Enhancing the Effectiveness of Wind Power Source Assessment

By

Darcy Shane Kavanagh

A Thesis Submitted to

Saint Mary's University, Halifax, Nova Scotia

in Partial Fulfillment of the Requirements for

the B.Sc. Honours Degree of Environmental Science.

April 2018, Halifax, Nova Scotia

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Abstract

With a growing demand for energy, and a desire to reduce anthropogenic climate change, the use of renewable energy sources is becoming increasingly popular. A major source of renewable energy that is readily available is wind energy. Unfortunately, however, the variability of the wind speed is a major factor inhibiting the growth of the industry. Using a multiscale method known as detrended fluctuation analysis, wind speed data from Corvallis, Montana, and Boutiliers Point, Nova Scotia, was analyzed. From this project, a new tool was developed, which involves a new way of characterizing wind patterns: the wind speed consistency index (w). This index shows the extent to which high wind speed values correspond to high persistency, and responds specifically to the need of having a measure of the relationship of wind speed and its consistency.

April 19^{th}, 2018

1. Turning to the Wind

As the human population continues to grow, so too does its need for energy. With limits on our current main sources of energy (e.g. fossil fuels), a sustainable supply will only be possible from renewable energies. Wind energy is a renewable form of energy, and in spite of considerable regional differences, it is available nearly all over the world. Furthermore, the global planetary energy cycle appears to be undisturbed by energy production of the wind, allowing wind power to be considered a sustainable form of renewable energy (Emeis, 2013).

1.1. Wind as a resource

It has been projected that on a global scale, the wind embodies 1700 terawatts (TW) of power. Taking into account unattainable locations such as over mountains and in protected areas, we are left with around 40 to 85 TW of attainable energy (Jacobson & Delucchi, 2009). However, in 2015 the total world consumption of energy was just 17.4 TW, meaning the world could have all of the energy it needs, plus more, just from wind (Seger, 2016). Unfortunately, however, the world is still lacking in the field of wind energy. In 2017 the world had a global installed wind power capacity of just 0.54 TW, a mere fraction of the above listed potential (Fried, 2018).

However, by switching to more renewable energy sources, it may be possible to actually lower our global power demand. This is because, typically, electrification is a more efficient way to use energy (subject to the efficiency of the source generating the energy). For example, to move a vehicle, only 17 to 25 percent of the energy within gasoline is used. The remainder is lost, or wasted, as heat. With an electric car, however, 75 to 86 percent of the electricity is used, making the transportation much more efficient (Jacobson & Delucchi, 2009).

Apart from being a substantial source of energy, the use of wind aids in the process of reducing anthropogenic climate change. This is because the generation of electricity from wind requires no fuel other than the wind, and does not produce pollution or greenhouse gases. Using the U.S. as a point of reference, in 2016, 226 million megawatt-hours (MWh) of wind energy was generated, avoiding an estimated 159 million metric tons of CO_2, the equivalent emissions of 33.7 million cars (American Wind Energy Association, 2017).

Another notable feature of wind energy is its being domestically sourced. A nation’s wind supply is abundant and virtually inexhaustible. Even in areas of lower wind speeds, technological advancements have made harnessing wind energy possible. This gives nations the opportunity to harness energy for themselves, instead of having to obtain energy via trade. This energy independence can help to stabilize the cost of electricity, while helping to reduce a nation’s vulnerability to fluctuations in energy prices, and disruptions to supply.

1.2. Wind infrastructure and resource use

When making the switch towards a more renewable-heavy energy mix, it is important to develop infrastructure that will be as reliable, if not more, than the existing infrastructure used to harness energy from non-renewable sources. With a lack of development in the energy storage field, the infrastructure must be dependable, especially during peak hours. Using the U.S. as a reference, the average coal plant is offline 12.5% of the year, for scheduled and unscheduled maintenance. Being a more autonomous system, the modern wind turbine, however, is offline less than 2% on land, and less than 5% at sea (Jacobson & Delucchi, 2009). Furthermore, with wind turbines being individual systems, the downtime of one does not affect the performance of another, and only affects a small portion of the total production as a whole. The downtime of a coal, nuclear, or natural gas plant, however, causes a much larger portion of production to be lost.

A common misconception about wind energy is its dependency on rare earth elements, such as neodymium, for efficient energy production. These rare earth elements have been used in the past to create permanent magnet generators due to their small size and high efficiency at all wind speeds. People often interpret this assumed dependency as a burden for multiple reasons. One reason is the geographic location of the world's low-cost sources of rare earth elements. China is currently the leading exporter of rare earth elements, which leads people to believe the shift to wind energy will result in a shift of dependence on Middle Eastern oil, to a dependence on Far Eastern metals (Jacobson & Delucchi, 2009). Another reason people see this as a burden is the extensive environmental strain that results from the extraction of rare earth elements. However, being the second largest producer of wind power, with around 52,000 commercial wind turbines as of June 2017, the U.S. wind industry uses a negligible amount of rare earth elements (EVWind, 2017). In fact, as of May 2017, only about 2% of the wind turbines in the U.S. used rare earth elements. Furthermore, those who have used them in the past were working diligently to switch to more conventional permanent magnets made of copper and steel, in order to reduce their usage (Alvarez, 2017).

A significant benefit of wind energy that is often overlooked is the fact that it does not require water. Water has many roles in the power sector, most notably electricity generation and fuel extraction and production. In the U.S., around 65% of the electricity produced comes from coal, natural gas, and nuclear fed thermal power plants (Union of Concerned Scientists, 2017). These thermal plants use water for steam, as well as for cooling. To put this into perspective, in the U.S., it is estimated that the power sector uses 22 to 62 trillion gallons annually. This means the power sector uses more water than any other sector, including agriculture (American Wind Energy Association, 2017). This vast amount of water usage impacts water quality and water security, both of which are becoming major global issues. In fact, reports estimate that by as soon as 2050 the world’s population will face severe water stress, stemming from a growing population, an increase in water demand, and an increase in water usage (The Organization for Economic Co-operation and Development, 2013). This stress can be reduced, however, by shifting towards more water-conscious energy production, such as that of wind energy.

Along with a lack of water usage, wind energy requires fairly little land to produce energy as well. In fact, together an entire wind farm including towers, substation, and access roads uses only about 5% of its allotted land (Canadian Wind Energy Association, 2018). Furthermore, many of the activities that took place on the land before the wind farm was built can continue undisturbed after construction is completed. For example, livestock can graze around the turbines, and crops can be planted right up to the base.

1.3. The cost of wind power

However much we may wish that the environmental impact be the main focus when developing energy, the economics associated will always take priority. There is a vast misconception that renewable energy sources are much more expensive, which acts as a deterrent for some people. The truth is, however, wind energy ranks as one of the lowest-cost options for new electricity generation. In the U.S., wind energy is, in fact, the lowest-cost option of any new supply, without any subsidies (Canadian Wind Energy Association, 2017). These prices are projected to fall even further as technology continues to advance, and improvements continue to be made. Furthermore, with the possibility of new regulations and policies coming into play, such as a carbon tax, along with the factoring in of externality costs based on the damage done to the environment and human health, wind energy becomes even more cost-competitive.

Another beneficial factor of wind energy is its cost dependability. Traditional energy sources, such as fossil fuels, are subject to price volatility, as resource prices rise and drop. However, as wind is a renewable energy source, the fuel that turns the turbine blades is free. What this means is that once a wind farm has been constructed, the price of the electricity it produces is set, and the price associated with the energy resource per se is not expected to change for a long time. This long-term cost-certainty provides protection and comfort for consumers (Canadian Wind Energy Association, 2017).

The process of electricity production, as well as the infrastructure needed to transport it, is subject to change based on the geographic area. As a result, the prices of electricity change depending on geographic area as well. In Canada, the province of Quebec has an average residential electricity price of 8.31 cents/kWh (Natural Resources Canada, 2018). However, in their most recent request for wind proposals, Hydro-Quebec was awarded contracts that set a new average low price for wind energy at 6.3 cents/kWh (Canadian Wind Energy Association, 2017). Furthermore, the overall construction and transmission costs of wind energy can be seen as an investment that is paid back through the sale of electricity and energy (Jacobson & Delucchi, 2009).

1.4. Health effects

There is some controversy surrounding the use of wind energy. One of the reasons people protest its implementation is due to reports of changes in overall health from those who live in the general vicinity of the windfarm. The article “Changes in quality of life and perceptions of general health before and after operation of wind turbines”, published in June 2016, offers a fairly recent view into this subject area, and provides a well-researched comparison of both the quality of life and general health of individuals from before and after the presence of wind turbines (Jalali, 2016).

