in the constant stress layer of flow, the vertical profile of the horizontal mean wind speed can be described by [14]:

$$\bar{u}_{av}(z) = \frac{u_*}{\kappa} \ln\left(\frac{z - d}{z_0}\right)$$

Equation 1

where $\bar{u}_{av}$ is the spatially averaged mean wind speed at height z, u_* is the friction velocity with units [ms^{-1}], κ = 0.4 is the Von Karman constant and d and z_0 are the displacement height and roughness length respectively.

Note that given the wind speed at some reference height, Equation 1 can be applied to calculate the wind speed at some new height z without explicit knowledge of u_*, providing the remaining parameters are known. The variables d and z_0, collectively called the aerodynamic parameters, are of particular interest since they describe the characteristics of the surface roughness. The displacement height, in effect, shifts the origin of the vertical z-axis to a height d in order to account for the blocking effect of local obstacles, while the roughness length z_0 serves as a parameterization of the drag force exerted by the roughness elements. These parameters are non-trivial to estimate, particularly in complex environments [15, 16].

In the current methodology, we require both regional estimates (over several kilometres) and local estimates (over several hundred metres) of the aerodynamic parameters. Regional estimates are obtained using the blending method of Mason [17] where spatially averaged values for d and z_0 are derived from the fractionally weighted land cover at the location of interest [9]. As an extension of the Met Office approach, we increase the size of the regional area from a 1 km x 1 km to a 4 km x 4 km grid square centred on the site of interest in order to account more fully for contributions to the regional surface roughness. In addition, directionally dependent surface roughness is incorporated through division of the grid square into a further four subsectors. The subsectors are then used to estimate the roughness of the upwind fetch within a 90 degree angular sector. This approach has been shown to be of particular importance in cases where there are sudden changes in roughness such as at coastal sites [9]. The starting point for estimates of the local aerodynamic parameters is a visual assessment of the local (~250 m x 250 m) site character using satellite images. In line with the Met Office approach [8], the site is classified according to one of seven categories (high height and density residential, low height and density residential, open country etc.) and appropriate estimates of d and z_0 are applied. Due to the difficulty in relating general site descriptions to specific values of

the aerodynamic parameters, as well as the wide range of possible site characteristics, these estimates have a high degree of uncertainty [8, 15].

Using the principles outlined above, a methodology can be developed to predict the spatially averaged, hub-height wind speed at a specific site given a reference wind speed at a known height. The approach may be summarized as follows [9]:

(I) For a specific UK location defined on a grid of 1 km^2, a reference mean wind speed at 10 m above open, level ground, is obtained from the Met Office National Climate Information Centre (NCIC) database [18]. Since the NCIC wind speeds are based on a 30 year average over the period 1971 – 2000, and the EST observations used for validation of the method are based on a single year of wind data, a correction factor was applied to account for inter-annual variability. Three of the reference sites used in this study (Rf1, Rf4 and Rf8) had suitably long-term data records and these were used to compare the mean wind speeds for the periods 1971 – 2000 and April 2008 – March 2009. Based on this comparison, the NCIC wind speeds were multiplied by a correction factor of 0.97 in order to reflect the lower wind speed observations during the EST observation period. A similar approach was used by Sissons *et al.* to correct the EST observations relative to a 10 year mean [6].

(II) The reference wind speed is then scaled up to a height of 200 m, where the flow is considered independent of the local and regional roughness. This is achieved using Equation 1 along with the aerodynamic parameters z_0 = 0.14 m and d = 0, representative of open country. Note that while a smaller roughness length (~0.03 m) would be expected for short-grass, extended regions of short grass without interruption from hedges and bushes are relatively unlikely in UK rural areas [8]. Hence, in practice, z_0 = 0.14 m is considered more representative of open country and is in line with the methodology developed in reference [8].

(III) The wind speed is then scaled down to an intermediate height known as the blending height (the height at which the flow is 'horizontally homogenous and in equilibrium with the local surface' [17]), again using Equation 1. Here, aerodynamic parameters representative of the regional area are applied. The blending height is taken to be the larger of 10 m or two times the maximum canopy height of any land use within the regional grid square. This is in accordance with previous studies [8, 9] and is based on the assumption of a blending height of 2-5 times the height of the roughness elements [19]. Note that strictly this height will also be a function of the distance from the roughness change, although this may be impractical to implement in a simple automated approach designed to be applied to multiple sites.

