Analysis Of Wind Data

Mohamed Ali Ashfaq Ahamed[†]

[†] *Department of Mathematics and Statistics, Memorial University of Newfoundland, St. John's (NL) A1C 5S7, Canada*

E-mails: aamohamedali@mun.ca

Abstract
The motive of this project is to obtain knowledge of wind turbines and the potential impacts of wind energy in Newfoundland and Labrador. Despite the vast research on the need to transition to renewable energy (RE), fossil fuels remain the world's primary energy source. The most identified barriers to renewable energy in Newfoundland and Labrador are sounds and risk to birds.

1 Introduction

1.1 Background

Light detection and ranging (LiDAR) is an experimental technique for measuring the line-of-sight portion of wind speed remotely, mostly used in the wind energy sector. Usually, measurements are taken in a few places upstream of the wind turbines. Time-dependent velocity signals with significant noise are provided by LiDAR measurements. A schematic representation of a wind turbine and a few measurement points are shown in the picture below.

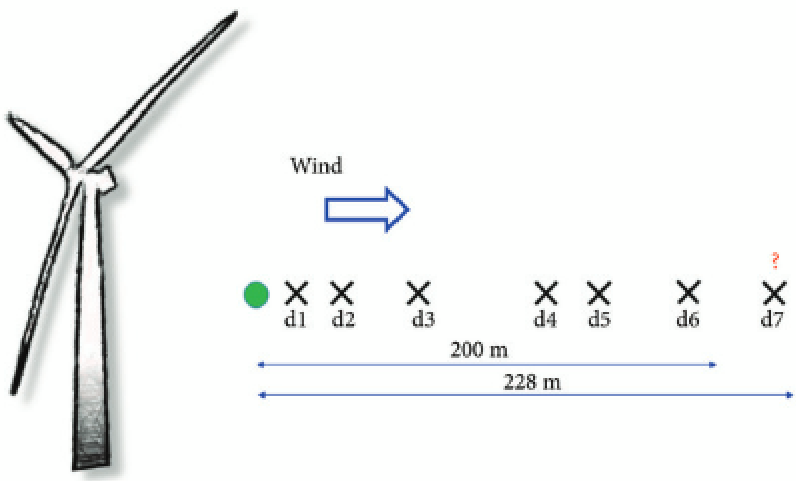

Figure 1: This illustrates the Wind turbine and location where the measurements are taken.

1.2 Context

- Potential of wind farms in Newfoundland

  The onshore wind potential for Newfoundland and Labrador is remarkable by any measure. In per capita terms, it dwarfs the province's own needs and at current energy prices could generate $200,000 per household of annual revenue if a market existed for it. In absolute terms, the estimate of Newfoundland and Labrador's renewable energy potential is the largest in the country. Although it includes some hydroelectricity and a dispersed wind catchment area, both of which would help with the reliability of power, the resource would clearly be developed only if it was exportable. This might involve new transmission systems such as a direct-current link connecting to Quebec and U.S.A markets. In addition, while we have sited high-potential wind areas only near existing roads and transmission lines, clearly the nature of the transmission infrastructure to these locations would need to change drastically for the exploitation of new energy resources on the scale of those envisioned here for Newfoundland and Labrador, as well as for other provinces. For very large developments, new roads and population centres may be developed to suit the location of the wind, rather than vice versa, in which case the geography of our analysis may be taken as only representative.

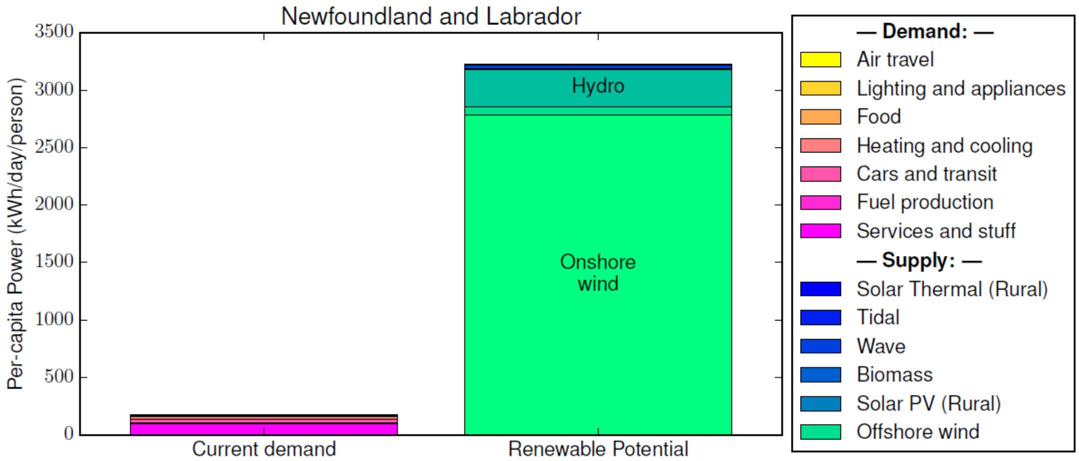

Figure 2: The above figure illustrates the demand for wind energy in Newfoundland and labrador