For the study, data was collected in Ontario, Canada, using a sample size of 43 individuals. Ontario is currently the Canadian leader in wind energy, housing 2023 turbines at the time of the study. Using standard scales, such as the Canadian Community Health Survey, the general health and quality of life were calculated for each individual. Upon being in the repeated presence of wind turbines, there was a much more dramatic decline in the mental component score for those residents who had a negative view towards wind turbines, compared to those who did not. This view varied in terms of how they felt, their concerns for the possibility of the turbines decreasing the value of their property, and their overall impression on the aesthetic factor of the turbines.

Health related complaints from those living near wind turbines ranged from headaches and nausea, to sleep disturbances and a lack of concentration. Studies done prior to this article have shown that a complex mixture of personal factors and noise is what gives rise to a majority of the health effects, instead of solely noise. The studies concluded that, along with the noise, multiple subjective variables relate to heath complaints, ranging from nocebo responses to personality characteristics. Previous studies, however, have lacked documentation of the health status of individuals prior to their exposure to wind turbines. This study, however, uses a pre and post data design to examine the effects of individual factors and annoyance in the connection between general health and wind turbine exposure.

The distance one lives in relation to a wind turbine also has an impact on documented health effects. A study conducted by Nissenbaum (2012) showed that those living within 1.4 km of two wind turbine installations suffered from disturbed sleep, and impaired mental health. A possible factor causing these health effects is a low frequency given off by the turbines, known as infrasound. In the field of wind energy, infrasound is caused by the interaction between wind turbulence and the turbine blades, and measures between 1 and 20 Hz (Bolin et al., 2011). This infrasound is not audible at close range, and even less so the farther away one gets from the turbine.

Despite infrasound being below the threshold of hearing, some say it can be felt by the human body. This is because the body produces infrasound itself (i.e. the heartbeat), so some argue that the interaction between this external infrasound and the body can lead to health effects in the form of 'vibroacoustic disease', or 'wind turbine syndrome' (Bolin et al., 2011). However, there is a lack of empirical evidence in this field, other than the fact that reported health effects decrease with distance from wind turbines. Furthermore, multiple studies have suggested that >2km is what they would consider a safe distance for residency near a wind farm (Hanning, 2012).

1.5. Uncertainty

The uncertainty involved in wind energy is one of the decisive factors affecting the implementation of wind power. Due to the nature of wind, there is no constant flow of energy, as there is no certain flow of the wind. As a result of this uncertainty, the amount of energy produced can fall below the amount of energy invested, resulting in wind energy self-cannibalizing its own revenue stream (Hansen, 2017). It is for this reason that it is crucial to take wind variability into consideration when studying wind energy, so to gain more certainty in regard to wind energy production.

The best thing we can do to address wind speed uncertainty is by characterizing it in a useful way. Fortunately, this is a topic of increasing popularity, and wind variability research is being conducted all around the world. Studies are being done on both short-term and long-term fluctuations in wind power, seasonal patterns, coastal versus inland patterns, and the effects of spatial diversity, to name a few. However, to further complicate things, wind uncertainty varies on a wide range of time scales. This is why it is important to study wind variability with respect to these multiple time scales as well, so to better understand the way the wind works, temporally, and if it will work financially.

The objective of this project is to enhance the power of time scale-dependent evaluation and categorization of wind speed variability, in order to support science-based decision making. Essentially, the goal is to establish a relationship between wind speed and its consistency. This will be attempted by using linear regression and detrended fluctuation analysis (DFA), to determine the relationship between mean wind speed and a number (the Hurst exponent H) that characterizes the wind speed variability on a range of scales. To this end, we calculate the slope of the best fit line created when plotting the mean wind speed (M) against its consistency (H). The resulting slope will give the wind speed consistency index (w), yielding a reliable relationship between wind speed and its persistence.

2. Characterizing the Wind on Various Temporal Scales

Though wind can be highly stochastic, it can also be somewhat predictable. The level of predictability, however, depends on our understanding of how the wind works. The amount of energy we are able to harvest from the wind is also based on our understanding of the wind. Currently, it is perceived that short-term fluctuations (fluctuations from one hour to the next) in wind power is a stochastic process that bears a very narrow range of standard deviation values around its respective mean. Long-term fluctuations (from one month or more) have distinctive patterns associated with them which vary seasonally and yearly (Wan, 2012). It is important to note that these fluctuations are location-sensitive and may change depending on the geographical location at which the measurements were recorded.

2.1. Long-term variations

From one year to the next, the wind power generated by a single wind power plant can be quite variable. In a technical report produced by Wan (2012), output data from four wind power plants located in the USA was analyzed and checked for trends in the variability. On an inter-annual scale, Wan normalized the annual production values at each site with their respective production capacity, and compared them across time frames. His results suggested significant variation in inter-annual wind energy production at each of the individual power plants. From this information, he also concluded that there were no common features or pattern between the sites, on an annual level (Wan, 2012). What was also curious was the fact that each plant had large differences between their highest production year and their lowest production year, with one plant producing 47% more energy in its highest production year than in its lowest production year.

Klink (2015) conducted research regarding the ‘fastest 2-min winds’ recorded at land-based coastal automated weather stations in the United States of America. The fastest 2-min wind speeds were calculated, based on data collected from automated surface observing systems (ASOS) located along the Atlantic Coast, the Pacific Coast, and the Gulf of Mexico, and maintained by the U.S. National Weather Service (Klink, 2015). She found that there were seasonal trends in the fastest winds, and synoptic-scale forcing as well. During the winter months, along the Atlantic Coast, there is a correlation between the occurrence of extratropical cyclone activity, and the fastest 2-min winds. During the summer months, however, the fastest 2-min winds occur on days with thunderstorms. From this, Klink concluded that in addition to more obvious sources such as strong winds and large-scale tropical storms, more localized features, such as thunderstorms, are also important contributors to fast winds. This finding points to the need for more research, since Vose et al. (2014) show that along the Pacific coast an increase in cold-season extratropical activity is not associated with an enhanced pattern of the fastest 2-min winds.

When looking at a time scale of months, patterns in variability become much more clear than on a time scale of years. Within a year, a wind power plant generally has high production months and low production months. These differences often correlate with seasons, and are driven by the geographic location of the plant. Wan (2012) observed that the average wind production during the spring and winter months maintained a level of consistency throughout the years. The summer months, however, had an average wind production level that was only about 64% of that of the winter months. The summer months generally had smaller differences between the highest and lowest level of production. They were more consistent, despite the lower average wind speeds.

Upon comparing the results of Wan (2012) and Klink (2015), one can see that the presence of the fastest 2-min winds during the winter months for stations located at the Pacific, western Gulf, and northern Atlantic coasts correlate with the higher production variations and higher average wind production at wind power plants in these same areas. This may be because the fastest 2-min winds of the winter months make the production levels higher than average. This results in higher production variations, as well as higher overall average wind production during this time.

2.2. Short-term variations

Short-term variations in wind speed and, consequently, wind power output is usually measured on a scale of minutes, hours, and days. From an industry point of view, a daily forecast of hourly winds is useful for deciding load scheduling strategies, and a weekly forecast of day-to-day winds makes for efficient scheduling of maintenance (Zhou et al., 2011). The short-term wind variability for the four central-US wind power plants was gauged by comparing the coefficient of variation (COV) of the wind power output at each plant (Wan, 2012). The COV is a measurement denoted by the ratio of the standard deviation to the mean (average). For the usage of wind speeds, the resulting COV is known as the turbulence intensity, which is driven by the surface roughness of the ground and the stability of the atmosphere. Wan (2012) found that higher COV values of a particular year generally correlated with low energy production. Because the lower energy production implies lower mean wind speeds, it was concluded the year generally had higher wind speed variability (Wan, 2012).

Wan (2012) also examined short-term fluctuations in the wind power output at the four plants using the statistics of step changes. A step change is known as wind power level differences recorded by successive measurements, using the hourly average power outputs at each of the wind power plants. The respective standard deviations were calculated, yielding the step changes and their standard deviations for each month, as well as the entire year. The results showed that there was no year-to-year variability in electricity production caused by the observed short-term wind fluctuations (Wan, 2012).

On a diurnal scale, there can be times when wind energy production is high, and times when it is low. According to Wan, average wind power dips during the early evening hours (6:00pm to 7:00pm). The early evening low is more prominent the further south the wind power plant is located, especially in the summer months (Wan, 2012).

2.3. Factors affecting wind speed

Wind power has been harnessed for thousands of years, from propelling ships by sails to grinding grain. The first ever turbine constructed to produce electricity was created in 1891, by a Danish man named Poul la Cour (Masters, 2004). Since then, the wind generation of electricity has witnessed both success and downfall, but with the world beginning to shift its vision towards more renewable sources of energy, the popularity of wind energy is on the rise.