(IV) Equation 1 is then applied a final time to scale the mean wind speed down to the turbine hub-height using aerodynamic parameters representative of the local area. A Weibull wind speed distribution [20] is used along with the predicted mean wind speed to enable the wind power density to be estimated.

It is important to note that the above methodology is formulated to predict only the spatially averaged mean wind speed and associated wind power. While for well exposed locations this is likely to be a reasonable approximation, for turbines mounted close to buildings or other obstructions, there can be significant local deviations from this spatial average [13, 21]. These deviations will depend on factors such as the geometry of the obstructions, the position of the turbine within a building array and the prevailing wind direction. Such factors must be assessed using suitable correction factors or detailed flow modelling [13], both of which are likely to be highly site specific. These corrections are beyond the scope of the boundary layer scaling model presented here which is designed to be implemented using simple parameterisations of the regional and local surface characteristics. However, it has previously been demonstrated [21] that providing certain siting recommendations are adhered to, the spatially averaged mean wind

speed can be considered as a good approximation of the lower bound to the wind speed experienced at the proposed turbine location.

2.3 Quantifying prediction uncertainty

As with any modelling approach, the final mean wind speed and wind power density predictions are subject to uncertainties. These arise firstly from assumptions and simplifications inherent in the model itself and secondly from uncertainties in the model input parameters. In the following discussion we are concerned with the uncertainties arising from the latter. At each stage of the model implementation, appropriate input parameters must be chosen. These include the input reference wind speed, the regional and local aerodynamic parameters, the blending height and the Weibull shape factor required to construct a distribution of wind speeds. Uncertainties in the values of these parameters combine to produce uncertainties in the final model predictions. Since accurately estimating the regional and local aerodynamic parameters is known to be particularly challenging, these are considered as the dominant error source in the mean wind speed prediction. These errors combine with the uncertainty in the Weibull shape factor to produce errors in the final wind power prediction.

To quantify the effect of these uncertainties, a quasi-random sampling approach, implemented in the MATLAB programming environment, was applied to each individual site prediction using a Sobol sequence [22]. A Sobol sequence is a low discrepancy numerical sequence that allows a multi-dimensional parameter space to be filled efficiently with minimal gaps. Given a model output based on a number of input parameters, sampling using a Sobol sequence allows an efficient estimation of the overall output uncertainty related to various combinations of input parameters. For the mean wind speed prediction, a five dimensional Sobol sequence of length 1024 was used to sample a range of values for the four aerodynamic parameters of regional and local z_0 and d as well as the blending height. An approximate uncertainty in the default aerodynamic parameter values for each terrain of +/- 35% was estimated, based on the ranges

recommended in a comprehensive study by Grimmond and Oke [15]. A range of +/- 35% was also used for the blending height since it was found that larger ranges resulted in parameter combinations within the Sobol sequence that were not physically viable. For the mean wind power density prediction, a six dimensional Sobol sequence of length 1024 was used, with the Weibull shape factor as the sixth sampling parameter. Weibull shape factors in the range $k = $ 1.5 - 2.3 were employed based on the results of a previous study that obtained Weibull shape factors from 38 UK sites [9]. Using such a sampling approach gives distributions of wind speed and power density predictions which reflect the propagation of uncertainties within the input parameters to the outputs. Presented here are the mean predictions of wind speed and power density from these distributions with uncertainties represented by plus or minus twice the standard deviation (+/- 2σ) across the 1024 samples.

In addition to estimating the overall prediction uncertainty using a sampling approach, it is also informative to understand the relative contributions to this uncertainty from each of the six input parameters. Ultimately, such information could be used to improve the model by obtaining better estimates of the most significant parameters. To investigate these contributions, a global sensitivity analysis was conducted using the GUI-HDMR (graphical user interface – high dimensional model representation) software tool in MATLAB, which has successfully been applied in a number of environmental modelling contexts [23]. Given a quasi-random sample across specified input parameters, (in the present case these are obtained from a six-dimensional Sobol sequence as described above), and the corresponding model output (predicted wind power density) the GUI-HDMR applies a variance-based sensitivity analysis to estimate the relative importance of each of the input parameters. The output sensitivity to each parameter is quantified by means of first-order S_i, and second-order S_{ij}, sensitivity indices. The first-order indices represent the fractional contribution of the ith parameter to the output variance and the second-order indices represent the contribution from interactions between

pairs of input parameters. The sum across all indices should be 1. In the current study, first- and second-order indices were calculated for each of the ten test sites. Second-order effects were however found to be small and hence are not considered in the following discussion. A detailed description of the GUI-HDMR is available in reference [23].

