Analysis of Wind Velocity and the Quantification of Wind Turbulence in Rural and Urban Environments Using the Levy Index and Fractal Dimension

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Analysis of Wind Velocity and the Quantification of Wind Turbulence in Rural and Urban Environments using the Lévy Index and Fractal Dimension

Jonathan Blackledge, Eugene Coyle, Niall McCoy, Derek Kearney, Keith Sunderland and Thomas Woolmington

Abstract—This paper is concerned with a quantitative and comparative analysis of wind velocities in urban and rural environments. It is undertaken to provide a route to the classification of wind energy in a rural and urban setting. This is a common problem and the basis of a significant focus of research into wind energy. In this paper, we use a non-Gaussian statistical model to undertake this task, and, through a further modification of the data analysis algorithms used, extend the model to study the effect of wind turbulence, thereby introducing a new metric for this effect that is arguably superior to a more commonly used and qualitatively derived measure known as the Turbulence Intensity.

Starting from Einstein’s evolution equation for an elastic scattering process, we consider a stochastic model for the wind velocity that is based on the Generalised Kolmogorov Feller Equation. For a specific ‘memory function’ - the Mittag-Leffler function - it is shown that, under specified conditions, this model is compatible with a non-Gaussian processes characterised by a Lévy distribution that, although previously used in wind velocity analysis, has been introduced phenomenologically. By computing the Lévy index for a range of wind velocities in both rural and urban environments using industry standard cup anemometers, wind vanes and compatible data collection conditions (in terms of height and sampling rates), we show that the intuitive notion that the ‘quality’ of wind velocity in an urban environment is poor compared to a rural environment is entirely quantifiable. This quantifies the notion that a rural wind resource is, on average, of higher yield when compared to that of the urban environment in the context of the model used. In this respect, results are provided that are based on five rural and urban locations in Ireland and the UK and illustrate the potential value of the model in the context of the model used. In this respect, results are provided that are based on five rural and urban locations in Ireland and the UK and illustrate the potential value of the model in the context of the model used.

Index Terms—Wind velocity, wind turbines, non-Gaussian statistics, Lévy index, rural and urban analysis, wind turbulence, Fractal Dimension.

I. INTRODUCTION

A primary factor in the development of a wind farm is an understanding of the potential wind energy associated with the site, i.e. the geographical location of the farm, [1], [2]. This is the key to the economic viability of any wind energy project which must focus on the development of wind farms in effective and efficient regions, subject to the structural and environmental conditions that provide an optimum solution within the engineering and commercial constraints imposed, [3], [4]. Understanding the relationship between on-shore rural and urban environments (and off-shore wind energy schemes), has been, and remains fundamental in the development of the wind industry throughout the world, [5]. For some time now, it has been ‘understood’ by industry experts that the wind velocity in a rural environment is of a higher ‘quality’ and energy yield when compared to the wind velocity in an urban environment, [6]. The term ‘understood’ is often taken for granted, rather than taking all of the facts into consideration and fully justifying the actual results, [7], [8]. In this context, the purpose of this paper is to look at using recently developed stochastic models (originally developed for algorithmic financial trading and used to launch and develop http://tradersnow.com, for example) to investigate a possible correlation between the wind velocity in both rural and urban environments based on a statistical parameter called the Lévy index. This represents a significant departure from conventional statistical analysis of wind velocity data which is typically based on Gaussian-type models where the wind velocity is taken to be a Rayleigh-type distributed. The statistical model considered in this paper is non-Gaussian and is used to provide two distinctive and original contributions:

• quantification of the intuitive understanding that potential wind energy is less in urban regions based on computing the Lévy index;
• quantification of wind turbulence in terms of a new metric that is arguably superior to the conventional Turbulence Intensity based on computing the Fractal Dimension (which is simply related to the Lévy Index).

II. FUNDAMENTALS OF WIND ENERGY

The power generated by a wind turbine is based on a range of design factors but they all relate indirectly to Betz law, which states that the power $P$ in Watts is given by, [9]  

$$P = \frac{1}{2} \alpha \rho A v^3$$  

(1)

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where \( v \) is the upwind speed (i.e. the wind velocity that is incident on the turbine) in metres per second (\( \text{ms}^{-1} \)), \( A \) is the area mapped out by the turbine blades in \( \text{m}^2 \), \( \rho \) is the density of air in \( \text{kgm}^{-3} \) and \( \alpha \approx 0.593 \) is the coefficient of performance. This result is derived by considering the energy generated by a change in the upwind and downwind velocities together with the change in the mass of air that occurs as it ‘travels’ through the turbine. A derivation of equation (1) is given in [10], for example, which includes the idealised conditions upon which this equation is based. This law is the ‘design guide’ associated with the development of wind turbines world-wide. There are two important factors associated with optimising the output power: (i) the diameter of the turbine blades; (ii) the wind velocity which scales of the velocity cubed. The cubic velocity scaling law cannot be maintained in practice over all ranges of wind velocity, and, depending upon the design characteristics of the turbine, there is a natural threshold for the wind velocity beyond which the output power does not increase. This is due to a range of influencing factors including the turbulence phenomena that occur at high wind velocities through interaction with the turbine blades when Betz law breaks down. However, within the framework of Betz law, and given a turbine with a fixed blade diameter, the velocity cubed scaling law is of fundamental importance in determining the output power. Clearly, the wind velocity is time dependent and this dependence cannot, in general, be classified in a deterministic sense. Stochastic models that lead to the design of statistical data analysis algorithms are therefore required that ideally provide a statistical parameter or parameter set that can quantify the wind resource subject to a range of influencing factors.

III. INFLUENCING FACTORS

There are a range of influencing factors that can affect the performance of a wind turbine and a wind farm. The current industry knowledge is based on the ‘roughness principle’. Commonly found in the rural environment, there tends to be little in the way of large obstacles to cause sufficient turbulence which affect the wind quality, and, in turn, the energy yield of wind turbines. This is due to the relatively laminar flow that is a characteristic of a ‘good site’ as illustrated in Figure 1.

By contrast, in the urban environment, there is generally an abundance of built obstacles representing adverse roughness of the ‘ground truth’ generating turbulence and thereby curtailing the potential energy yield and the output power of wind turbines located in such an environment as illustrated in Figure 2.