Apart from it being highly variable, the speed of the wind can increase or decrease depending on numerous location-dependent factors. These include the rotation of the earth, differential solar heating of both land and sea masses, large-scale pressure differences and Coriolis forces. In addition the pattern of the wind is driven by the shape of the underlying terrain. A terrain that is rougher (i.e. a forest, a city, etc.) will result in an increase in turbulence and a decrease in mean wind speeds, because the structures will create aerodynamic drag (Deaves & Lines, 1998). Turbulence can also be created through vertical advection within a stable or unstable atmosphere (Wan, 2012).

The regional weather pattern and overall climate of an area are integral factors in the production of wind and wind-power outputs. Winds are driven by pressure gradients, and the strongest winds result from the strongest gradients. There is also a strong correlation between strong gradients and tropical and extratropical cyclones (Klink, 2015). Therefore, by studying an area's history in terms of large synoptic-scale weather events, it may be possible to facilitate industry-related decision making. Climate change can alter large-scale dynamics which, as a result, impact the radiation balance and wind patterns. It will also affect synoptic and regional weather patterns, which could then cause alterations in wind speed and variability (Greene et al., 2010). It is for this reason that it is important to take climate change scenarios into consideration when planning wind farms.

One way to address the unpredictable variability of wind speed is by maximizing the spatial diversity of a wind farm, through a process known as geographic smoothing. Through this process, the correlation of wind speeds – and wind power generation – begins to diminish as the geographic distance between the measurements increases (Shahriari & Blumsack, 2017). Using this knowledge, Santos-Alamillos et al.(2014) hypothesized that by interconnecting advantageously-distributed wind farms based on a proven computer-generated spatial balancing pattern, it may be possible to guarantee a certain level of wind power output at all times (Santos-Alamillos et al., 2014). To test their hypothesis, they used principal component analysis (PCA) on wind energy resources to analyze spatiotemporal balancing. They were able to target the optimal wind farm location to reduce fluctuations in wind power. Their results showed the possibility for a considerable reduction in wind power fluctuations by organizing wind farms so as to take advantage of the balancing pattern derived from the PCA. They concluded that a firm output capacity could be obtained, though the numbers were highly dependent on the season, and which sites were interconnected. They further interconnected randomly-located wind farms, and the output was far less than those of plants that were connected by the spatial balancing pattern. Another study done by Gunturu & Schlosser (2015) showed that aggregating generating units within a smaller area only yields benefits up to a certain number of units is deployed, and then runs an increased risk of temporal correlation.

2.4. Conclusion

From synthesizing various bodies of work relating to wind speed variability, I gained a better understanding of the different temporal scales that can be used to analyze wind speed and wind power output, and how variable the results within each scale can be. A product of the sun, the speed of the wind fluctuates continuously, causing variability in the level of power produced by a wind power plant. In order to make the most efficient use of wind power plants, and harness the highest levels of energy, accurate forecasting of wind variability is critical. Wind speed fluctuations from short-term to long-term can vary greatly depending on the geographic location of the wind power plant. They can be caused by influences such as large synoptic-scale factors, or the presence of a ‘rough’ surface surrounding the turbine. And as stochastic as the wind may be at times, patterns and trends can be identified in its ways. Using the knowledge gained from completing this literature review and a Matlab environment, my project will analyze wind speed records from Boutiliers Point, Nova Scotia, and Corvallis, Montana, and apply a range of wind speed variability evaluation methods. From this, I will have a goal of creating a tool, or set of tools, aimed at effectively addressing questions related to wind power and supporting key goals in the temporal-scale-dependent characterization of wind speed variability.

3. Wind Pattern Analysis

3.1. Objectives

The main goal of the thesis was to find a way to establish the relationship between wind speed and its consistency, in a useful and reliable manner. So, what we propose is to establish the quantitative relation between mean wind speed and persistence. The true issue with uncertainty is that current statistical methods address only the wind speed values, and not their succession in time on multiple time scales.

The importance of the values of wind speed is well-known, and classical statistical methods are capable of accurately characterizing the pattern from this point of view: measures of central tendency (e.g. mode, mean, median, etc.), and measures of dispersion (e.g. variance and statistical moments of higher order). However, the sequence of the values (i.e. their succession in time) is also important in the case of wind speed and the functioning of the wind turbine. This is because the sequence dictates whether or not a turbine will stop (figure 2b), slow (figure 2c), or run smoothly, depending on where various levels of wind speed are located along the timeline, and how they are located in relation to one another. The mean and the other statistical measures mentioned above are not capable of reflecting this succession, they only refer to the actual values, not their order in time. It is for this reason that the temporal succession of the values should be included in the pattern assessment, and thus there is a need for a methodology that characterizes the relationship between wind speed and its consistency.

3.2. Analyzed data sets

When choosing data to use for this project, it was important to find data sources that were very different from each other, but, at the same time, observed at similar sample rates for a similar amount of time. With these criteria in mind, two different data sets were used for the study. The first was collected for the Canadian Wind Energy Atlas near Boutiliers Point, Nova Scotia, 44.67 °N, 63.95 °W. The elevation of the data collection site was 11 m, and datasets were recorded for heights of 80 m and 120 m (http://www.windatlas.ca/index-en.php). The methodology involved in the preparation of the data is described in (Frey-Buness et al., 1995). The second data set used was collected at the AgriMet Weather Station, near Corvallis, Montana, 46.31°N, 114.1°W. The elevation of the data collection site was 1058 m, and datasets were recorded for a height of 10 m (https://www.usbr.gov/pn/agrimet/agrimetmap/covmda.html). The data was prepared by its collectors, and presented in a clean, useful, and free form, hence our reason for using it.

Using Matlab functions according to Suteanu (2012) the data sets were graphed and analyzed as a function of the wind speed values over time. The data sets can be seen for heights of 80 m and 120 m at Boutiliers Point, and 10m at Corvallis, in figures 1 a, b, and c, respectively.

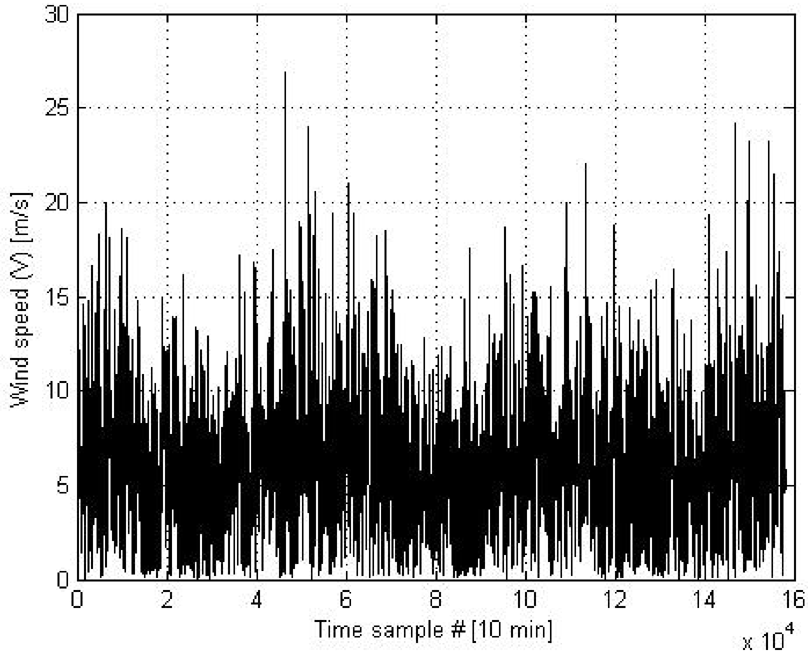

Figure 1a. Graphical representation of the analyzed wind speed time series from Boutiliers Point, Nova Scotia. Height: 80 m. Time interval: December 2007 – October 2011. Sampling rate: 10 minutes.