2.4   Measure-correlate-predict approaches

The measure-correlate-predict (MCP) technique is a data-led method which increases the value of short-term wind measurements recorded at a potential wind energy site by correlating these with concurrent data recorded at a nearby reference site. In this work, the short-term concurrent wind measurements at the target and reference sites are referred to as the training data. The correlation obtained from the training data is applied to long-term historical data records from the reference site to construct a long-term time series of predicted wind speeds at the target site. The long-term predicted time series can then be used to extract statistical descriptors of the wind resource including the mean wind speed and average wind power density. Since long-term wind speed records are routinely held by airports and national weather forecasters, this technique provides a means of reducing the onsite measurement time required at the target site.

MCP is already utilized in the large-scale wind industry where the relationship between the reference and target sites is typically estimated from a measurement period covering a year or more [24]. However, recent studies [10, 11] applying the MCP approach to measurement periods of much less than one year have shown promising results providing appropriate precautions are taken relating to seasonal variability and data coverage. Based on these observations, we have applied the MCP techniques of variance ratio regression (VR) and linear regression (LR) to achieve a more detailed investigation of the available wind power at each site. Full details of the MCP approaches can be found in reference [10], hence only a brief overview is provided below.

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2.4.1 Linear regression

A linear correlation between concurrent wind speed observations at the reference and target sites, u_{tar} and u_{ref}, can be described by the linear equation [25]:

$$u_{tar} = \alpha + \beta u_{ref} + \varepsilon$$

Equation 2

where α and β represent the regression coefficients obtained by minimising the sum of squares of the residuals and ε is an error term which represents the residual scatter about the mean prediction. Given a linear regression on the observed data, a predicted target site wind speed $\hat{u}_{tar}$, can be obtained using the extracted regression parameters and the concurrent reference site wind speed u_{ref}. To account for the residual scatter about $\hat{u}_{tar}$, which is important in accurately predicting the mean wind power density [10], the residual scatter term ε, is modelled using a zero-mean Gaussian distribution of the form:

$$\varepsilon \sim \mathcal{N}(0, \hat{\sigma}_{res}^2)$$

Equation 3

Here $\hat{\sigma}_{res}$ represents the sample standard deviation of the residuals as estimated from the training data using the expression [26]:

$$\hat{\sigma}_{res} = \sqrt{\frac{1}{N-2} \sum_{i=1}^{N} (u_{tar} - \hat{u}_{tar})^2}$$

Equation 4

where N is the number of training observations.

A representation of the residual scatter is reconstructed by adding random draws from the Gaussian distribution described by Equation 3 to the individual mean predictions $\hat{u}_{tar}$ at the target site.

2.4.2 *Variance ratio method*

In the case of simple LR where the error term ε is not included, it is known that the variance of the predicted wind speeds about the mean is not properly accounted for. In response to this, Rogers *et al.* [27] proposed a variation of simple LR. In this approach, the predicted target site wind speeds are linearly related to the observed reference site wind speeds by the expression:

$$\hat{u}_{tar} = \left[\bar{u}_{tar} - \left[\frac{\hat{\sigma}_{tar}}{\hat{\sigma}_{ref}} \right] \bar{u}_{ref} \right] + \left[\frac{\hat{\sigma}_{tar}}{\hat{\sigma}_{ref}} \right] u_{ref}$$

Equation 5

where $\hat{\sigma}_{tar}$ and $\hat{\sigma}_{ref}$ are the sample standard deviation about the mean $\bar{u}_{tar}$ and $\bar{u}_{ref}$ at the target and reference sites respectively, as estimated from the training period. Since the ratio $\hat{\sigma}_{tar}/\hat{\sigma}_{ref}$ represent the gradient of the linear regression in Equation 5, this approach is referred to as the variance ratio (VR) method [27].

To account for variations in the upwind surface roughness, and in line with previous approaches [10, 27], the LR and VR approaches were applied sector-wise to data which had been binned into 30 degree angular sectors according to the reference site wind angle. This results in 12 separate regression equations for each reference/target site pair. For sectors that have recorded less than 20 data entries during the training period, a global fit was applied to all angular sectors.

