Chapter

Wind Speed Analysis Using Signal Processing Technique

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Abstract

In this study, wind energy, the formation of this energy, and the necessary stages for the production of electrical energy will be discussed. Then, the countries' investments in wind energy will be mentioned. In the mathematical background, statistical methods and signal processing methods are used in the calculation of wind energy efficiency. In this chapter, a detailed analysis of the use of wind speed data with signal processing techniques will be made using the hourly wind speed data of Istanbul for the last 10 years. This data will be analyzed by the Fourier method. Afterward, analyses will be made with short-time Fourier transform (STFT) and bi-spectrum analysis method, and these results will be compared. The data obtained from the study can be considered as a framework for the wind farms to be constructed.

Keywords: wind speed, STFT, bi-spectrum analysis, data analysis

1. Introduction

The growth increase of the world population and the development of technology and industry cause the need for energy consumption. Energy consumption in the world increases by an average of 4–5% every year [1, 2]. Energy production from fossil fuels is less preferred due to reduced reserves and environmental sensitivity. Research has shown that humanity consumes a thousand years of fossil fuel formation in 1 day. Here, it shows that renewable energy sources are the most optimal solution in energy production [1–4].

Today, the most widely used renewable energy sources are hydraulic, wind, solar, geothermal, and biomass energy. Renewable energy sources are the ones that can renew themselves continuously, have no additional costs other than investment costs, and do not cause environmental problems. Among renewable energy sources, wind energy is the most popular today. Wind consists of solar radiation heating the ground surfaces differently [2, 4–7]. There are some advantages of using wind energy. Wind energy is a source of energy that does not create environmental pollution, is abundant in the atmosphere, and does not require very high technology for energy production. The conversion of wind energy to electrical energy is provided by using wind turbines [4–8]. The recent development of wind turbine technology increases the amount of energy produced and reduces initial costs. This form of energy production, which is also friendly to the environment, has been supported by many developed countries and turned into a state policy [1–3].

Determination of wind energy potential is the most important feasibility study before wind turbines are installed. There are many studies in the literature in different disciplines for determining wind potential. Wind power has reached a capacity of over 600GW in 2018 worldwide. According to 2018 statistics, China has a maximum capacity of 221 GW, using more than one-third of the world's capacity. America 96.4 GW, Germany 59.3 GW, India 35 GW, and Spain 23 GW capacity are ranked with [7–10].

However the advantages and disadvantages of wind energy vary according to sources [11]. The following are the benefits of wind energy: It is a clean source of energy and has no emissions. It is a local energy source, not dependent on external sources. It uses 1% of the investment area, and agriculture and animal husbandry activities can be done in these areas. It is a cheap source of energy. Idle areas can be used for turbine installation. It creates high employment. The drawbacks of wind energy are as follows: Image can create pollution. It may create noise pollution. It may disrupt radio and TV signals. In bird migration routes, it may harm birds [12–15].

As with most renewable energy sources data, wind speed is analyzed in non-stationary signals group. As can be expected, extreme winds during the typhoon and thunderstorms show non-stationary characteristics. The analysis of these data cannot be characterized by the use of static mathematical models. The frequency contents and amplitudes of these non-stationary signals may vary with time. In this study, signal-based analysis methods are used in the analysis of wind speed. Weibull distribution is known to be the most important statistics used in low wind speed analysis [16, 17]. Detailed data processing methods are needed to investigate the wind speed potential. In the analysis, the continuity of the wind speed is first investigated by statistical methods. The next stage is the efficiency and cost research. Fourier-based time-frequency methods with Weibull distribution provide a great convenience in wind speed analysis. The general purpose of this study is to analyze the wind speed data with spectral methods and to compare these analysis results.