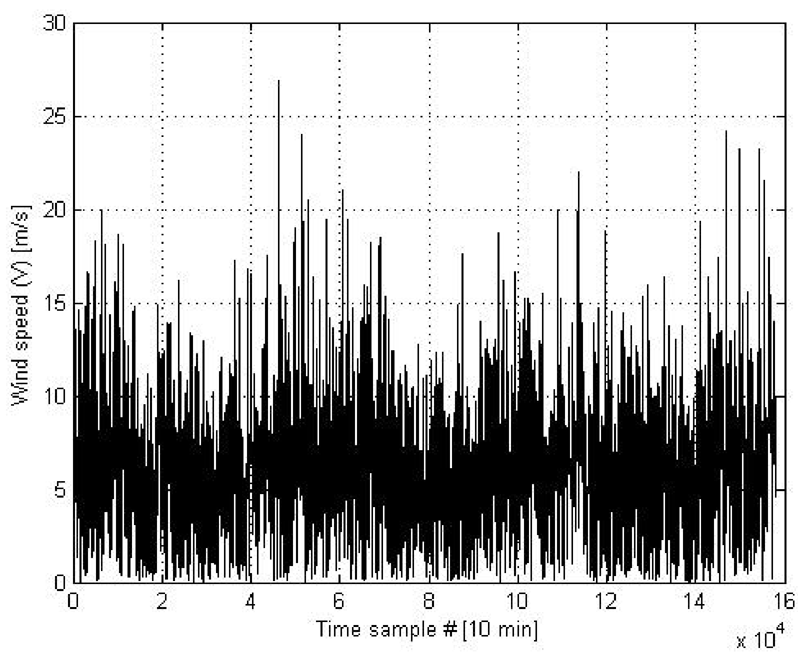

Figure 1b. Graphical representation of the analyzed wind speed time series from Boutiliers Point, Nova Scotia. Height: 120 m. Time interval: December 2007 – October 2011. Sampling rate: 10 minutes.

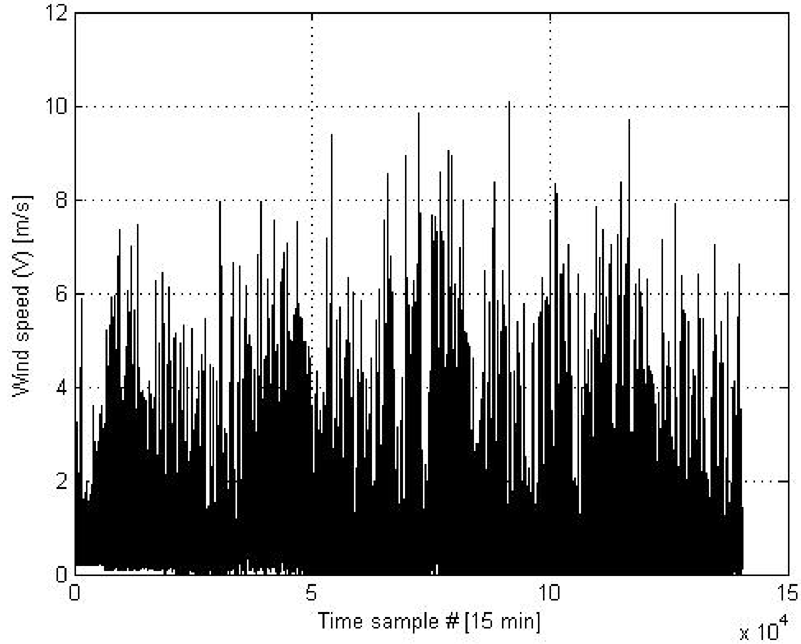

Figure 1c. Graphical representation of the analyzed wind speed time series from Corvallis, Montana. Height: 10 m. Time interval: January 2010 – January 2014. Sampling rate: 15 minutes.

3.3. Assessment of persistence

The variability of wind speed plays a critical role not only in the amount of energy we are able to harness, but also for the efficiency with which it can be harnessed. This variability is not only important in terms of the values themselves, but also in terms of the sequence of the values within a time series. With a minimum and maximum wind speed dictating when a turbine will run, it is of utmost importance to ensure the functioning of a wind turbine is within these bounds as much as possible. No matter where the turbine is placed, there will always be intervals of ‘down time’. However, it is the occurrence of these ‘down times’ on a temporal scale that needs to be paid attention to.

As seen in figure 2a, the same values (thus the same results for the mentioned statistical measures) can be distributed in time in many ways. Furthermore, the way in which the values are distributed in time can lead to very different situations in terms of turbine behaviour. For example, as seen in figure 2b, if many low values are clustered, the turbine may stop. If this is the case, putting it in motion again takes a significant amount of energy - thereby, wind energy that would have otherwise been effectively converted by the turbine will only lead in this situation to the restarting of the turbine, resulting in a very small amount of converted energy being contributed to the overall energy production. If such clusters of low values are dispersed among high values of wind speed, the turbine works inefficiently, since it stops and needs to be restarted - repeatedly.

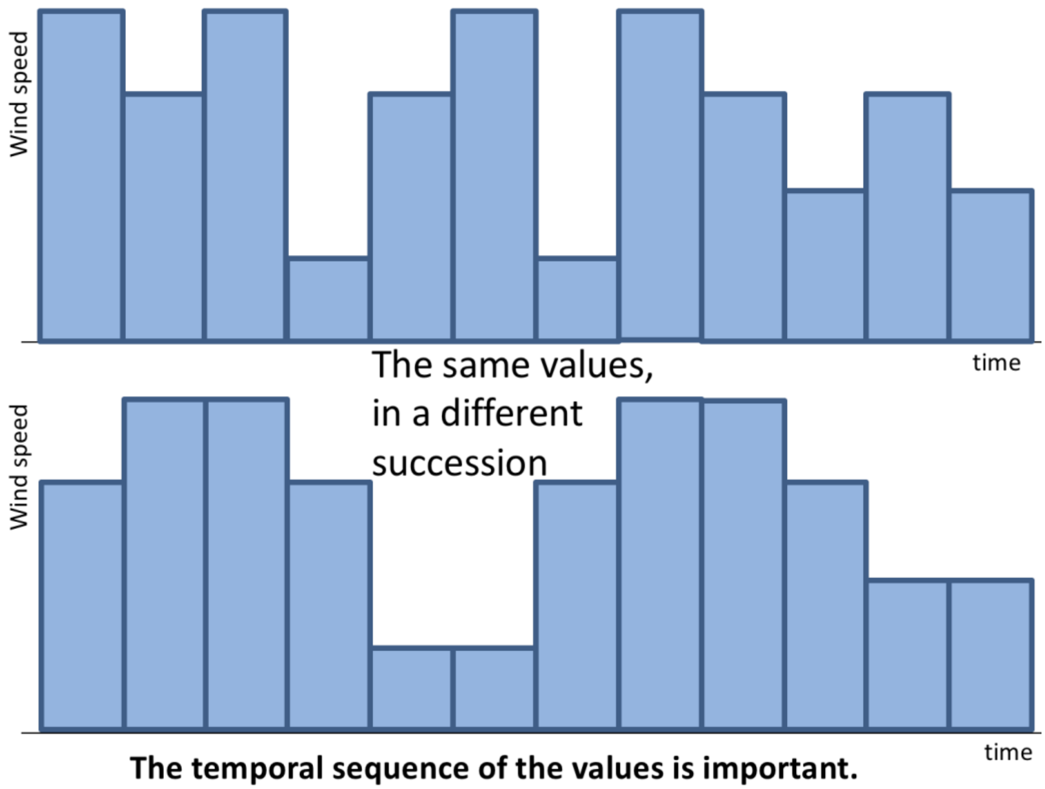

Figure 2a. A diagram illustrating the importance of the temporal sequence of wind speed values.

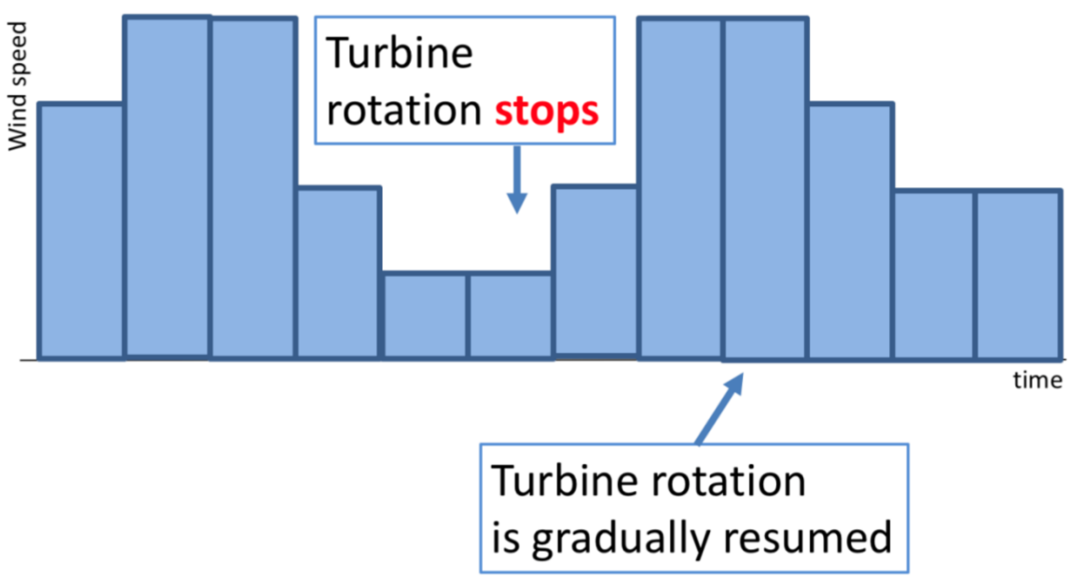

Figure 2b. A diagram illustrating how clusters of low wind speed can cause a turbine to cease rotation.