2.4.3   Application of MCP approaches to data of limited length

In order to rigorously test the success of new MCP approaches, non-overlapping periods should be used for training the algorithms and testing their performance. This implies the use of wind data covering multiple years. However, the aim of the current case study is not to test new MCP approaches but rather to establish to what degree the specific 12 month wind resource, covering the period April 2008 – March 2009, may have been predicted if the measurement period was restricted to just three months. While this negates the need for wind data covering multiple years, the fact that the wind data used in this study cover a single year leads to two specific challenges related to seasonal variability which must addressed. Firstly, seasonally varying synoptic weather patterns are likely to affect the regression parameters extracted during the 3 month training period and secondly, since the total data period covers just 12 months, the use of non-overlapping training and testing periods will result in seasonal bias.

To account for these issues the following approach was used: (I) regression parameters were estimated using a full 3 month training period, (II) based on the extracted parameters, the MCP approaches were implemented to predict a time-series of wind speeds for the remaining 9 months of the year, (III) an annual wind resource prediction was made by combining the 9 months of predicted wind speeds with the 3 months of measurements during the training period. These steps represent a single prediction of the annual wind resource based on just 3 months measurements. To account for seasonal variability, the training period was next shifted by one month and the above steps were repeated to obtain a second prediction of the annual wind resource. This process was repeated for all months of the year in order to include training periods covering all combinations of seasons. This process results in 12 separate predicted wind speed time series for the period April 2008 – March 2009. This approach replicates the range of possible predictions that may be obtained using any arbitrary 3 month training period to predict the full 12 month wind resource.

2.5 A viability criterion

In this work, the modelling (SE) and data-led (LR and VR) approaches to wind resource assessment were applied in a two-stage process involving site pre-screening followed by more detailed wind power predictions. The pre-screening stage involved the application of only the SE model in order to test sites against some criterion of viability. Sites passing the criterion were judged to be worthy of more detailed investigation using onsite measurements and the MCP approaches.

Defining a viability criterion is non-trivial since one may consider environmental viability (the ability of a turbine to produce sufficient energy to repay its embedded carbon) and financial viability, (the ability of a turbine to produce sufficient energy to repay the financial investment). These will vary greatly depending on the materials and costs of specific turbines as well as the availability and level of government sponsored financial incentives. In the context of small-scale wind turbine installations, recent studies concerned with assessing city-wide wind energy potential [28, 29] have used a mean wind speed viability criterion of 4-5 ms[-1], these values are also in line with industry advice offered by the UK trade body RenewableUK [30].

While a minimum mean wind speed is a useful starting point, the available wind power will depend both on the mean wind speed and the distribution of wind speeds at the proposed site. Hence, it is useful to express this criterion in terms of a minimum wind power density. Assuming a Weibull distribution of wind speeds, the mean Betz power density in the wind $\bar{p}_d$, can be expressed as [31]:

$$\bar{p}_d = \frac{16}{27}0.5\rho\overline{u^3} = 0.5\rho\bar{u}^3\frac{16}{27}\frac{\Gamma(1+3/k)}{[\Gamma(1+1/k)]^3}$$

Equation 6

where the factor 16/27 represents the Betz limit, ρ = 1.225 kgm^{-3} is the air density, Γ is the

gamma function, k is the Weibull shape factor and $\overline{u^3}$ represents the mean of the cubed wind

speeds, (as opposed to the cube of the mean wind speed, $\bar{u}^3$).

Using a minimum mean wind speed of 4 ms^{-1} and a Weibull shape factor k = 1.9, as

representative of UK sites [9], this equates to a viability criterion of $\bar{p}_d \geq$ 47 Wm^{-2}. An intuitive

feel for this number can be gained through some simple calculations. Assuming 50% of the

available Betz power can be converted to electrical power [4], (this is a broad approximation

since efficiency will vary with wind speed and turbine design), for a small-scale turbine with a

blade diameter of 2 m, this equates to an average power production of 74 W and an annual

energy production of 647 kWh. For a larger turbine with a blade diameter of 6 m, this equates to

an average power production of 664 W and an annual energy production of 5821 kWh. Note

that efficiencies may be reduced for building mounted turbines in urban areas due to turbulent

wind flows. In the following analysis, the minimum power density criterion of $\bar{p}_d \geq$ 47 Wm^{-2} is

applied to screen for viable sites. Locations predicted to have a power density below this value

are deemed non-viable and are excluded at the site pre-screening stage.