Understanding the ‘quality of the wind velocity’ is of particularly interest to those in the wind energy industry, as it allows the developer to identify specific sites to develop, concentrating on which sites produces the greatest energy yields. Within the urban environment, there are numerous factors influencing the wind velocity. The overriding factor of the built environment in the urban setting is that of roughness. There are also the numerous properties of the urban environment and atmospheric influences to be accounted for resulting in an extremely complex environment to accurately model.

![Figure 1. Illustration of the laminar flow that is typical of a rural site in which there can be an increase or ‘speed up effect’ of the upwind velocity over a smooth hill thereby providing a greater power output of a wind turbine through the \( v^3 \) scaling law’ (top illustration). In contrast, ‘bad sites’ (bottom illustration) such as cliff tops dissipate wind energy through the turbulence generate by discontinuities that ‘break-up’ laminar flows (Source: Greenspec 2011).](image1)

![Figure 2. Illustration of the effect of obstacles such as buildings which generate a zone of maximum turbulence downwind but with decreasing height and of the same order of magnitude as the height of the building \( H \) (top). Turbines located downwind are placed away from the turbulence zone at a distance of the order of \( 10H \) and the turbine blades placed atconst a height greater than \( H \). Typical wind speeds are shown in the bottom left-hand diagram and the basic issues associated with roof mounted wind turbines illustrated in the bottom right-hand side diagram (Source: Greenspec 2011).](image2)

Referring to the idealised model illustrated in Figure 3, a standard scaling law for the effect of roughness on the wind velocity at a height \( z \) is given by, [11]

\[
v(z) = \frac{v_f}{\kappa} \log \left( \frac{z - d}{z_0} \right)
\]

(2)

where \( v(z) \) denotes the wind velocity at a height \( z \), \( v_f \) is the friction velocity (which is dependent on the roughness of the ground), \( \kappa \) is the (dimensionless) von Karman constant (typically of the order of 0.41), \( z \) is the height above the earth’s surface, \( d \) is the displacement height and \( z_0 \) is the height above the earth’s surface roughness (where the wind velocity appears to approach zero). The friction velocity depends upon the shear stress \( T \) at the boundary of the flow and is given by, [12]

\[v_f = \sqrt{T/\rho}\]

where \( \rho \) is the density of air. This log-based
scaling law describes the velocity profile of a turbulent fluid flow near a boundary with a non-slip condition and must be fully and accurately introduced when taking into account wind gusts and strong winds (especially in urban environments). Equation (2) is a semi-empirical relationship used to describe the vertical distribution of horizontal mean wind speeds within the lowest portion of the boundary layer.

As the wind speed decreases to zero, closer to ground level, this results in an atmospheric boundary layer. Thus, equation (2) can be accurate up to 200 m. In rural environments, however, the impact of such ‘roughness factors’ are less common and mostly attributed to forestry etc. (as illustrated in Figure 3) which can be removed as required and with the required permission of the appropriate environmental agencies.

![Figure 3. Rural (top) and Urban (bottom) roughness models associated with equation (2) (Source: Mertens 2006).](image)

It is intuitively obvious that, whatever the cause, turbulence reduces the energy output from a wind turbine since turbulence dissipates energy over a larger volume (at least for an adiabatic system). It is also clear that turbulence is extremely difficult to model in a fully deterministic sense, based on the principles of fluid dynamics. Thus, in the following section we develop a stochastic model from first principles.

### IV. STOCHASTIC MODEL FOR THE WIND VELOCITY

We consider the temporal behaviour of the wind velocity in terms of the space-time evolution of a field $v(x, t)$ working in one-dimension. The temporal behaviour of the wind velocity is then taken to be the time dependent behaviour of this field at a point in space $x$. In [10] and [13], a stochastic model for the wind velocity is developed using a fractional partial differential equation of the type

$$\frac{\partial^\gamma}{\partial^\gamma} v(x, t) - \frac{\partial}{\partial t} v(x, t) = -\delta(x) s(t), \quad \gamma \in (0, 2]$$

where $\gamma$ is the Lévy index and $s(t)$ is a ‘white noise’ stochastic ‘source function’ with a uniformly distributed Power Spectral Density Function (PSDF) and arbitrary Probability Density Function (PDF). Ignoring scaling constants, it is shown that the Green’s function solution to this equation is

$$v(t) = \frac{1}{t^{1-1/\gamma}} \otimes t s(t)$$

(3)

where $\otimes t$ denotes the convolution integral over $t$ and $v(t) = v(0, t)$. This solution has the self-affine scaling relationship

$$Pr[v(at)] = a^{1/\gamma} Pr[v(t)]$$

where $Pr$ denotes the PDF and a PSDF given by (for scaling constant $c$)

$$|V(\omega)|^2 = \frac{c}{|\omega|^{2/\gamma}} \quad \text{where} \quad V(\omega) = \int v(t) \exp(-i\omega t) dt$$

Following [14] and [15], we now consider an extension and generalisation to this model which is based on developing a solution to the Generalised Kolmogorov-Feller Equation (GKFE) which is derived in the following section. The aim is to show that the solution to the GKFE considered provides a model for the PSDF that is effectively the same as that considered in [10] and [13] and that the wind velocity field can be considered to be a random scaling fractal signal characterised by a Lévy index. In turn, this index is related to the fractal dimension of the signal, and, as discussed later on in this paper, this dimension can be used to characterise the turbulent behaviour of the wind velocity providing an index that is arguably superior to the conventional Turbulence Intensity.

#### A. Derivation of the Generalised Kolmogorov-Feller Equation

For an arbitrary PDF $p(x)$, Einstein’s evolution equation is, [16]

$$u(x, t + \tau) = u(x, t) \otimes_x p(x)$$

where $u(x, t)$ is a ‘density function’ representing the concentration of a canonical ensemble of particles undergoing elastic collisions. This function is interpreted as a field representing the distribution of physical properties such as the mass, velocity, temperature and pressure, for example.