  The stack on the left shows the sum of all energy currently consumed, as both electricity and combustion, in Newfoundland & Labrador. On the right is a breakdown of available renewable energy resources.

  A large majority of respondents (65%) classified the current state of wind energy development in NL as 'unfavourable'. The most frequently reported barriers were political (71% of respondents), economic (65%), and knowledge related(53%). Potential benefits of wind energy development were economic, environmental, and societal in nature.

- Barriers in constructing wind farms

While wind energy helps birds on a global scale by curbing climate change, wind power facilities can harm birds through direct collisions with turbines and other structures, including power lines. Wind power facilities can also degrade or destroy habitat, cause disturbance and displacement, and disrupt important ecological links. Placing wind projects in the path of migratory routes makes this problem worse, especially for larger turbine blades that may reach up into the average flight zone of birds that migrate at night. An estimated 140,000 to 500,000 bird deaths occur per year due to turbine collisions, which is substantial, but significantly less than deaths caused by outdoor cats and building collisions.

Wind turbines most commonly produce some broadband noise as their revolving rotor blades encounter turbulence in the passing air. Broadband noise is usually described as a "swishing" or "whooshing" sound. This can be caused by mechanical components or, less commonly, by unusual wind currents interacting with turbine parts. This problem has been nearly eliminated in modern turbine design. However, well-designed wind turbines are generally quiet in operation, and compared to the noise of road traffic, trains, aircraft, and construction activities, to name but a few, the noise from wind turbines is very low. Manufacturers have made many changes to reduce wind turbine noise such as rotors being upwind, Towers and nacelles being streamlined, Soundproofing in nacelles has been increased, Wind turbine blades have become more efficient, and Gearboxes are specially-designed for quiet operation. Even though manufacturers are minimizing the noise of wind farms but the construction noises such as truck traffic, heavy equipment, and Foundation blasting of this site can't be minimized.

1.3 Outline

1. A modeling study for a wind farm using the PCA approach, where wind measurements will be simulated.

2. Discussing the objective and methodology of the project, indicating how mathematical methods through principal components can play an important role in the wind energy industry.

3. Plotting $u1(t)$, $u2(t)$ and showing the correlation between the winds using a scattered plot of the fluctuating wind. Discussing these three plots.

4. Finding and presenting the principal direction and principal values using singular value decomposition.

5. Defining a confidence region of the wind data by projecting over the principal components, where $\phi^T U$ denotes projection of U along the principal directions Φ.

$$c_m = m\Phi^T \frac{\Sigma}{\sqrt{N}}\tau.$$

   for $m = 1, 2, 3.....$ which is a projection of the unit circle $\tau = [cos(2\pi\theta), sin(2\pi\theta)]$ along the columns of the matrix Φ (or principal directions). Note that Σ represents the singular values and $\frac{\Sigma^2}{N}$ represents the wind fluctuations. Finally, plotting three curves c1, c2, and c3 (using distinct colors), and superimposing them onto the scattered plot of U.

6. Using the symmetric matrix below

$$H = \begin{bmatrix} \sqrt{3} & \frac{-1}{4} \\ 1 & \frac{\sqrt{3}}{4} \end{bmatrix}$$

to transform the wind signals U to $V = H^k U$, where k indicates matrix power. Plotting the scattered plots of the wind HU, H^2U, H^3U, etc to see the effects of those linear transformations. The second index power of linear transformation includes a scattered plot of the transformed wind H^2U superimposed with three confidence curves $c1, c2, c3$.

1.4 Hypothesis

The simulation of wind data is measured based on two assumptions. First, there is mean wind at every locations of the wind farm. Second, atmospheric turbulence causes random fluctuations that are additive white Gaussian noise.

2 Methods

1. Generate a synthetic wind data $U \in \mathbb{R}^{2XN}$ measured at two different locations for a duration of an hour with a sampling rate of 100 hertz. In other words, 100 samples are taken every second. I am assuming the mean wind speeds are 1m/s and 2m/s at location 1 and location 2 respectively. Add random fluctuation to the mean wind speed at these two locations to model the atmospheric turbulence. I can plot the generated measurement at location 1, location 2, and the scattered plot of location 1 vs location 2 with the generated data.