3   Results and Discussion

The first stage in assessing the wind resource is to obtain a prediction of the mean wind speed.

Figure 2 shows the predicted and observed mean wind speeds at the ten target sites over the

full 12 month period using the SE model as well as the MCP approaches of LR and VR. As a

benchmark, wind speeds from the NCIC database, used as input for the SE model, have also

been included. Since the NCIC wind speeds represent expected values over open terrain, these

have been scaled to the anemometer height using Equation 1 with no correction for the local

site characteristics (i.e. using aerodynamic parameters representative of open country z_0 = 0.14

m and d = 0). For the MCP approaches, the predicted mean wind speeds are displayed as

predicted wind speed ranges rather than point values, representing the variable predictions

obtained using training data from different seasons. The MCP predictions cover a range of +/-

0.1 to 0.6 ms^{-1} across the different seasons using LR and this range tends to be centred close to

the observed values. The SE predictions exhibit significantly more scatter with regular over or

under predictions and an estimated uncertainty of +/- 0.3 to 0.7 ms^{-1} reflecting the uncertainty in

the input aerodynamic parameters. Despite these uncertainties, SE offers a notable

improvement over the uncorrected NCIC wind speeds, thus highlighting the value of the model.

Note that in the case of the SE predictions, not all the error bars cross the observed values,

(represented by the dotted line) indicating that some modelling uncertainties are unaccounted

for. This is not surprising since the process detailed in Section 2.3 only accounts for

uncertainties in the model input parameters and does not consider the specific model

assumptions or the fact that the mean wind speed predictions are a spatial average. The

unaccounted for errors are particularly noticeable for sites with a low observed mean wind

speed, indicating that local obstructions to the wind flow may be causing local sheltering of
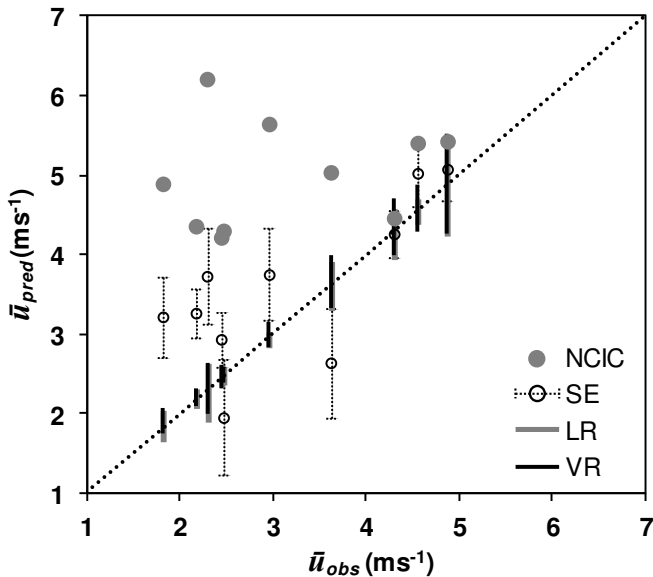
these sites.

Figure 2: Predicted ($\bar{u}_{pred}$) verses observed ($\bar{u}_{obs}$) mean wind speeds at ten target sites using the SE model (circles) and the MCP approaches of LR and VR (solid bars). The NCIC wind speeds scaled to anemometer height (filled circles) are also shown. The error bars attached to the SE predictions represent an uncertainty of +/- 2σ. The MCP predictions are represented by solid bars indicating the range of predictions obtained for training data collected during different seasons. The dotted line represents a one-to-one relationship.

3.1   Site pre-screening

In order to apply the site pre-screening procedure, an estimate of the mean wind power density

$\bar{p}_d$, must be made for each target site. Figure 3 shows the observed and predicted values of $\bar{p}_d$

for each site based on the SE mean wind speed predictions. The mean and uncertainty ranges

for the predicted $\bar{p}_d$ are obtained using Equation 6 along with the sampling process outlined in