Alternatively, as seen in figure 2c, if those low values are distributed close to other not-so-low values of wind speed, the turbine might slow down several times, without actually stopping. Furthermore, as seen in figure 2d, if those very low values are even better distributed in time (e.g. individual values or very small groups of values embedded in blocks of high values, with high tendency) the very low values would hardly slow down the turbine. It is these ‘blocks of high values’ - or the persistence of high wind speeds - that we are looking for.

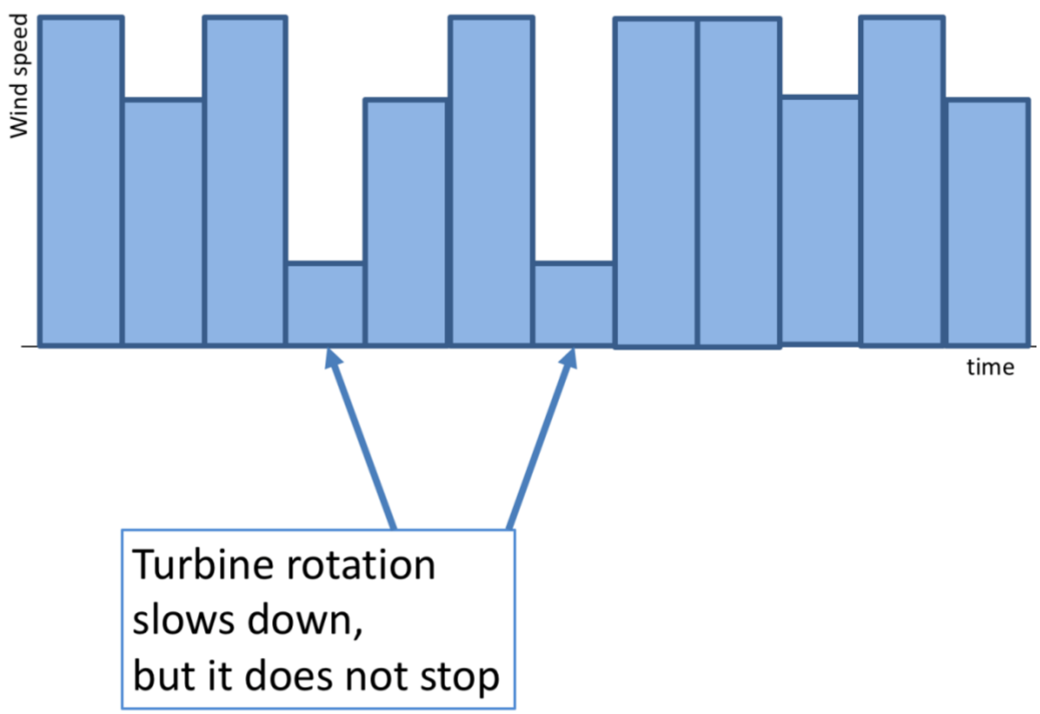

Figure 2c. A diagram showing how the distribution of low wind speeds among higher wind speeds can cause a turbine to slow, but not stop.

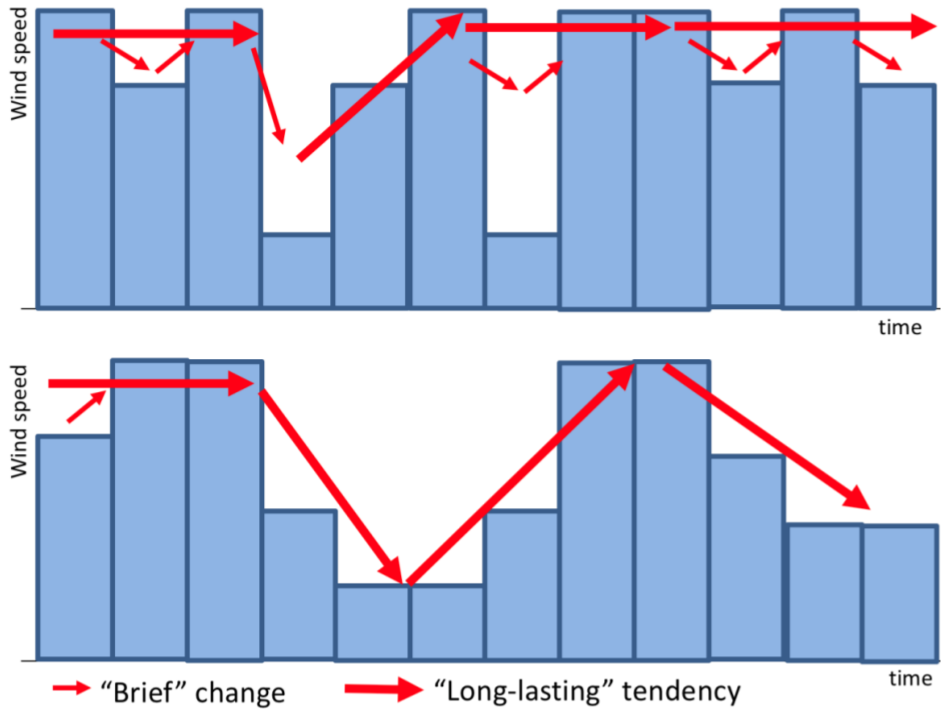

Figure 2d. A diagram showing how the tendency of the wind speed to be high or low is distributed in time can affect the impact which low wind speed values have on a turbine.

To assess the persistence of the wind speed, a method known as detrended fluctuation analysis (DFA) was used (Kantelhardt et al, 2001; Varela et al., 2016; Varotsos et al., 2012). With a goal of analyzing patterns in a multiscale perspective, there were numerous multiscale time series analysis methods that could have been used. From a real-world perspective, however, their accuracy can be an issue. DFA, however, has been proven to have the ability to perform well even in the presence of trends, and effectively identify scaling aspects in time series that reflect natural variability (Suteanu, 2011). Furthermore, DFA provides meaningful information about pattern properties on a wide range of temporal scales, accurately indicating the limits of the scale ranges, as well as the degree of persistence (Suteanu, 2014).

It is important to note that DFA is not a new concept. However, it is the way in which we are using it that is novel. In the past, the method has been used for studies of various observables, such as surface air temperature variability (Suteanu, 2011). In our case, we use DFA to analyze wind speed values on multiple time scales, in order to produce a number that reflects the persistence of wind speed, showing the extent to which wind speed changes erratically over time.

DFA works by choosing a window of a certain size (s) and moving the window of that size along the time series. For each position of the time window, the size of the fluctuation of the time series is determined. The size of the fluctuation is calculated as the mean square difference between the points in the time series and a straight line that is the best fit for that particular window in the time series. After the size of the fluctuation of the time series is determined for each position of the window, the mean size of the fluctuation (F) is calculated.

The procedure is repeated for a range of values for (s), and for each value of (s), a mean size of the fluctuation (F) is found. Once the mean size of the fluctuation (F) is found for each value of (s), the values of (F) versus the values of (s) are then represented in a graph. It is important to note that the range for (s) is chosen based on the fact that when (F) depends on (s) according to a power law, an exponent (H) can be determined, which shows the variability of the time series on the whole analyzed range of scales. For this range, the graph (F) vs (s) represents a straight line in log-log coordinates, as a result of it being derived from a power law.

Once the graph is plotted, the slope of the line of best fit for (F) vs (s) is determined. This slope represents the Hurst exponent (H), as seen in figures 3 and 4. The Hurst exponent (H) for this type of time series takes values between zero and one. It reflects the variability that characterizes the time series on the studied scale range. Higher values of (H) represent higher persistence (i.e. the tendency of the time series to be smoother - to change from increasing to decreasing values more gradually, and more rarely.)

Being recorded for a height of 10 m, the wind from the site in Corvallis, Montana, experiences high turbulence due to surface roughness. As a result, the irregularity in the wind speed is strong, and therefore (H) is usually low. As seen in figure 3c, this evaluation confirms this irregularity, and (H) is indeed lower in this area. The opposite happens at Boutiliers Point, where the data was recorded at greater heights from the ground. This increase in distance from the ground results in a decrease in wind irregularity caused by surface roughness, and therefore results in a higher value for (H), as seen in figures 3a and 3b.