2. Find the mean of U, and using that find the variance matrix. Diagonilize the variance matrix as below.

$$U = \phi \Sigma \psi^\top.$$
$$UU^\top = \phi \Sigma \psi^\top \psi \Sigma^\top \phi^\top.$$
$$\frac{UU^\top}{M} = \phi \frac{\Sigma^2}{M} \phi^\top.$$

The left singular vector of Φ is principal directions and Σ is principal values of the generated wind data.

3. Define few confidence region of generated wind data by projecting over the principal components along the principal directions with the parametric curve given by

$$c_m = m\Phi^T \frac{\Sigma}{\sqrt{N}} \tau.$$

for $m = 1, 2, 3.....$ I can plot three curves $c1, c2$, and $c3$ and superimpose them on to the scattered plot of U. The curves $c1, c2$, and $c3$ are shifted with respect to the mean wind.

4. Finally with given transformation matrix i can transform the wind signals U to $V = H^k U$ and plot the scattered curves HU, H^2U, H^3U. Further, I can do the principal components analysis using singular value decomposition. Using the principal direction Φ i can plot the curves $c1, c2$, and $c3$ on the scattered plot of the second matrix power to observe the confidence regions.

3 Results

1. Plots for the generated data

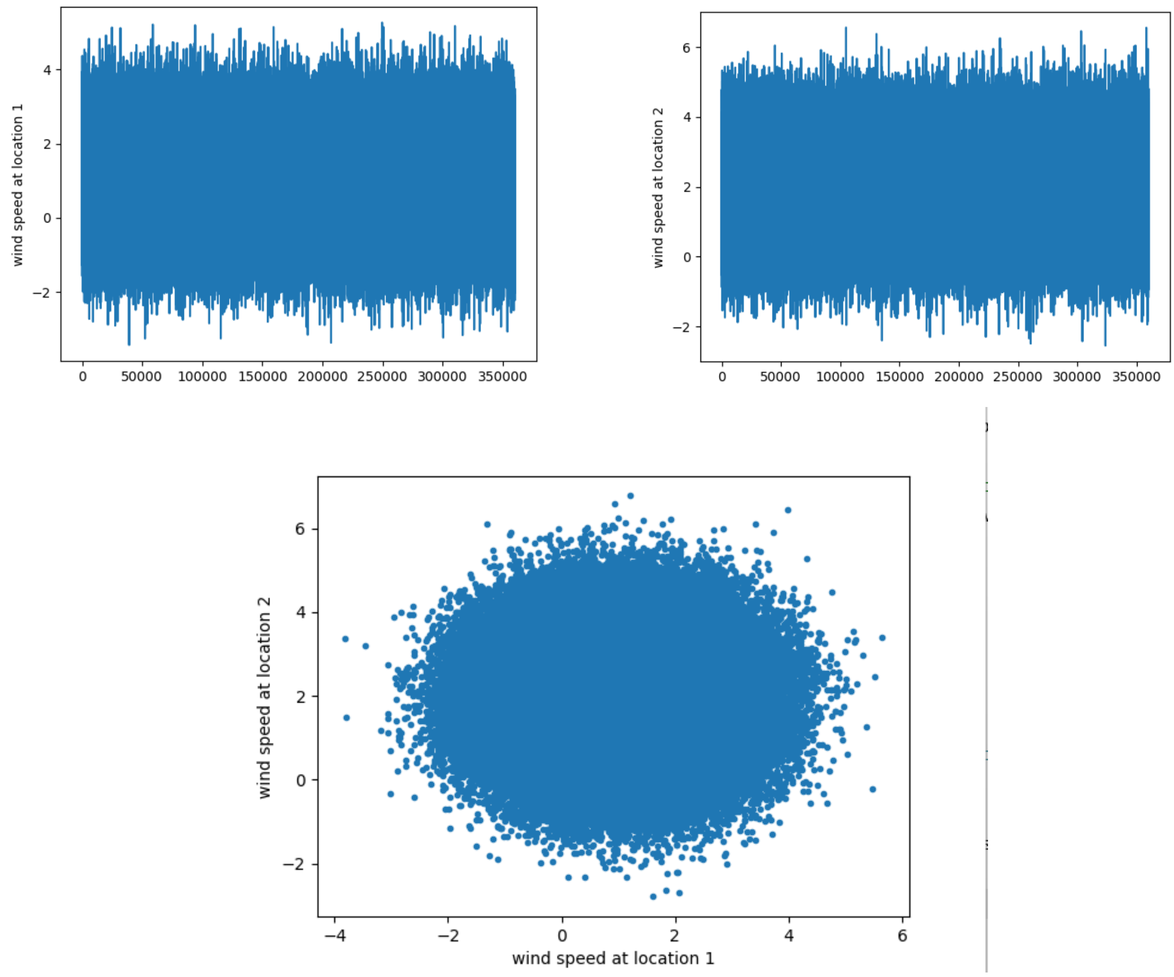

Figure 3: The above plots illustrates the wind measurements at location 1, location 2, and the scattered plot of location 1 & location 2