Section 2.3 to account for uncertainties in the input parameters. On average, the calculated

uncertainty in $\bar{p}_d$ is around +/- 50% with higher values observed at complex urban sites and

lower values observed at open rural sites. As with the mean wind speed predictions, the

estimated uncertainties in $\bar{p}_d$ do not cross the observed values in some cases indicating

additional errors that are not accounted for in the sampling process. In particular, there appears

to be a net positive bias in the predicted mean wind speed and wind power density for the sites

considered in this study. Despite this however, the predictions and their associated uncertainties
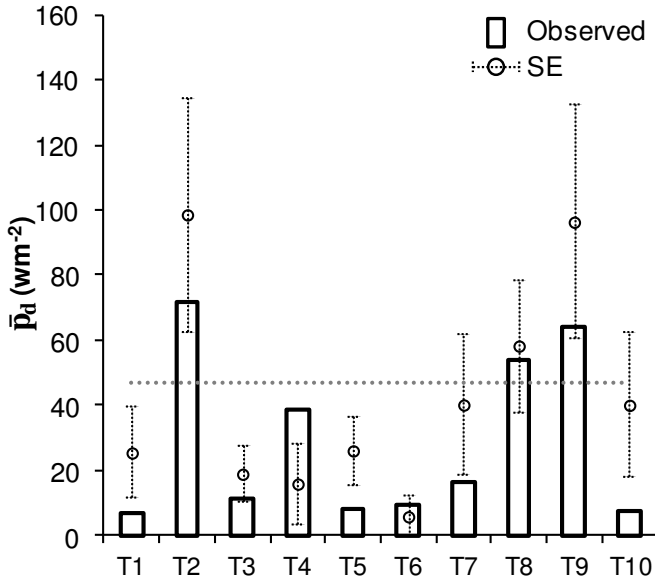
do allow the general trends to be captured.

Figure 3: Observed and predicted mean wind power density $\bar{p}_d$, for ten target sites obtained using an SE model. The circles represent the mean prediction and the error bars show an uncertainty of +/- 2σ. The dotted horizontal line represents the viability criterion of $\bar{p}_d \geq 47$ Wm^{-2}.

To implement the site pre-screening process we wish to identify sites which are likely to be unsuitable as judged by the viability criterion of $\bar{p}_d \geq 47$ Wm^{-2}. To reduce the likelihood of mistakenly excluding viable sites, only sites where even the most optimistic wind power prediction is below the viability criterion should be excluded. Taking this approach, all sites where the predicted $\bar{p}_d$ plus the associated uncertainty (top of each error bar) is below the viability criterion should be deemed unsuitable.

Figure 3 shows that based on this methodology, five of the ten sites (T1, T3, T4, T5 and T6) would be deemed non-viable and excluded from further investigation. Figure 3 also shows that based on the onsite wind speed observations, these exclusions would be correct since none of these sites reach the minimum power density criterion. Given that turbines were installed at all ten sites, this result shows that even a site pre-screening process involving no onsite measurements would have been very valuable in identifying these sites at an early stage and avoiding further investments.

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Of the five sites that passed the viability criterion, onsite observations show that three (T2, T8 and T9) exhibited a $\bar{p}_d \geq 47$ Wm^{-2} while the remaining two fell well below this level. Hence, for the sites considered in this study, the pre-screening approach has successfully predicted five out of the seven non-viable sites without excluding any of the three viable sites. Based on a less conservative approach, namely the mean wind power prediction, all seven non-viable sites would have been correctly excluded, although two of these (T7 and T10) only marginally so. It is clear from Figure 3 that there are significant errors and uncertainties in the predicted $\bar{p}_d$ using the SE approach, indicating that it would be unwise to make financial projections based on these values. However, when used as a site pre-screening tool, the accuracy requirements are less strict requiring only that the general trends be predicted.

3.2   Global sensitivity analysis

Table 2 shows the first-order sensitivity indices calculated using GUI-HDMR, for each of the six model input parameters at each site with respect to the output prediction $\bar{p}_d$. Parameters with larger index values (lighter shading) indicate that the output is more sensitive to that parameter.