Consider a Taylor series for the function $u(x, t + \tau)$, i.e.

$$u(x, t + \tau) = u(x, t) + \tau \frac{\partial}{\partial t} u(x, t) + \tau^2 \frac{\partial^2}{2! \partial^2 t} u(x, t) + ...$$

For $\tau << 1$

$$u(x, t + \tau) = u(x, t) + \tau \frac{\partial}{\partial t} u(x, t)$$

and we obtain the ‘Classical KFE’ , [17] and [18]

$$\tau \frac{\partial}{\partial t} u(x, t) = -u(x, t) + u(x, t) \otimes_x p(x)$$

(4)

Equation (4) is based on a critical assumption which is that the time evolution of the field $u(x, t)$ is influenced only by short term events and that longer term (historical) events have no influence on the behaviour of the field, i.e. the ‘system’ described by equation (4) has no ‘memory’. This statement is the physical basis upon which we introduce the condition $\tau << 1$ thereby allowing the Taylor series expansion of the $u(x, t + \tau)$ to be made to first order. The question then arises as to how longer term temporal influences can be modelled, other
than by taking an increasingly larger number of terms in the Taylor expansion of \( u(x, t + \tau) \) which is not of (closed-form) analytical value.

For arbitrary values of \( \tau \),
\[
\frac{\tau}{\partial t} u(x, t) + \frac{\tau^2}{2!} \frac{\partial^2}{\partial t^2} u(x, t) + \ldots = -u(x, t) + u(x, t) \otimes_x p(x)
\]

We model the effect on a solution for \( u(x, t) \) of the series on the left hand side of this equation in terms of a ‘memory function’ \( m(t) \) and write
\[
\tau m(t) \otimes_t u(x, t) = -u(x, t) + u(x, t) \otimes_x p(x)
\]

where \( \otimes_t \) is taken to denote the causal convolution integral over \( t \). This is the Generalised KFE (GKFE) which reduces to the Classical KFE when
\[
m(t) = \delta(t)
\]

Note that for any memory function for which there exists a function or class of functions of the type \( n(t) \), say, such that
\[
n(t) \otimes_t m(t) = \delta(t)
\]

then we can write equation (5) in the form
\[
\tau \frac{\partial}{\partial t} u(x, t) = -n(t) \otimes_t u(x, t) + n(t) \otimes_t u(x, t) \otimes_x p(x)
\]

where the Classical KFE is recovered when \( n(t) = \delta(t) \).

Any solution obtained to the GKFE will be dependent upon the choice of memory function \( m(t) \) used. There are a number of choices that can be considered, each or which is taken to be a ‘best characteristic’ of the stochastic system in terms of the influence of its time history. However, it may be expected that the time history of physically significant random systems is relatively localised in time. This includes memory functions such as the Mittag-Leffler function \([19]\)
\[
m(t) = \frac{1}{\Gamma(1 - \beta) t^\beta}, \quad 0 < \beta < 1
\]

where
\[
n(t) = \frac{1}{\Gamma(\beta - 1) t^{2-\beta}}
\]

given that
\[
\int_0^\infty \frac{\exp(-st)}{\Gamma(\beta) t^{1-\beta}} dt = \frac{1}{s^\beta} \quad \text{and} \quad \int_0^\infty \delta(t) \exp(-st) dt = 1
\]

B. Green’s Function Solution to the GKFE

Equation (6) can be written in the form
\[
\tau \frac{\partial}{\partial t} u(x, t) + u(x, t) = u(x, t) - n(t) \otimes_t u(x, t)
\]

\[
+ n(t) \otimes_t u(x, t) \otimes_x p(x)
\]

so that the Green’s function solution is given by
\[
u(x, t) = g(t) \otimes_t u(x, t) - g(t) \otimes_t n(t) \otimes_t u(x, t)
\]

\[
+ g(t) \otimes_t n(t) \otimes_t u(x, t) \otimes_x p(x)
\]

where the Green’s function is given by
\[
g(t) = \frac{1}{\tau} \exp(-t/\tau), \quad t > 0
\]

which is the solution to
\[
\tau \frac{\partial}{\partial t} g(t - t_0) + g(t - t_0) = \delta(t - t_0)
\]

and we assume the initial conditions \( u(x, t = 0) = 0 \) and \( g(t = t_0) = 0 \). We can now analyse this solution in Fourier-Laplace space by taking the Fourier transform and the Laplace transform of equation (7) and using the convolution theorems for the Fourier and Laplace transform, respectively, to obtain
\[
\tilde{u}(k, s) = \tilde{g}(s) \tilde{u}(k, s) - \tilde{\bar{g}}(s) \tilde{n}(s) \tilde{\bar{u}}(k, s) + \tilde{\bar{g}}(s) \tilde{n}(s) \tilde{\bar{u}}(k, s) \tilde{\bar{p}}(k)
\]

where
\[
\tilde{u}(k, s) = \int_0^\infty \int_{-\infty}^{\infty} u(x, t) \exp(-ikx) dx \exp(-st) dt
\]

\[
\tilde{g}(s) = \int_0^\infty g(t) \exp(-st) dt, \quad \tilde{n}(s) = \int_0^\infty n(t) \exp(-st) dt
\]

and
\[
\tilde{\bar{p}}(k) = \int_{-\infty}^\infty p(x) \exp(-ikx) dx
\]

From equation (8) we can write
\[
\tilde{u}(k, s) = -\frac{\tilde{\bar{g}}(s)}{1 - \tilde{\bar{g}}(s)} \tilde{\bar{u}}(k, s) + \frac{\tilde{\bar{g}}(s)}{1 - \tilde{\bar{g}}(s)} \tilde{n}(s) \tilde{\bar{u}}(k, s) \tilde{\bar{p}}(k)
\]

\[
= -\frac{\tilde{n}(s)}{\tau s} \tilde{u}(x, t) + \frac{\tilde{n}(s)}{\tau s} \tilde{\bar{u}}(k, s) \tilde{\bar{p}}(k)
\]

given that \( \tilde{\bar{g}}(s) = (1 + \tau s)^{-1} \) and thus obtain the equation
\[
\tilde{u}(k, s) = \tilde{h}(s) \tilde{\bar{u}}(k, s) \tilde{\bar{p}}(k)
\]

where
\[
\tilde{h}(s) = \frac{\tilde{n}(s)}{\tau s + \tilde{n}(s)}
\]

or, upon inverse transformations
\[
u(x, t) = h(t) \otimes_t u(x, t) \otimes_x p(x)
\]

with
\[
h(t) \leftrightarrow \frac{\tilde{n}(s)}{\tau s + \tilde{n}(s)}
\]

where \( \leftrightarrow \) denotes the Laplace transformation, i.e. mutual transformation from \( t \)-space to \( s \)-space.