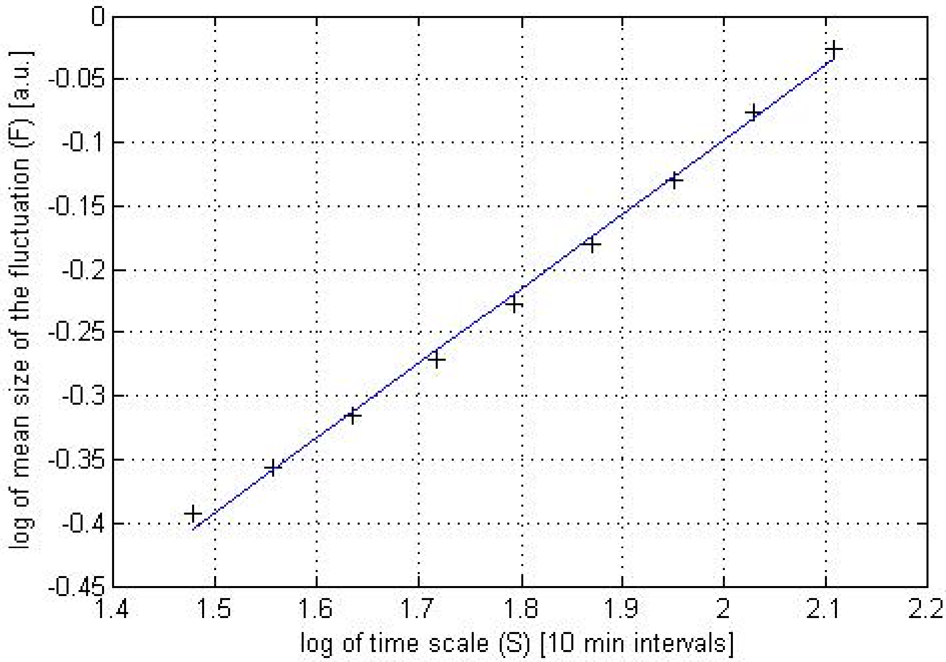

Figure 3a. Establishing the persistence exponent (H) for the analyzed time series from Boutiliers Point. Height: 80 m. Hurst exponent H = 0.59.

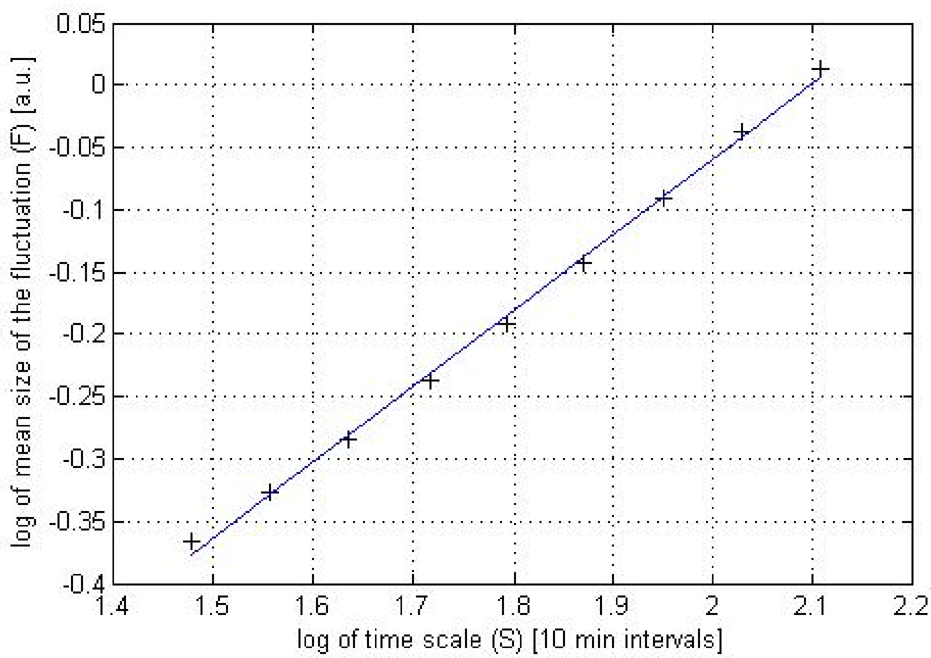

Figure 3b. Establishing the persistence exponent (H) for the analyzed time series from Boutiliers Point. Height: 120 m. Hurst exponent H = 0.61.

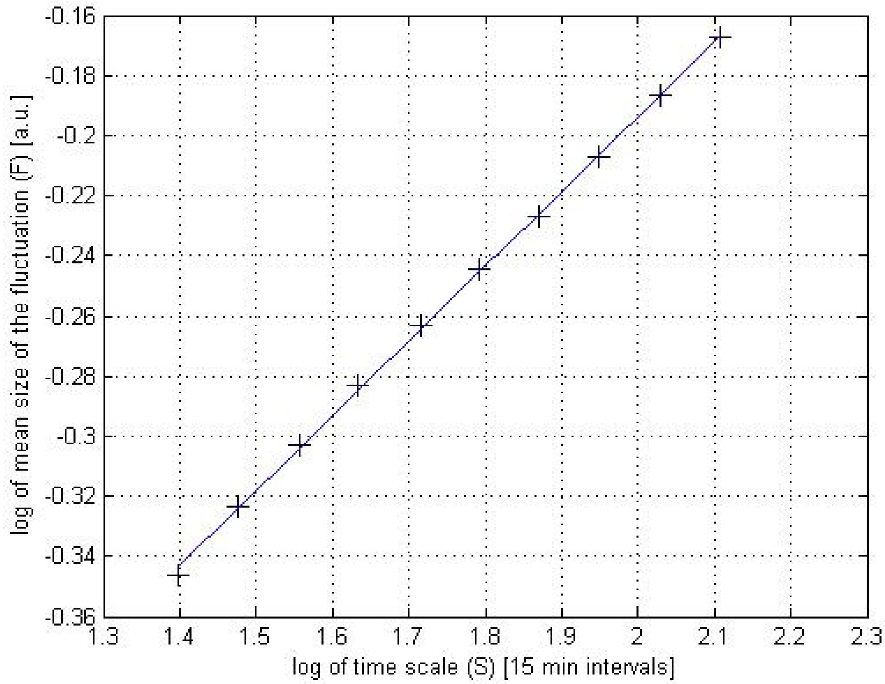

Figure 3c. Establishing the persistence exponent (H) for the analyzed time series from Corvallis. Height: 10 m. Hurst exponent H = 0.25.

The examples shown in figures 4a through 4c further illustrate the fact that the larger height above the surface leads to a higher persistence, at least within this time interval. Furthermore, when you look at the time scale of months, (H) can have values that are different from those obtained for the whole year. In some cases, they may be lower (figure 4c), and in others they may be higher (figure 4a and 4b).

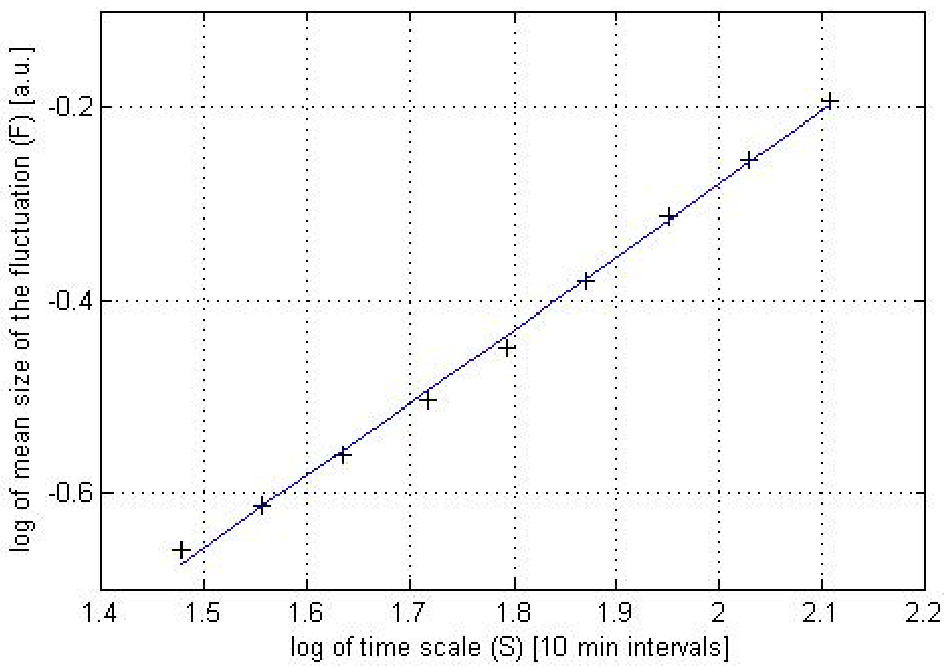

Figure 4a. Establishing the persistence exponent (H) for the analyzed time series from Boutiliers Point, for the month of February 2010. Height: 80 m. Hurst exponent H = 0.75.