Parameter	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	Average
d_{reg} (m)	0.047	0.106	0.095	0.008	0.107	0.024	0.054	0.097	0.105	0.089	**0.073**
$z_{0,reg}$ (m)	0.015	0.035	0.037	0.005	0.037	0.011	0.023	0.028	0.036	0.063	**0.029**
z_{bh} (m)	0.007	0.188	0.062	0.013	0.035	0.010	0.010	0.130	0.197	0.013	**0.066**
d_{local} (m)	0.352	0.000	0.167	0.593	0.112	0.626	0.344	0.000	0.000	0.337	**0.253**
$z_{0,local}$ (m)	0.284	0.054	0.209	0.224	0.171	0.210	0.263	0.074	0.067	0.190	**0.174**
k	0.263	0.589	0.390	0.132	0.500	0.069	0.269	0.644	0.568	0.254	**0.368**

Table 2: First-order sensitivity indices S_i for the six SE model input parameters of regional displacement height and roughness length (d_{reg}, $z_{0,reg}$), blending height (z_{bh}), local displacement height and roughness length (d_{local}, $z_{0,local}$) as well as Weibull shape factor (k) at each target site. Indices are calculated with respect to the output of predicted wind power density ($\bar{p}_d$). Shading indicates the relative contribution of each parameter to the uncertainty, from smallest (dark) to largest (light).

On average, the single parameter with the highest sensitivity index is the Weibull shape factor k. However, the combined contribution of the remaining five parameters related to the mean wind speed prediction is proportionally larger, highlighting the importance of these parameters.

While there are site specific differences, overall the SE model is most sensitive to the local aerodynamic parameters and less sensitive to the regional parameters. Hence, particular care should be taken in obtaining accurate estimates of the local roughness length and displacement height. In most cases, the blending height uncertainty has a smaller contribution to the overall uncertainty than the local aerodynamic parameters. However, for the rural sites (T2, T8 and T9) where the local displacement height is fixed at zero, the blending height becomes a more significant parameter.

3.3 Detailed site assessment using MCP

Using the two stage process set out in this study, only the five sites that passed the site pre-screening stage, (T2, T7, T8, T9 and T10), would be considered for further analysis using onsite measurements and the MCP approaches. For completeness however, the MCP analysis is undertaken for all ten target sites. Figure 4 shows the wind power density predictions for each site using the MCP approaches of LR and VR as detailed in Section 2.4. The predicted values of $\bar{p}_d$ are shown as ranges representing the variable predictions obtained using training data from different seasons.
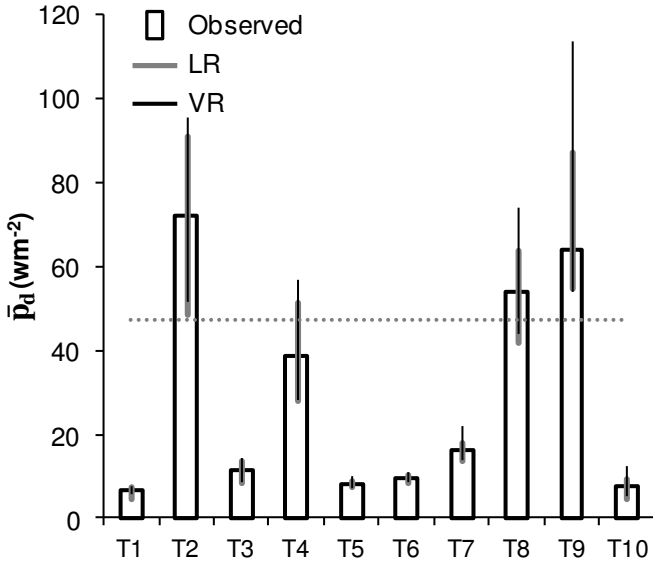
Figure 4: Observed and predicted mean wind power density $\bar{p}_d$, for ten target sites obtained using the MCP approaches of LR and VR with a training length of three months. The bars represent the range of predictions obtained for training data collected during different seasons. The dotted horizontal line represents the viability criterion of $\bar{p}_d \geq 47$ Wm^{-2}.

It is apparent from Figure 4 that significant improvements in accuracy are obtainable through the application of the MCP approaches. For all sites, the observed $\bar{p}_d$ is within the ranges predicted by the MCP analysis and the average uncertainty due to seasonal variation is around +/- 22% using LR. The large reduction in the error and uncertainty ranges compared to the SE approach highlight the added value of onsite measurements even if these are restricted to just 3 months. The two non-viable sites that passed the initial pre-screening stage, T7 and T10, are clearly picked up at the secondary MCP stage as having a very low wind resource. The MCP predications also show that the site T4, which was deemed non-viable in the initial pre-screening stage, is actually marginal and could be deemed as a viable site depending on the season used for training the MCP algorithms. Of the two MCP approaches, LR appears to be more accurate than VR in agreement with previous work [10]. While the MCP approaches offer more accurate predictions compared to the SE model, the short-term onsite measurement period (3 months) and associated seasonality do introduce uncertainties. For the three viable

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sites, (T2, T8 and T9), the maximum percentage error in $\bar{p}_d$ is between 21% and 38% using LR, hence these uncertainties must be taken into consideration when making financial projections.