2. Executing principal components analysis to find the principal direction and principal values.

$$\text{Principal direction}=\begin{bmatrix} -0.88695416 & -0.46185747 \\ -0.46185747 & 0.88695416 \end{bmatrix}$$

$$\text{Principal values}=\begin{bmatrix} 600.98594328 & 599.53465209 \end{bmatrix}$$

3. Plot of three curves $c1, c2$, and $c3$ superimposed onto the scattered plot of location 1 & location 2.

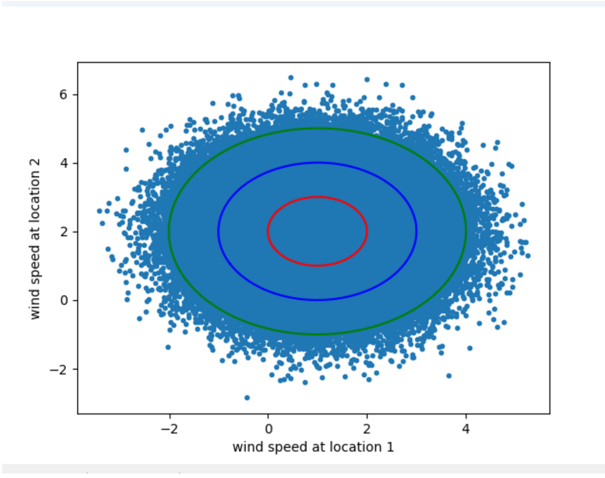

Figure 4: Scattered plot of wind measured at location 1 and wind measured at location 2 superimposed by three confidence region.

4. The scattered plot of three different transformed wind signals at the two locations.

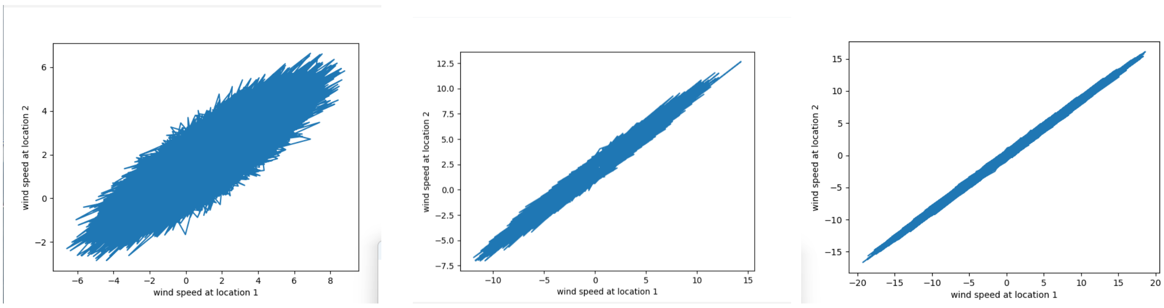

Figure 5: Transformed signals for the first, second and third index powers.

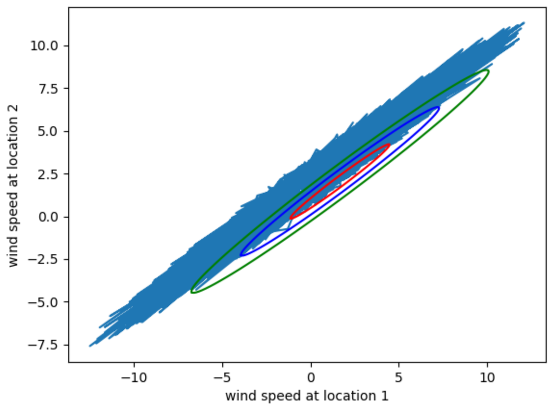

Figure 6: Transferred wind signal for the second index superimposed by the confidence curves.