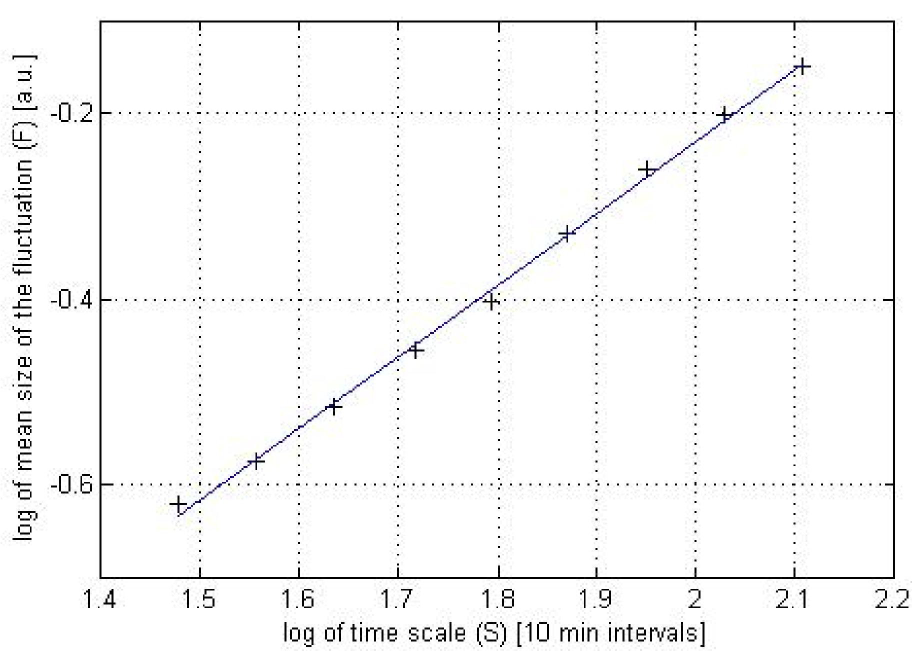

Figure 4b. Establishing the persistence exponent (H) for the analyzed time series from Boutiliers Point, for the month of February 2010. Height: 120 m. Hurst exponent H = 0.77.

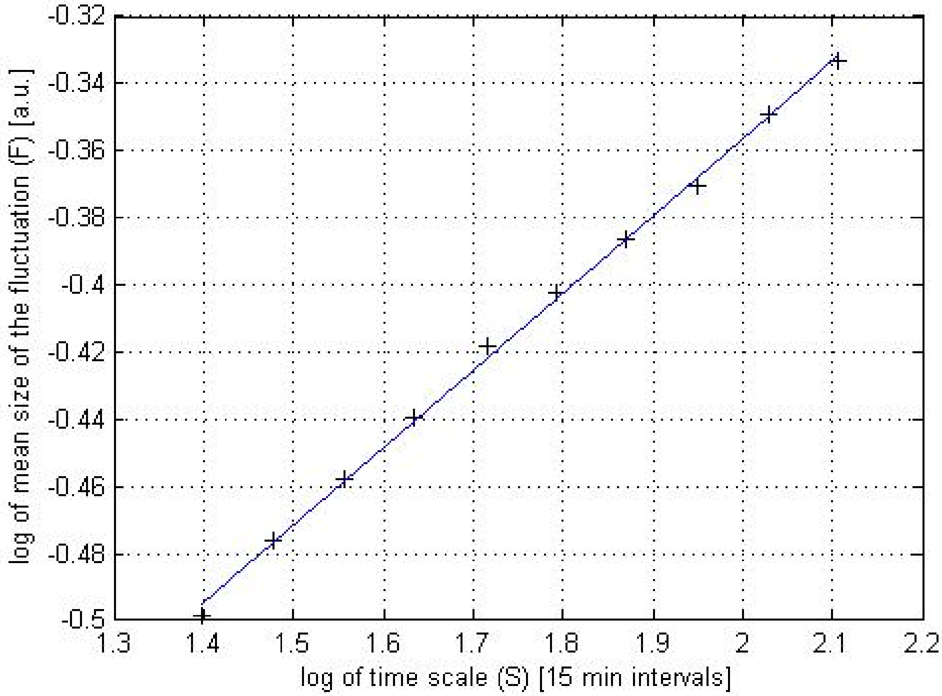

Figure 4c. Establishing the persistence exponent (H) for the analyzed time series from Corvallis, for the month of February 2010. Height: 10 m. Hurst exponent H = 0.23.

3.4. Relationship between mean wind speed and persistence

With the calculation of the Hurst exponent (H), the next step is to determine the relationship between the mean wind speed and the pattern persistence. To do this, we represented all the (H) values versus the (M) values in a graph, and found the line of best fit for all of the points. The slope (w) of this best fit line represents a characterisation of the description of the relationship between wind speed and its consistency (figures 5a to 5c). We called the slope (w) the **wind speed consistency index**. The wind speed consistency index (w) represents a new tool that can characterize wind patterns more effectively and reliably.

The wind speed consistency index (w) is a measure of the way in which wind speed consistency changes with wind speed values, and it works by determining mean wind speed values and applying DFA to successive segments of the time series. Higher values of (w) reflect wind patterns for which wind speed persistence increases with increasing wind speed values. They thus represent a situation that is more favorable from the point of view of wind power generation, as the wind in the area blows faster, more frequently. When the growth of (H) as a function of (M) is weak, this means that the consistency does not increase very much with wind speed.

As seen in figures 5a and 5b, the results for the data collected at Boutiliers Point for heights 80 m and 120 m are not very different from each other. This means that the area that would be covered by the wind turbine blades is quite homogeneous in terms of wind patterns. Furthermore, in comparison to Corvallis, as show in figure 5c, these areas both have higher values of (w). This means that the placement of wind turbines at 10 m in Corvallis would not be worthwhile, as the speed of the wind is not very consistent over time. The placement of turbines at heights of 80 m to 120 m, at Boutiliers Point, however, would result in a much more efficient generation of energy, as the wind speed remains higher and is more consistent, for longer. While a direct comparison of the two locations would not be very useful in practice, considering their geographic differences, analyzing both with the hypothetical idea of choosing one location to build a wind farm shows the usefulness of the wind consistency index (w). This index can be used as a part of a bigger toolbox, when trying to determine the optimum location for a wind turbine.

To this end, successive time series windows of N days have been analyzed and, for each window, the mean wind speed (M) and the Hurst exponent (H) have been calculated. Over 140 time windows were analyzed. A set of tests involving a range of values for the length N showed that a strong and relevant relationship between (M) and (H) can be identified for N corresponding to approximately 1 month. Too far above 1 month led to a loss of accuracy in graphs like figure 5a, as a result of less points to be plotted. Furthermore, too far below 1 month led to an increase in the uncertainty surrounding the Hurst exponent (H). Afterwards, we represented all the (H) values versus the (M) values, and found the line of best fit for all of the points. The slope (w) of this best fit line is the **wind speed consistency index**.

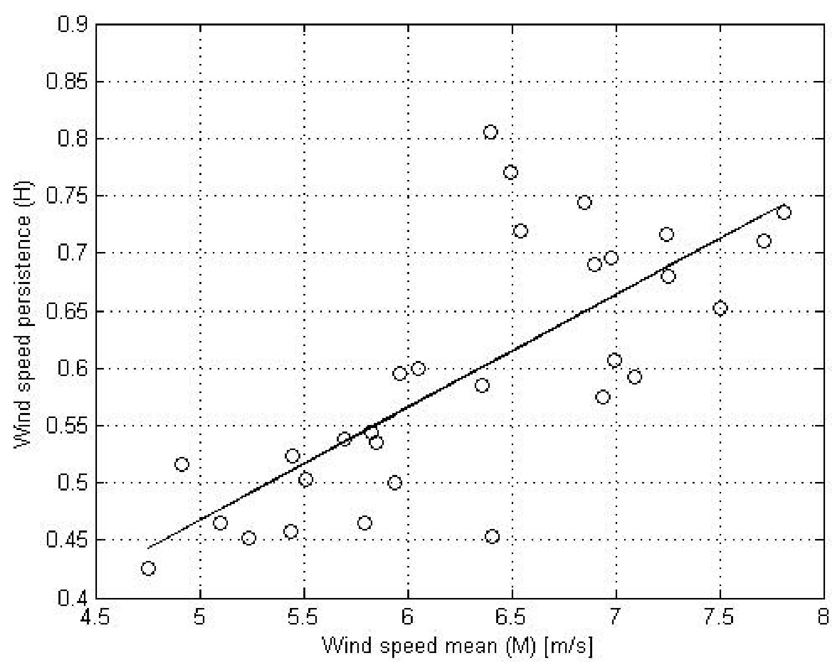

Figure 5a. Establishing the wind speed consistency index (w) for Boutiliers Point. Height: 80 m. The resulting index w80 is 0.098.