2. Statistical and mathematical background for wind speed analysis

The wind speed is evaluated in a group of non-deterministic, nonlinear signals with no specific statistical and parametric values. Variation of wind speed according to time, day, and season requires statistical analysis to determine its potential. Anemometer is used to measure wind speed. Wind measurements in practice are minute, 10 minute, and hourly data. The data in the longer range is obtained by averaging these data. These data are divided into classes of wind speeds of 1 m/s each, and the energy in a given region is calculated by this frequency distribution. At this stage, Weibull distribution was found to be the most optimal approach for wind speed distribution [16].

2.1 Statistical analysis

The wind potential of a region is determined by a series of detailed statistical and mathematical methods to be performed in the region. Frequency of wind speed data and collection over a long period of time, data collection methods, etc. significantly affect the accuracy of the analysis result. Statistical parameters are used to analyze the data collected over time. It is possible for data to exhibit a sinusoidal property, while the mean and median values are expected to be close to zero, but it is possible that these values have moved away from zero. In the analyses, the most basic mean value μ and standard deviation, σ, can produce significant results in non-periodic signals [16–21]. For a particular set of signs {xi}, they are defined as in the following equations:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

$$\sigma = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}(x_i-\mu)^2} \tag{2}$$

Eqs. (1) and (2) above are *N* data numbers. Here, the standard deviation refers to the average distribution of variables in a data set. A small standard deviation value means that the values of the data group are distributed around the average. In practice, the data is expressed by the normal probability distribution (Gaussian) called the central limit theorem. Here, the two functions obtained from the Gaussian distribution, skewness (α) and kurtosis (β), are given in Eqs. (3) and (4):

$$\alpha = \frac{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^3\right]}{\sigma^3} \tag{3}$$

$$\beta = \frac{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^4\right]}{\sigma^4} \tag{4}$$

Frequency distribution of wind speed is determined by different statistical distributions such as Gamma, Rayleigh, and Weibull. Among these methods, Weibull distribution is the most preferred method. This method is well suited to wind distribution [21–25].

2.1.1 Weibull parameters method

The Weibull distribution was introduced by Waloddi Weibull in 1951 to estimate the life expectancy of machines. Continuous random variables are used to describe random events in which the variable can take any value in a given range. The Weibull distribution is continuous and at the same time flexible distribution and is applied in many random statistical applications.

In wind speed analysis, it can be used to identify wind speed changes in an area at an acceptable level of accuracy. Weibull distribution is determined by the shape and scale variable. The area expressed as a probability distribution is 1 in total. The Weibull distribution curve is skewed. As a result of the calculations, if the Weibull distribution parameter, k = 3 and 4, is obtained, the distribution is similar to the normal distribution. If parameter k takes the value of 1 as a result of calculations, the distribution is an exponential function. The Weibull distribution function is the most common method used to calculate wind speed and density in wind speed analyses [16–25]:

$$(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{\left(\frac{v}{c}\right)^k} \tag{5}$$

In Eq. (5) above, v is the wind speed, f is the frequency, k is the shape parameter, and c is the scale [22–25].

2.2 Time-frequency methods for wind speed analysis

The conventional Fourier transform only yields a spectral distribution over time and cannot represent the transient properties of a non-stationary process. In order to define the time-varying properties of non-stationary processes, methods such as short-term Fourier transform (STFT), Wigner-Ville distribution (WVD), and wavelet transform (WT) have been developed.

STFT uses a fixed-width window to capture the time-frequency distribution, so limited resolutions are captured in the analysis with STFT. In this sense, it may be possible to achieve better results with wavelet transform. Time-frequency methods are discussed in the following section [26].

2.3 Fourier transform and STFT

The Fourier transform (FT) method is used to extract information from the signal and to process the signals. This method is one of the most effective methods used for signal analysis. With FT, a signal can be represented as the sum of the different amplitudes, frequencies, and the fundamental components in the phase. Processing here provides a great convenience in the computer environment. The basic equations for Fourier transform are given in Eqs. (6) and (7) below [27, 28]:

$$f(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(k) e^{ikx} dk \tag{6}$$

$$F(k) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(x) e^{-ikx} dx \tag{7}$$