4 Analysis

- Since I generated data for an hour with a sample rate of 100 hertz. I have used 360,000 wind speed measurements to plot the graphs at location 1 and location 2 which is why the graph looks well-packed. The plot clearly predicts the fluctuation of wind. Using the scattered plot produced, I can come to a conclusion that wind speed at location 1 and wind speed at location 2 are weakly co-related. But the wind which passes through location 1 might increase or decrease dramatically while it passes through location 2. This implies the speeds measured should have been highly co related to each other as the measuring points are very close to each other.
- Figure 4 illustrates the 1st standard deviation, 2nd standard deviation, and 3rd standard deviation for the scattered plot of U.
- As you can see from the transformed plotted graphs in figure 5, the speeds at location 1 and location 2 are highly co-related to each other. As I increase the power of the transformation matrix the graphs gradually become linear and end up in a straight line. In other words, both wind measurements are getting closer to each other and becomes equal. When I am superimposing the curves $c1, c2$, and $c3$ by doing principal component analysis, the curves are almost one over the other.

5 Appendix 1

```
import numpy as np
from numpy.linalg import matrix_power
import matplotlib.pyplot as plt

######################
#Author- Ashfaq
#Memorial University Of Newfoundland


# constructing the syntheic data at points d1 and d2

N=100*60*60 # number of samples in an hour

u=np.random.randn(2,N) # synthetic data


u[0]+=1 # adding the mean at location 1
u[1]+=2# adding the mean at location 2

#projecting the synthetic data with mean value
U=np.array([u[0],u[1]])

Ubar=np.mean(U,axis=1,keepdims=1)
V=U-Ubar
```

```
#calculating the PCA using SVD

Phi, Sig, PsiT=np.linalg.svd(V,full_matrices=0)

#presenting the principal direction.
print('The Principal direction using SVD is ', Phi)

#presenting the principal values.
print('The Principal values using SVD is ', Sig)

#defining the confidence region
theta=np.linspace(0,2*np.pi,100)

tau=np.array([np.cos(theta),np.sin(theta)])
c1=Phi.T*Sig/np.sqrt(N)@tau+Ubar
c2=2*Phi.T*Sig/np.sqrt(N)@tau+Ubar
c3=3*Phi.T*Sig/np.sqrt(N)@tau+Ubar

plt.figure()
plt.plot(u[0],u[1],'.') # scattered plot
plt.xlabel('wind speed at location 1')
plt.ylabel('wind speed at location 2')
#plotting the graphs
plt.figure()
plt.plot(u[0],u[1],'.') # scattered plot
plt.xlabel('wind speed at location 1')
plt.ylabel('wind speed at location 2')
#plotting the confidence region
plt.plot(c1[0],c1[1],color='red')
plt.plot(c2[0],c2[1], color='blue')
plt.plot(c3[0],c3[1],color='green')


plt.figure()# measurement at location 1
plt.plot(u[0])
plt.ylabel('wind speed at location 1')


plt.figure()# measurement at location 2
plt.plot(u[1])
plt.ylabel('wind speed at location 2')

#plots of linear transformation
plt.figure()
H=np.array([[np.sqrt(3),-1/4],[1,np.sqrt(3)/4]])
plt.plot(np.dot(matrix_power(H,1),U)[0],np.dot(matrix_power(H,1),U)[1])
plt.xlabel('wind speed at location 1')
```

```
plt.ylabel('wind speed at location 2')

#definning the confidence region for the second power
secondPower=np.dot(matrix_power(H,2),U)
meanOfIt=np.mean(secondPower, axis=1,keepdims=1)
UsecondPower=secondPower-meanOfIt
#using svd
Phi, Sig, PsiT=np.linalg.svd(UsecondPower,full_matrices=0)
c1=Phi.T*Sig/np.sqrt(N)@tau+meanOfIt
c2=2*Phi.T*Sig/np.sqrt(N)@tau+meanOfIt
c3=3*Phi.T*Sig/np.sqrt(N)@tau+meanOfIt

plt.figure()
plt.plot(np.dot(matrix_power(H,2),V)[0],np.dot(matrix_power(H,2),U)[1])
plt.xlabel('wind speed at location 1')
plt.ylabel('wind speed at location 2')

plt.figure()
plt.plot(np.dot(matrix_power(H,2),V)[0],np.dot(matrix_power(H,2),U)[1])
plt.plot(c1[0],c1[1],color='red')
plt.plot(c2[0],c2[1], color='blue')
plt.plot(c3[0],c3[1],color='green')

plt.xlabel('wind speed at location 1')
plt.ylabel('wind speed at location 2')

plt.figure()
plt.plot(np.dot(matrix_power(H,3),V)[0],np.dot(matrix_power(H,3),V)[1])
plt.xlabel('wind speed at location 1')
plt.ylabel('wind speed at location 2')
plt.show()
```