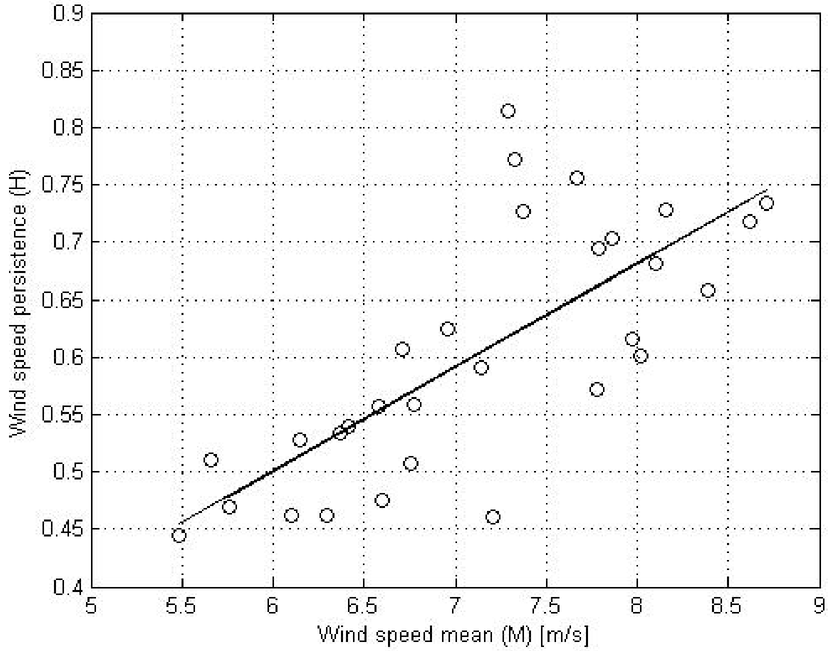

Figure 5b. Establishing the wind speed consistency index (w) for Boutiliers Point. Height: 120 m. The resulting index w120 is 0.090.

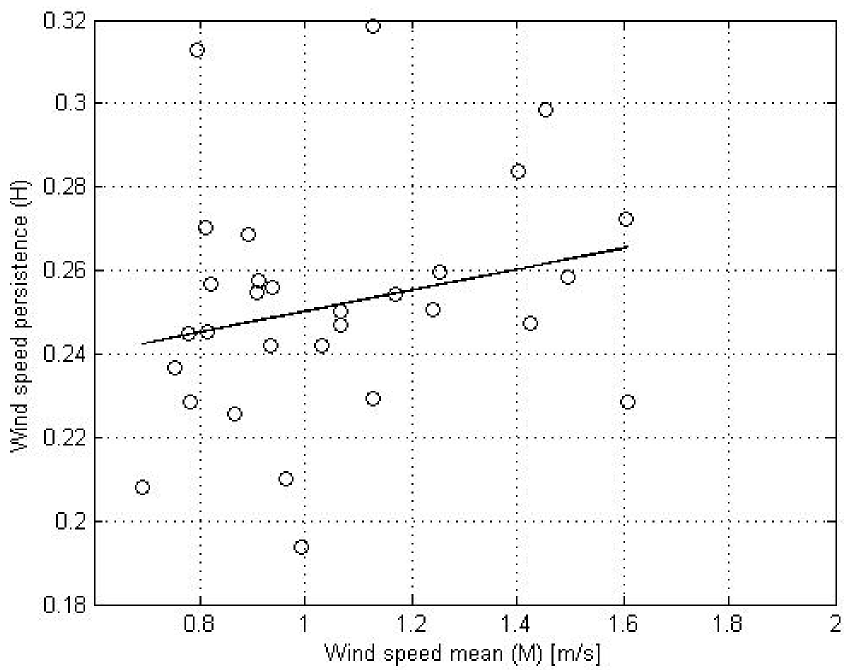

Figure 5c. Establishing the wind speed consistency index (w) for Corvallis. Height: 10 m. The resulting index w10 is 0.025.

3.5. Conclusions

When analyzed with an effective multiscale method – Detrended Fluctuation Analysis – the wind speed time series proved in all cases to be self-affine (i.e. the shapes in the time series graph were similar to each other on different scales, on scale ranges from hours to days). Furthermore, DFA led to an accurate determination of the Hurst exponent (H), with a typical 95% confidence interval of ±0.01. The values of the (H) exponent characterize the persistence in the pattern, taking into consideration the actual succession of the values in the time series, on a range of scales (hours to days). In the case of this project, these (H) values support a clear distinction of the wind patterns from each other: both four-year-long time series from Boutiliers Point, with large height values (80 m and 120 m, respectively) are described by high persistence (H = 0.59 and H = 0.61), while the time series from Corvallis (10 m height) lead to low persistence (H = 0.25). Since the interval of possible values of (H) for this category time series is [0, 1], and the uncertainty for the (H) values is low (with a 95% confidence interval of ±0.01), the (H) values determined in the two locations can be considered to be very different from each other.

These results of DFA indicate that large values of height involve higher wind speed persistence than lower heights, which can be explained by the fact that the surface roughness enhances wind turbulence, and the impact of the surface roughness on wind speed patterns decreases with height. While the latter of these two conclusions was to be expected, the evaluations performed here offer a quantitative view on this factor. Furthermore, data analysis using DFA on shorter time intervals (Figures 4a through 4c) also showed that the time series persistence changes over time. However, despite the change, the distinction between the height characteristics (80 m and 120 m, vs. 10 m) is still preserved.

The introduction of a new index characterizing the dependence of persistence on mean wind speed makes it possible to see to what extent wind speed is associated with wind consistency. When deciding the location to place a wind turbine, benefiting from high wind speed is not enough. High wind speed should be also characterized by high wind consistency. Thanks to the procedure introduced in this project, the relation between the mean wind speed (M) and the persistence exponent (H) leads to the wind speed consistency index (w).

The wind speed consistency index (w) was found to be positive in all of the analyzed cases, which means that time intervals with higher wind speed are also characterized by higher persistence. However, the actual values themselves are very different from one location (large height values) to another (low height values). This shows that not only do higher values of the height benefit from stronger wind, but that the consistency of the wind is stronger there as well.

It is important to note that the introduction of the wind speed consistency index (w) is not meant to replace existing methods, but rather to bridge a gap, and create another effective tool that can be used to strengthen scientific decision making, and help the wind energy sector grow. With that being said, these results show that the wind speed consistency index (w) introduced and calculated here represents a useful tool for wind pattern analysis, and it can effectively complement the existing methodology for wind pattern evaluation.

4. Conclusions and Implications for Further Work

Wind is a tremendous source of clean, renewable energy. The need for energy of this sort continues to grow with each passing day. Not only is renewable energy needed to gradually replace the depleting sources of non-renewable energy, but it is also needed if we wish to reach important emission-reduction goals. With its ample supply, its lack of greenhouse gas emissions, and its continuously declining cost, wind energy provides a breath of fresh air in regards to our efforts to slow anthropogenic climate change. It is the uncertainty of wind, however, that is slowing the progression of the wind energy industry. In order to contribute to an effective way of addressing this uncertainty, we used a recently developed methodology to assess variability, not just in terms of wind speed values, but in terms of time as well.

From this, we developed a new tool, which involves a new way of characterizing wind patterns: the wind speed consistency index (w). This index shows the extent to which high wind speed values correspond to high persistency. Using data from Corvallis, Montana, and Boutiliers Point, Nova Scotia, we concluded that records obtained closer to the ground resulted in high intermittency and low persistence, whereas areas with records from larger heights had less intermittency, and higher persistence. As a result of this study, we now have a novel and innovative tool that can characterize wind patterns more reliably. It responds specifically to the need of having a measure of the relationship of wind speed and its consistency.

In future studies, it would be interesting to characterize data from a larger number of data sets, ranging from a larger diversity of conditions (i.e. elevations, sensor height, etc.). More specifically, it would be interesting to test data from Corvallis recorded for heights of 80 m and 120 m, as well as data from Boutiliers Point recorded for a height of 10 m.

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