Consider the iteration of equation (9) defined by
\[
u_{n+1}(x, t) = h(t) \otimes_t u_n(x, t) \otimes_x p(x)
\]

for an initial solution \( u_0(x, t) \) where \( n = 1, 2, \ldots, N \). The equivalent iteration in Fourier-Laplace space is
\[
\tilde{u}_{n+1}(k, s) = \tilde{h}(s) \tilde{\bar{u}}_n(k, s) \tilde{\bar{p}}(k)
\]

with initial solution \( \tilde{u}_0(k, s) \) so that, after \( N \) iterations,
\[
\tilde{u}_N(k, s) = [\tilde{h}(s)]^N \tilde{\bar{p}}(k)^N \tilde{u}_0(k, s)
\]
and upon inverse Fourier-Laplace transformation, has the iterative form

\[ u_N(x, t) = \prod_{j=1}^{N} p(x) \prod_{k=1}^{N} h(t) \otimes_x \otimes_t u_0(x, t) \]  

(11)

where

\[ \prod_{j=1}^{N} f(t) \equiv f(t) \otimes_t f(t) \otimes_t f(t) \otimes_t \ldots \]

denoting the \( N \)th convolution of \( f(t) \).

The criterion for convergence of this (iterative) solution can be considered by introduction of the error function \( \epsilon_n(x, t) \) at any iteration \( n \) so that \( u_n(x, t) = u(x, t) + \epsilon_n(x, t) \). From equation (10) we can then write (transforming to Fourier-Laplace space)

\[ \tilde{\epsilon}_{n+1}(k, s) = \tilde{h}(s)\tilde{p}(k)\tilde{\epsilon}_n(k, s) \]

so that

\[ \tilde{\epsilon}_n(k, s) = [\tilde{h}(s)\tilde{p}(k)]^n\tilde{\epsilon}_n(k, s) \]

and it is clear that, since we require \( \tilde{\epsilon}_n \to 0 \) and \( n \to \infty \), \( [\tilde{h}(s)\tilde{p}(k)] < 1 \) \( \forall (k, s) \). The condition for convergence therefore becomes

\[ \|\tilde{h}(s)\tilde{p}(k)\| \leq \|\tilde{h}(s)\| \times \|\tilde{p}(k)\| < 1 \]

or, for Euclidian norms, and, using Rayleigh’s theorem,

\[ \|h(t)\|_2 \times \|p(x)\|_2 < \frac{1}{\sqrt{2\pi}} \]

\section{C. Impulse Response for the Mittag-Leffler Memory Function}

Form equation (11), if the initial solution is an impulse (i.e. \( u_0(x, t) = \delta(x)\delta(t) \)) then the Impulse Response Function (IRF), denoted by \( r(x, t) \), is given by

\[ r(x, t) = \prod_{j=1}^{N} p(x) \prod_{k=1}^{N} h(t) \]

with ‘transfer function’

\[ \tilde{r}(k, s) = [\tilde{h}(s)\tilde{p}(k)]^N \]

For a memory function \( m(t) \) modelled by the Mittag-Leffler function (for \( 0 < \beta < 1 \))

\[ m(t) \leftrightarrow \frac{1}{s^{1-\beta}} \quad \text{and} \quad \tilde{h}(s) = \frac{1}{1 + \tau s^\beta} \sim \frac{1}{\tau s^\beta} \]

so that

\[ h(t) \sim \frac{1}{\tau t^{1-\beta}} \]

Similarly, if we consider a Mittag-Leffler PDF of the form

\[ p(x) = \frac{1}{\Gamma(1-\gamma) |x|^\gamma} \quad 0 < \gamma < 1 \]

then the IRF becomes

\[ r(x, t) \sim \prod_{j=1}^{N} \frac{1}{\Gamma(1-\gamma) |x|^\gamma} \prod_{k=1}^{N} \frac{1}{\tau \Gamma(1-\beta) t^{1-\beta}} \]

\section{D. Temporal IRF for Early Evolutionary Behaviour}

The function \( r(x, t) \) is a space-time IRF. A temporal IRF can be considered by integrating over \( x \). Physically, the resulting IRF can be taken to be a characteristic of a time series recorded at an arbitrary point in space. Further, if we consider the early evolutionary behaviour of \( u_N(x, t) \) (i.e. the case when \( N = 1 \)), we obtain the simplified expression for the field \( u(t) \) given by

\[ u(t) = \int_{-\infty}^{\infty} u_1(x, t)dx = \frac{1}{\tau \Gamma(\beta) t^{1-\beta} \otimes_t s(t)} \]  

(12)

where

\[ s(t) = \int_{-\infty}^{\infty} p(x) \otimes_x u_0(x, t)dx \]

This result demonstrates that the model developed in [10] and [13], where the wind velocity is given by equation (3), is a special case of the solution to the GKEF considered here (i.e. equation (12) where, ignoring scaling constants, \( \beta = \gamma^{-1} \) and the field \( u \) is taken to be the wind velocity) and describes the early evolution of a time series governed by the GKEF. In turn, the GKEF is an expression of Einstein’s evolution equation subject to a specialised Memory Function - the Mittag-Leffler function - which yields the fractional diffusion equation. This relationship is compounded further in the following analysis for the case when \( \tau << 1 \). Using the convolution theorem, in Fourier space, Einstein’s evolution equation is

\[ \tilde{u}(k, t + \tau) = \tilde{u}(k, t) + \tau \frac{\partial}{\partial t} \tilde{u}(k, t) = \tilde{u}(k, t)\tilde{p}(k), \quad \tau << 1 \]