FT, short-time Fourier transform (STFT) and spectrogram were developed based on Eqs. (6) and (7). With this method, time-frequency localization can be obtained clearly. Here, an $x\ (t)$ signal of fixed window size and frequency resolution is used. The generalized equation for STFT is given below in Eqs. (8) and (9). In addition, the spectrogram equation is shown in Eq. (10) [27, 28]:

$$STFT\{x(t)\} \equiv X(\tau, f) = \int_{-\infty}^{\infty} x(t) g(t-\tau) e^{-j2\pi ft} dt \tag{8}$$

$$STFT\{x(n)\} \equiv X(m, f) = \sum_{n=-\infty}^{\infty} x(n) g(n-m) e^{-j\omega n} \tag{9}$$

$$\{x(t)\} \equiv |X(\tau, f)|^2 \tag{10}$$

2.4 Reassigned spectrogram

This analysis yields successful results for non-stationary signals. Contains a detailed analysis of spectral content of non-stationary signals. Within the limits of the analysis, it is possible to obtain better resolution using only more information from the power spectrum. The basis of the calculation is that the instantaneous frequency (IF) in each FFT frequency band is equal to the first derivative of the short-term FFT (STFT) phase at time T, and this is given in Eq. (11) [29, 30]:

$$\mathrm{IF} = \partial/\partial t\,(\arg(\mathrm{STFT}(\omega, T))) \tag{11}$$

2.5 Welch analysis

Welch analysis is one of the most effective methods used for spectral estimation. The purpose of spectral estimation is to determine the frequency-dependent distribution of the power in a signal. The Welch method, a nonparametric method, is used as a more effective method. In this method, the time series is divided into sections that may overlap, and then the improved periodogram of each section is calculated and the average of the periodograms of these sections obtained is calculated. The average of these improved periodograms reduces the variance of all data over a single periodogram estimate. The Welch method estimates the power spectral density by averaging the improved periodograms. The first improved periodogram expression is given in Eq. (12):

$$\underset{xx}{\overset{\Lambda}{P}}(i)(f) = \frac{T_S}{K.M}\left|\sum_{n=0}^{M-1} x_i(n)w(n).e^{-j2\pi fn}\right|^2 \tag{12}$$

where $f = f$s is the normalized frequency variable, K is the normalized constant, and $w\ (n)$ is the windowing function. The expression of the constant K is given in Eq. (13). Power spectral density estimation is given in Eq. (14) [31–33]:

$$K = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n) \tag{13}$$

$$\underset{xx}{\overset{\Lambda}{P}} W(f) = \frac{1}{L}\sum_{i=0}^{L-1} \underset{xx}{\overset{\Lambda}{P}}(i)(f) \tag{14}$$

2.6 Bi-spectral analysis

Phase relations between frequency components are not taken into account in signal analysis using quadratic statistics or power spectrum. Therefore, these methods do not provide information against phase information. In addition, second-order statistics and power spectrum cannot make statistical definitions of non-Gauss processes. High-level statistics and spectrum studies are conducted for the more precise definition of random processes and the processing of phase information.

In addition to suppressing Gaussian probability-distributed activity, the bi-spectrum reveals signals originating from the nonlinear process—bi-spectral analysis; the background is used to detect low-level but diagnostic important signs masked by FKG. The power spectrum of the random signals is defined by AFD in Eq. (15), and the third-order heap spectrum is shown in Eq. (16). The expression in this equation is called the bi-spectrum. In this case, when the sign is a stationary random process with real value, it can be expressed as in Eq. (17) [33–35]:

$$P_2^x(f) = AFD\left(C_2^x(m).e^{-j2\pi mf}\right) \tag{15}$$

$$B^x(f_1, f_2) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} C_3^x(m,n).e^{-j2\pi\left(mf_1+nf_2\right)} \tag{16}$$

$$B(w_1, w_2) = X(w_1).X(w_2).X^*(w_1 + w_2) \tag{17}$$

3. Analysis and application

When applied as of 2014, Istanbul-Turkey wind data are used. Data are hourly wind speed from the State Meteorological Service. In addition, 2015 data were used for testing purposes for analysis. **Figure 1** shows the time-amplitude graph of the wind speed.