3.4 Seasonal variability

The uncertainty in the $\bar{p}_d$ predictions in Figure 4 is related to seasonal weather patterns which impact on the extracted regression parameters. Given an arbitrary three month MCP training period, the resulting prediction of the annual $\bar{p}_d$ could lie at any point within the ranges shown in Figure 4 making it unclear whether the prediction is an under- or over-estimate of the true wind resource. Figure 5 shows the variation in the predicted $\bar{p}_d$ for the three viable sites using LR trained over 12 different three month periods throughout the year. The observed values are also shown for comparison.
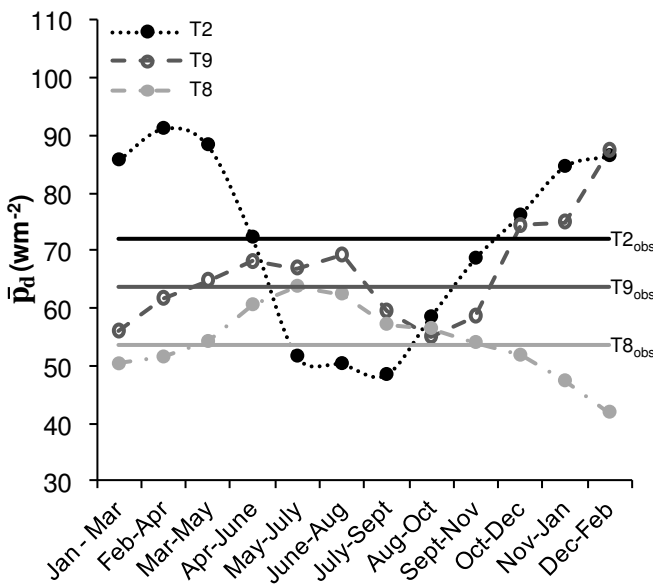

Figure 5: Predicted mean wind power density $\bar{p}_d$ for the viable target sites as a function of the three month season used for training the LR algorithm. The dotted lines are included as a guide to the eye. The solid horizontal lines show the observed values.

While there appears to be some similarity between the predictions at sites T8 and T9 during the first part of the year, overall there appears to be little correlation between the season used for training the MCP algorithms and the sign of the error in $\bar{p}_d$ at these sites. Hence, a cautious

approach would be to assume that the MCP prediction is at the top of the range shown in Figure 4. Previous work at a larger number of sites has indicated a possible relationship between the average magnitude of the error and the training season and this may lead to recommendations of the best seasons in which to obtain onsite measurements so as to minimise the overall prediction errors [10].

4   Conclusions

The feasibility of applying a two-stage approach to low-cost wind resource assessment for small-scale wind turbine installations using a combination of modelling and short-term onsite wind measurements has been investigated. The approach involves: (I) site pre-screening using predictions of wind power density obtained from an SE model with no direct wind measurements and (II) more detailed assessment using three months onsite wind measurements combined with MCP. As an extension to previous implementations of the SE model, the propagation of errors due to uncertainties in the input parameters was investigated and a global sensitivity analysis was conducted.

A case study of 10 UK sites where domestic-scale wind turbines were previously installed showed that based on a minimum wind power density criterion, five of the seven non-viable sites would have been identified in advance by using the site pre-screening procedure, taking account of the estimated uncertainties, without the need for onsite wind measurements. The remaining two non-viable sites could also have been identified by obtaining just three months onsite wind measurements in combination with MCP analysis. In addition, the MCP analysis would have provided more accurate and reliable predictions of the available wind resource at the three viable sites. However, MCP predictions based on very short-term measurement periods are subject to seasonal variability and this introduces additional uncertainties in the

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predicted wind resource. These uncertainties should be taken into consideration when making financial projections based on short measurement periods.

The results provide a framework for leveraging the advantages of both modelling and data-led approaches to wind resource assessment for small-scale installations where more comprehensive long-term wind measurements may not be financially or practically viable. Further work should consider applying this framework to a larger number of sites over longer time periods to investigate its general applicability.

Acknowledgements

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