If we now consider Lévy’s characteristic function (for constant \( a \) and Lévy index \( \gamma \))

\[ \tilde{p}(k) = \exp(-a | k |^\gamma) \sim 1 - a | k |^\gamma, \quad a << 1 \]

then it is clear that we can write the evolution equation (in Fourier space) as

\[ \tau \frac{\partial}{\partial t} \tilde{u}(k, t) = -a | k |^\gamma \tilde{u}(k, t) \]

Using the convolution theorem again, and, together with the Reisz definition of a fractional derivative, i.e.

\[ \frac{\partial^\gamma}{\partial x^\gamma} f(x) = -\frac{1}{2\pi} \int_{-\infty}^{\infty} | k |^\gamma \tilde{f}(k) \exp(ikx)dk \]

we can write

\[ \frac{\partial^\gamma}{\partial x^\gamma} u(x, t) - \sigma \frac{\partial}{\partial t} u(x, t) = 0 \]

where \( \sigma = \tau/a \). This is a fractional differential operator that has a the temporal IRF (ignoring scaling constants) \( 1/t^{1-\gamma} \). Moreover, in this form, it is clear that for \( \gamma = 1 \)

\[ \frac{\partial}{\partial x} u(x, t) = \sigma \frac{\partial}{\partial t} u(x, t) \]

an equation which describes flow in one-dimension subject to the continuity equation. In fluid dynamics, for example, the continuity equation states that, in any steady state process,
the rate at which mass enters a system is equal to the rate at which mass leaves the system and is given by (for a three-dimensional space vector $\mathbf{r}$)

$$\frac{\partial}{\partial t} \rho + \nabla \cdot (\rho \mathbf{v})$$

where $\rho(\mathbf{r}, t)$ is the fluid density and $\mathbf{v}(\mathbf{r}, t)$ is the flow velocity vector field. Thus, for a one-dimensional system characterised by a constant velocity field $v$ (which is constant over $x$ and $t$) and a density field $\rho(x, t)$ we obtain

$$\frac{\partial}{\partial x} \rho + v \frac{\partial}{\partial t} \rho(x, t) = 0$$

In this sense, the field $u(x, t)$ for $\gamma = 1$ may be taken to describe the flow of mass subject to a constant fluid velocity $v = \tau/a$. The case of $\gamma = 1$ is therefore representative of a steady state process. Moreover, the PDF associated with this process is a Chauchy function since

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-a | k |) \exp(i k x) dk = \frac{1}{\pi} \frac{a}{a^2 + x^2}$$

Similarly, given that

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-a k^2) \exp(i k x) dk = \frac{1}{\sqrt{\pi}} \frac{a}{a^2 + x^2}$$

it is clear that the case when $\gamma = 2$ describes a Gaussian system, the field $u(x, t)$ being the solution to the Classical Diffusion Equation

$$\frac{\partial^2}{\partial x^2} u(x, t) - \sigma^2 \frac{\partial}{\partial t} u(x, t) = 0$$

We note that, in general [20],

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-a | k |) \exp(i k x) dk \sim \frac{1}{x^{1+\gamma}}$$

Thus, in terms of using the field $u$ to model a single or combined velocity field (such as the polar wind speed discussed in Section VII), on the basis of the physical systems described by the cases when $\gamma = 1$ and $\gamma = 2$ given above, we can expect that for $\gamma \in [1, 2]$, larger values of $\gamma$ correspond to more urbanised environments where wind turbulence (which tends towards fully diffusive behaviours but is still fractionally diffusive according to our model) is greater. This idea appears to be validated in the data analysis associated with the case study discussed in the following section.

V. DATA ANALYSIS

On the basis of the stochastic model discussed in the previous section, it is possible to estimate the Lévy index, relatively simply. This is achieved using the PSDF method discussed in [21], for example. It is based on exploiting the basic relationship (which ignores scaling factors) [21]

$$\frac{1}{t^{\frac{1}{2} - 1/\gamma}} \leftrightarrow \frac{1}{\omega^{1/\gamma}}$$

where $\leftrightarrow$ denotes transformation from real to Fourier space (i.e. $t$- to $\omega$ space). Using the convolution theorem, equations (3) and (11) with $\beta = \gamma^{-1}$, and ignoring scaling by $[\tau \Gamma(\beta)]^{-1}$, transform to

$$\tilde{u}(\omega) = \frac{s(\omega)}{|\omega|^{1/\gamma}}$$

Thus, assuming $s(\omega)$ is a white noise spectrum that can be taken to be a ‘phase only’ function (with unit amplitude),

$$|\tilde{u}(\omega)|^2 = \frac{1}{|\omega|^{2/\gamma}}$$

This idealised model for the power spectrum is used to estimate the Lévy index based on standard linear regression methods. For the work reported in this paper, and using a MATLAB7 programming environment, the Orthogonal Linear Regression Method based on the m-code available at [22] is used. We note that the power spectrum of a random scaling fractal signal scales as $[21] |\omega|^{-(5-2D)/2}$ where $D$ is the fractal dimension. Thus, the relationship between the Lévy Index and the Fractal Dimension is

$$\frac{1}{\gamma} = \frac{5 - 2D}{4}$$

To accurately model both urban and rural environments, historical data from five rural and five urban wind measurement sites were used. All measurement devices were located at 50 m above local ground level to allow an accurate comparison and the locations spread across Ireland and the UK1. The measurement devices were all located on lattice towers of the type shown in Figure 4 with industry standard data loggers to store the data. The raw data sets were taken from their raw 10 minute average from industry standard cup anemometers and wind vanes. All data sets were calibrated by industry professionals and the author’s are in receipt of all relevant test certificates to verify the credibility of the calibrations.

![Fig. 4. A typical Met Mast used to record wind velocity data at 50m height with a 10 minute average using industry standard cup anemometers and wind vanes. (Source: Wind Prospect Group, 2012.)](image)

The key factor in determining a possible correlation between rural and urban wind velocity is the use of stochastic modelling. The modelling is often based on a statistical analysis of the available wind velocity data which is used to assess optimum regions for the construction of wind farms. In this

1Much of the specific data is confidential and the exact location of the data sources cannot be mentioned in the paper. However, for credibility reasons, the locations are available on receipt of a non-disclosure agreement between the authors and the reader.
TABLE I
Mean values of the Lévy index \( \hat{\gamma} \) for five rural sites.