When the time-amplitude and time-energy graphs are evaluated together, the wind speed reaches the highest values of the whole year in the first months of the year (first 1500 samples) (**Figure 2**).

Figure 3 shows the frequency-amplitude graph of the wind speed. The graph shows an amplitude that continues up to approximately 0.015 Hz, followed by a noticeable peak at 0.045 Hz, decreasing frequency amplitude. This peak can be defined as the fundamental frequency of wind speed.

The power value generated by the annual wind speed in the Welch power analysis consists of a peak that reaches a maximum value of 340 units. Accordingly, it remains remarkably small on a hill of approximately 30 units (**Figure 4**).

When evaluated together with the time-frequency spectrogram (**Figure 5**) and the reassigned spectrogram (**Figure 6**), the red regions with high amplitude reaching up to 0.02 Hz in the first months of the year (first 1800 samples) are remarkable. The second high-amplitude region (between 6500 and 8000 data) corresponds to the last months of the year at frequencies of 0.01 Hz. In addition, the continuous distribution in the 0.045 Hz region, which spans almost the whole year, is noteworthy.

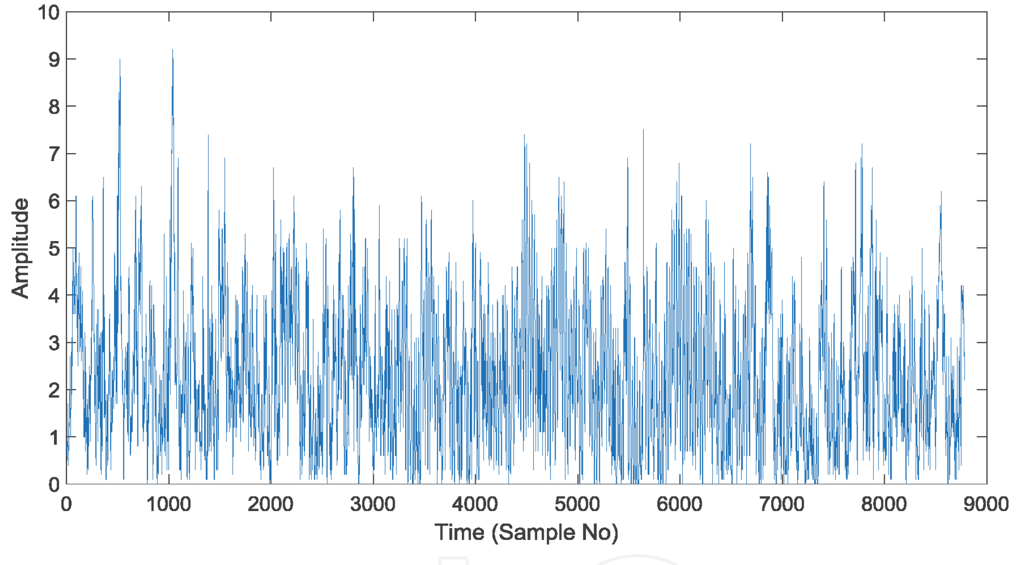

Figure 1.
Time-amplitude graph of wind speed.