<table>
<thead>
<tr>
<th>Site</th>
<th>Location</th>
<th>Longitude</th>
<th>Latitude</th>
<th>( \hat{\gamma} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Newport</td>
<td>55.5853</td>
<td>52.2527</td>
<td>1.3407</td>
</tr>
<tr>
<td>2</td>
<td>Waterford</td>
<td>52.8438</td>
<td>-7.1256</td>
<td>1.3672</td>
</tr>
<tr>
<td>3</td>
<td>Limerick</td>
<td>53.8995</td>
<td>-6.8051</td>
<td>1.3708</td>
</tr>
<tr>
<td>4</td>
<td>Cavan</td>
<td>53.8995</td>
<td>-6.4059</td>
<td>1.3481</td>
</tr>
<tr>
<td>5</td>
<td>Dundalk</td>
<td>53.8995</td>
<td>-6.4059</td>
<td>1.3688</td>
</tr>
</tbody>
</table>

TABLE II
Mean values of the Lévy index \( \hat{\gamma} \) for five urban sites.

<table>
<thead>
<tr>
<th>Site</th>
<th>Location</th>
<th>Longitude</th>
<th>Latitude</th>
<th>( \hat{\gamma} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mayo</td>
<td>55.3905</td>
<td>52.6401</td>
<td>1.3586</td>
</tr>
<tr>
<td>2</td>
<td>Wexford</td>
<td>53.7965</td>
<td>-6.6045</td>
<td>1.3692</td>
</tr>
<tr>
<td>3</td>
<td>Louth</td>
<td>54.6029</td>
<td>-6.6045</td>
<td>1.3481</td>
</tr>
<tr>
<td>4</td>
<td>Tyrone</td>
<td>52.3459</td>
<td>-2.9796</td>
<td>1.3407</td>
</tr>
<tr>
<td>5</td>
<td>Limerick</td>
<td>52.3459</td>
<td>-2.9796</td>
<td>1.3397</td>
</tr>
</tbody>
</table>

determined from the same set of measured data samples of wind speed, and taken over a specified time’ and should be considered as the standard deviation of the longitudinal wind speed \( \sigma_v \) normalised with the mean wind speed \( \bar{v} \), i.e.

\[
TI = \frac{\sigma_v}{\bar{v}}
\]

The complex morphology experienced in an urban environment results in a modified flow and turbulence structure in the urban atmosphere in contrast to the flow over ‘ideal or homogenous’ surfaces [28]. Thus, in [27], for example, it is proposed that the TI can be ‘linked’ to the surface roughness parameter via the following equation

\[
TI = \frac{1}{\log \frac{z-d}{z_0}}
\]

where \( d \) is the displacement height, which is taken to be equal to 0.66 of the average building height (denoted by \( z_H \) ) and \( z_0 \) is the surface roughness length. This equation is predicated on \( z \) (the observation height) being in excess of the wake diffusion height - \( z^* \), which is taken to be above the surface roughness sub-layer and into the inertial sub-layer as illustrated in Figure 5. This result suggests that there is an increasing level of turbulence with increasing roughness and decreasing height relative to the earth’s surface.

![Fig. 5. Wind Speed in the urban context with respect to the boundary layer transitions.](image)

VI. TURBULENCE INTENSITY

Urban wind regimes are characterised as having low wind speeds with more turbulent flows which result in limited energy realisation. Research has shown that the lower mean speeds are linked to the higher surface roughness lengths \( z_0 \) prevalent in urban environments, [23] and [24]. The manifestation of turbulence, however, is less well understood. Turbulent flows can be described as those in which the fluid velocity varies significantly and irregularly in both position and time [25]. While turbulent fluctuating flow impacts directly the design of wind turbines, they also influence the productivity of turbines particularly in areas of complex morphologies.

The Turbulence Intensity (TI) is the most common metric used to quantify the effect of wind turbulence as it is generally more useful to develop descriptions of turbulent in terms of statistical properties [26]. TI is defined in [27] as ‘the ratio of wind speed standard deviation to the mean wind speed, paper, data from five rural and five urban sites were analysed through determination of the Lévy index over a period of 12 months. The results are tabulated in Tables I and II and show that, bar one anomaly, the trend is that the mean values of the Lévy index \( \hat{\gamma} \) for the urban sites is consistently higher in comparison to the mean values of the same index for the rural sites. The average value of this index for the urban sites considered is 1.3688 which should be compared to the equivalent average value for the rural sites of 1.3457. Thus, in this case study, the Lévy index Rural-to-Urban ratio is 0.9832.

Some of the data used to generate the results in Table I are recorded at urban locations that are not ‘deeply embedded’ in an urban environment. For example, Sites 1 in Newport, South Wales, is in a coastal location on an urban boundary which may explain why the mean is relatively low compared with the other values. Site 3 in Limerick is a similar location close to the coast and on the boundary of the urban environment. However, both sites are impacted by the urban setting with a high density of ‘urban features’ in close proximity. Thus, the urban locations chosen are not optimal in terms of all the sites being fully embedded in an urban environment, but were chosen to provide data consistency given the limited data sets currently available.

With respect to the impact on the power output of wind turbines subjected to turbulence, the majority of the available research considers utility scale systems with capacities in the MW ranges [29]. For example, [30] considers empirically linking surface roughness and the power law wind shear coefficient to turbulence manifestation and presents a description of TI within the lower portion of atmospheric boundary layer, again, based on surface roughness, and concluding that the (kinetic) energy available at the turbine hub height can vary by as much as 20% depending on the level of TI present at a site. The effect of turbulence intensity on the wind turbine power curve is summarised in Figure 6 [31], [32] and [33]. High TI contributes to increased output power from a turbine at moderate wind speeds (cut-in), whereas low TI results in reduced output power at rated wind speed.

The evaluation of TI relies on the standard deviation. Therefore, an asymptotic characteristic is derived at relatively
low wind speeds (< 3.5m/s). Micro/small wind turbines are designed to commence generating at such wind speeds and in urban environments, mean wind speeds are characteristically low. Thus there is a lack of confidence in the quantification of TI in these environments. Wind speeds below the cut-in speed of a turbine are normally regarded as being non productive; however, this is not the case. In order to have an average wind speed that equals the cut-in speed of say 3.5m/s some values must be above and below 3.5m/s over a 10 minute window so that the mean is 3.5m/s. The question is how erratic is this deviation from the mean and can it be power productive?

Another issue concerning the evaluation of the TI is the qualitative nature of its definition. Given the theoretical model presented in this paper, in the following section we propose a method for evaluating the turbulence intensity based computing the Fractal Dimension of a time series of two-dimensional velocity data. This approach implies that turbulence (as measured by a statistic computed from a wind velocity field) is a self-affine phenomenon and we refer to this metric as the Fractal Turbulence Intensity. In turn, this metric is related to the Lévy Index used to characterise rural and urban environments via equation (13) which provides a ‘link’ between the approach discussed in Section V and that of the following section given the stochastic model developed in Section IV.

VII. FRACTAL TURBULENCE INTENSITY

Observations are made at two urban locations in Dublin, Ireland. St. Pius X National (Girls) School (Site 1), located in Terenure, Dublin 6W (53°20′15.96″N, 6°18′19.02″W) and Dublin City Council Buildings (Site 2), in Marrowbone Lane, located in Dublin 8 (53°20′15.96″N, 6°17′10.27″W) as shown in Figure 7. Site 2 is located closer to the city centre than Site 1 and is therefore more urbanised with a higher associated roughness length. This Site is also characterised by a higher building density in comparison to Site 1 which has a much lower concentration of buildings. As site 2 is closer to the city centre, the buildings consist mostly of office blocks and high-rise residential building. Buildings in the area often reach heights of 20 m and beyond, with some reaching 25 m with topographical complexities located at all angles relative to the anemometer used to record the wind velocity data. Site 1 has a more consistent building morphology and the anemometer is surrounded by a relatively lower average building height that consists mostly of two-storey residential buildings and vegetation which is also at similar heights - see Figure 7.

At both sites, high-resolution wind speed measurements are taken with a Campbell Scientific CSA3 three-dimensional sonic anemometer [34]. The observations are at 10Hz at an associated resolution-between 0.5 and 1.0 mm/s, with data that includes date and time-stamp, wind-speed, wind-direction and standard deviation. The CSA3 measures wind speed employing a right handed orthogonal coordinate system Three orthogonal wind components, which relate to the three dimensions in space, are each measured. Wind entering straight into the anemometer is from the x-direction giving wind velocity component \( v_x \); wind approaching from the left of the anemometer is from the y-direction giving wind velocity component \( v_y \); and, wind advancing upwards from the ground...
is from the $z$-direction generating wind velocity component $v_z$. Thus, effectively, the Easterly, Northerly and vertical components of the wind velocity are $v_x, v_y$ and $v_z$, respectively, giving a wind velocity vector field $\mathbf{v} = (v_x, v_y, v_z)$. Measurements of this field are taken to an accuracy of 0.01 m/s at a frequency of 10 Hz over a 40 day period from 4/4/2012 to 15/5/2012. Although, on a theoretical basis the Fractal Dimension of any signal is scale invariant so that the sample rate should not matter, in practice, because the computation of the Fractal Dimension uses a Power Spectral Density Function (as discussed in Section V), high data rates in a given sample subset are required to obtain reasonable accuracy. Since turbulence models in general are based on a 10 minute sampling period benchmark, this period is used to compute the Fractal Dimension on a moving window basis, each window consisting of 6000 samples (10 minutes at 10Hz).

The field used to compute the Fractal Dimension from the three-dimensional data available is given by the following model:

$$u(t) = \sqrt{v_x(t) + v_y(t)}$$

This provides a measure of the ‘polar wind speed’ in the horizontal plane which is taken to be the mid $(x, y)$-plane of the three-dimensional data field. Application of a combined wind speed model of this type is significant in the sense that, from a physical viewpoint, a turbulence effect is not compounded in a single wind speed direction, any measure of turbulence ultimately having to rely on some multi-dimensional mapping of a fully three-dimensional physical effect. Computation of the longitudinal TI at low wind speeds can have excessive values. This is due to the asymptotic nature of the formula which makes the TI measurement in urban areas particularly problematic with the standard turbulence model. Firstly, it is generally accepted that the standard deviation of wind speeds in an urban area is large due to an increased turbulence. Secondly, the average wind speed is considerably lower than that of laminar air flows due to the increased surface roughness. The net result is that the TI becomes asymptotically large as the mean wind speed approaches zero. To compensate for this effect is impossible to filter the data by truncating all values of the TI that exceed 1. Using this approach to filter the TI and the data processing method discussed in Section V to compute the Fractal Dimension (and as detailed further in [10]), Figure 9 compares the TI with the Fractal Dimension, normalisation of the data with respect to null entries resulting in the use of 4502 samples.

These results clearly show that there is correlation between the TI the Fractal Dimension of the horizontal polar wind speed, although it is noted that the Fractal Dimension which, for a Random Scaling Fractal Signal, is a value $D \in [1, 2]$, exceeds the upper bound in an analogous way to when $TI > 1$. Figure 10 shows a scatter-plot of the filtered TI denoted by $TI_f$ and the Fractal Dimension and application of linear regression clearly shows that these metrics are correlated, a correlation that, for this the data considered, is compounded in the equation

$$TI_f = 0.1928D + 0.1385$$

Fig. 9. The (filtered) Longitudinal Turbulence Intensity (Red) calculated in accordance with IEC 61400-2 and the Fractal Dimension of the horizontal polar wind speed (Blue).

Fig. 10. Scatter-plot (Blue) of the (filtered) Turbulence Intensity (vertical axis) and the Fractal Dimension (horizontal axis) together with a best fit linear regressed estimate (Red) showing a linear correlation between the two metrics.