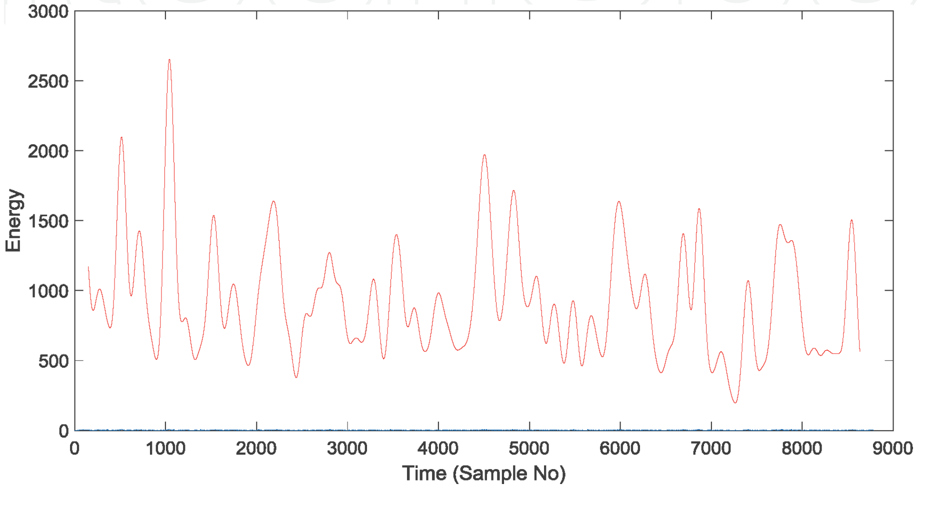

Figure 2.
Time-energy graph of wind speed.

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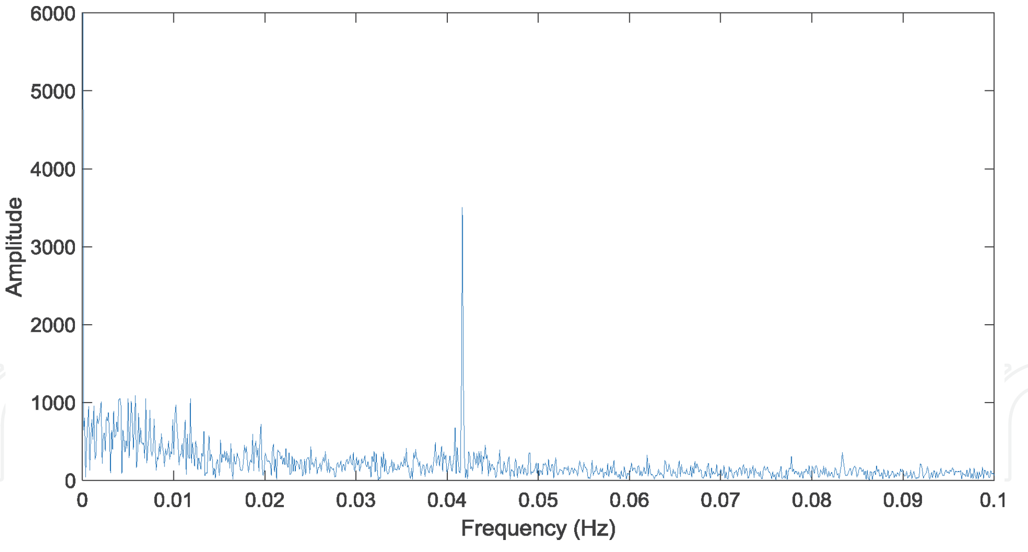

Figure 3.
Frequency-amplitude graph of wind speed.

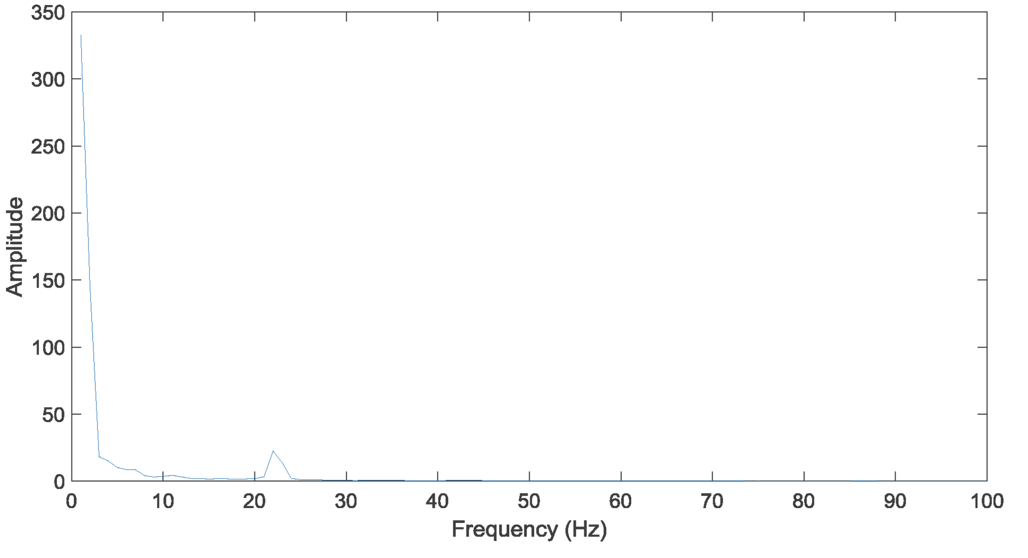

Figure 4.
Frequency-power graph of wind speed.

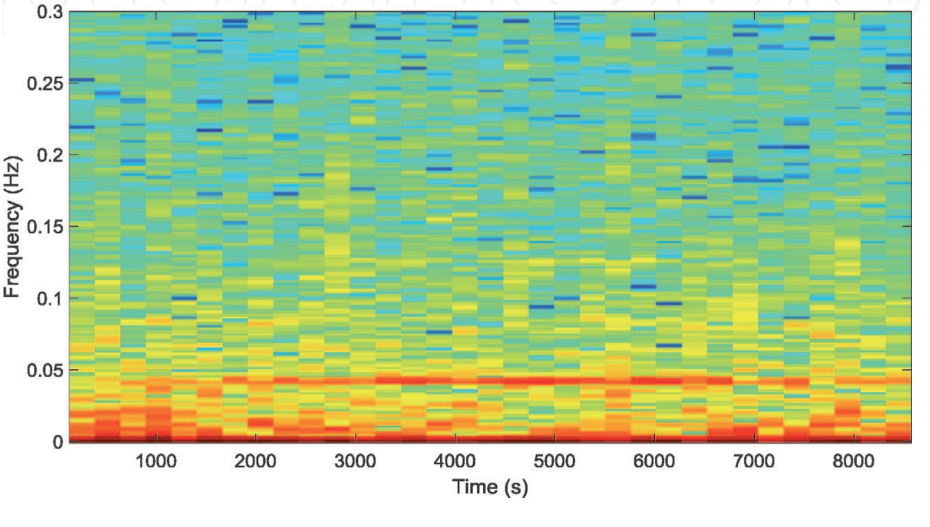

Figure 5.
Time-frequency spectrogram of wind speed.

The contour map of the bi-spectrum consists of two basic rings. The density ring consisting of high-amplitude peaks inside contains 0.1 Hz regions, and the outside small-amplitude ring covers 0.2 Hz regions (**Figure 7**).

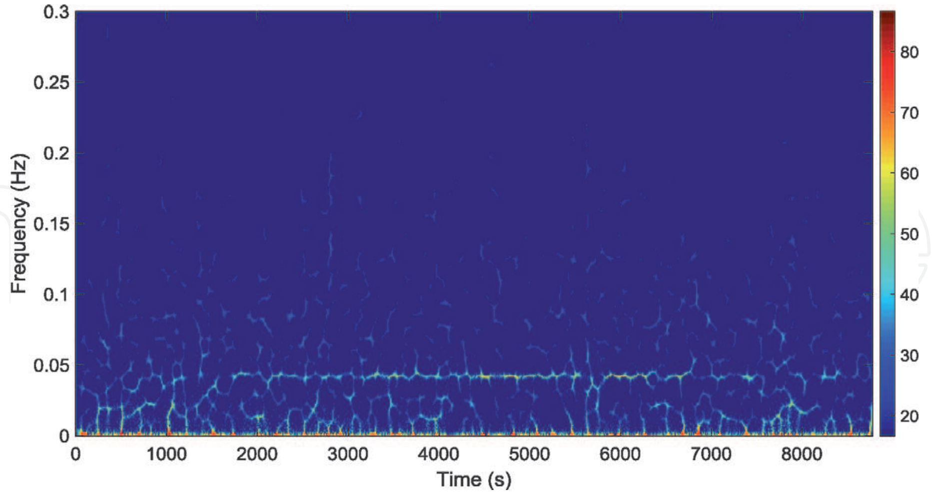

Figure 6.
Reassigned spectrogram of wind speed.