VIII. CONCLUSION

It is well known that the differences in wind resource in rural and urban environments are curtailed due to the influencing factors such as surface roughness. The aim of this paper has been twofold: (i) to quantify the differences through determination of the Lévy index; (ii) to investigate use of the Fractal Dimension as a measure of the Turbulence Intensity. In the first case, a direct comparison is considered between the urban and rural wind resources at selected locations across Ireland and the UK using similar reference heights and fully calibrated equipment so that there is data consistency within the bounds of the practical constraints associated with the technology used to measure the wind velocities. The results confirm that a rural resource is generally of a higher energy yield when compared to the urban resource at least in terms of the Lévy index as computed from the Power Spectrum. This is compounded in lower values of the Lévy index and, as a first study, paves the way for using this non-Gaussian statistical index to evaluate wind resource in general. With regard to the second principal contribution, the fact that conventional turbulence models cannot cater for erratic low mean wind speeds associated with an urban environment requires quantification of alternatives to be considered as given in Section VI.

The approach reported in Section VI is an alternative way of computing a Turbulence Intensity that has two advantages. First, it is based on a more fundamental concept of turbulence in terms of the model provided in Section IV and a fractal geometric interpretation thereby providing a
greater conceptual understanding of turbulence compared the heuristic conventional definition of the TI; second, the problem associated with asymptotic behaviour, which is characteristic of the conventional definition of the TI, and occurs at relatively low wind speeds, is eradicated. Moreover, it is noted that the Fractal Dimension of the polar wind speed and the filtered TI are correlated thereby providing evidence that the conventional qualitative and quantitative measure of wind turbulence proposed have an underlying connectivity.

The model, methodology and results reported in this paper now require a quantification procedure to be developed in order to assess and predict the power performance of wind turbines in rural environments and the degradation of this performance in urban environments. This is predicated on the basis, that, with respect to turbulence assessment, the significant reduction in processing overheads associated with computing the Fractal Dimension implies a more efficient means of quantification as well as a conceptual qualification of the model used (at least in terms of the Fractal Geometry of Nature [35] and methods of processing two- and three-dimensional data under a fractal based model [21]). For example, in [10] and [13], the following scaling law is proposed for the mean turbine power output \( \langle \log P \rangle_\tau \) (over a period of time \( \tau \)):

\[
\langle \log P \rangle_\tau \propto \frac{1}{\gamma}
\]

where \( \gamma \) is computed from the wind velocity over the same time period. Quantification of this scaling relationship is now required based on known turbine output power and wind velocity measurements. Finally with regard to urban environments in particular, it may be possible to find a correlation between the Fractal Dimension of the polar wind velocity and the roughness of the local area from a high resolution satellite image of the type given in Figure 8. By computing fractal parameters such as the Image Dimension (Fractal Dimension of a surface), the Information Dimension, Lacunarity and other Multi-Fractal parameters [21], for example, it may be possible to generate a single or combined image roughness measure. A correlation of this measure with the Fractal Turbulence Intensity reported could provide a way of estimating the wind turbulence and hence, subject to quantifying the inverse scaling relationship given above, predict the power performance of wind turbines in a rural environment from an satellite image alone! Such a solution would provide a simple and effective way of prospecting for wind resources in urban environments using on-line facilities such as Google Earth, for example.

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REFERENCES

Jonathan Blackledge holds a PhD in Theoretical Physics from London University and a PhD in Mathematical Information Technology from the University of Jyvaskyla. He has published over 200 scientific and engineering research papers including 14 books, has filed 15 patents and has been supervisor to over 200 MSc/MPhil and PhD research graduates. He is the Science Foundation Ireland Stokes Professor at Dublin Institute of Technology where he is also an Honorary Professor and Distinguished Professor at Warsaw University of Technology. He holds Fellowships with leading Institutes and Societies in the UK and Ireland including the Institute of Physics, the Institute of Mathematics and its Applications, the Institution of Engineering and Technology, the British Computer Society, the Royal Statistical Society and Engineers Ireland.

Eugene Coyle is Head of Research Innovation and Partnerships at the Dublin Institute of Technology. His research spans the fields of control systems and electrical engineering, renewable energy, digital signal processing and ICT, and engineering education and has published in excess of 120 peer reviewed and conference journal papers in addition to a number of book chapters. He is a Fellow of the Institution of Engineering and Technology, Engineers Ireland, the Energy Institute and the Chartered Institute of Building Services Engineers, was nominated to chair the Institution of Engineering and Technology (IET) Irish branch committee for 2009/10 and a member, by invitation, of the Engineering Advisory Committee to the Frontiers Engineering and Science Directorate of Science Foundation Ireland, SFI.

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Keith Sunderland is an electrical engineering graduate of Dublin Institute of Technology (DIT) with a first class honours degree in Electrical/Electronic Engineering. He is a member of the (DIT) Power Research Group as well as the Dublin Energy Lab and his research focuses on the applications of micro wind generation. More specifically, his interests are with respect to urban wind profiling and (distribution) network tolerance to increased technology proliferation and his PhD research is in collaboration with the School of Geography, Planning & Environmental Policy at University College Dublin (UCD). He is the DIT member of the Dublin Urban Boundary Layer Experiment (DUBLex), which is a cross institution collaboration (DIT, National University of Ireland, Maynooth and UCD) investigating urban climatology with respect to energy budgets, CO₂ fluxes and energy applications. He is currently the Assistant Head of Department, Electrical Services Engineering within the School of Electrical Engineering Systems (at DIT).

Thomas Woolmington joined the lecturing staff of Dublin Institute of Technology of the Electrical Services Department in September 2006 and has qualifications in the electrical services and education areas including a national craft certificate (Electrician), a BSc in Electrical Services Engineering and Energy Management and a Postgraduate Certificate in Third Level Teaching and Learning. In April 2009 he co-authored a paper with other members of the Solar Energy Society of Ireland (SESIE) on The Uptake of Micro-gen Training on Third Level Courses Between Ireland and Wales presented at the PV-SAT5 Conference held in Glyndwr University, Wales. In October 2009 he secured funding from Enterprise Ireland to undertake a feasibility study into photometric testing of LED luminaries using proprietary instruments and in April 2011 he registered on a PhD research programme at Dublin Institute of Technology which is concerned with the statistically self-affine modelling of turbulence on the power performance of wind turbines.