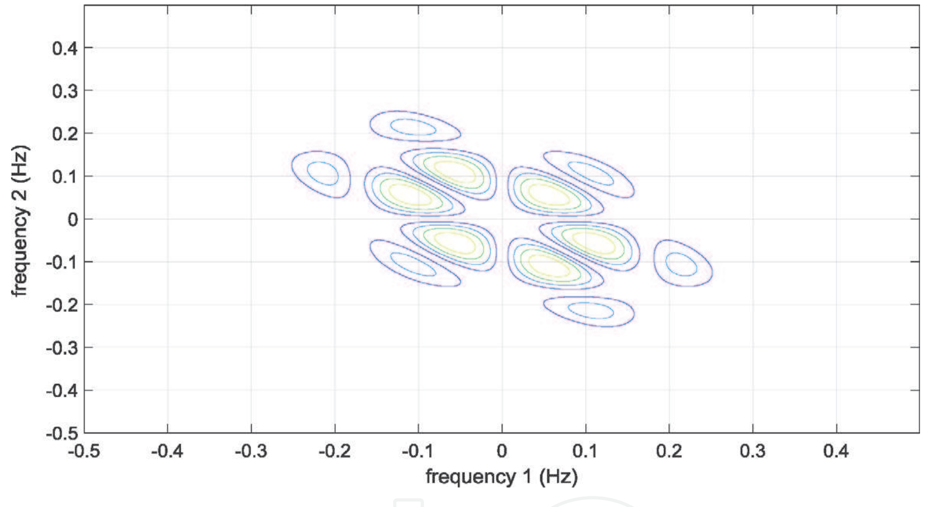

Figure 7.
Contour map of bi-spectrum estimation of wind.

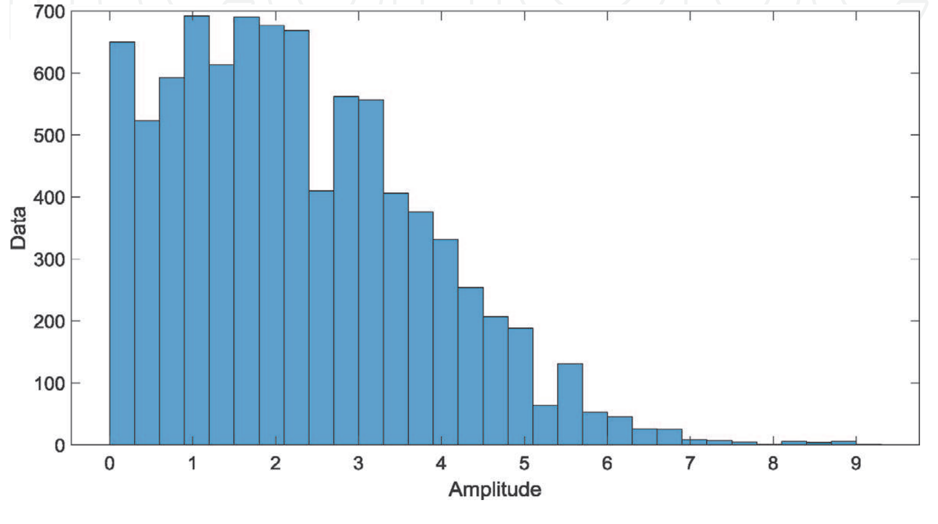

Figure 8.
Histogram of wind speed.

In **Figure 8**, wind velocities around 0–2.5 amplitude and 3 amplitude of wind velocity were observed at most. This can be seen with annual rh4mean = 2.3360 average value and rh4var = 2.2962 varying values.

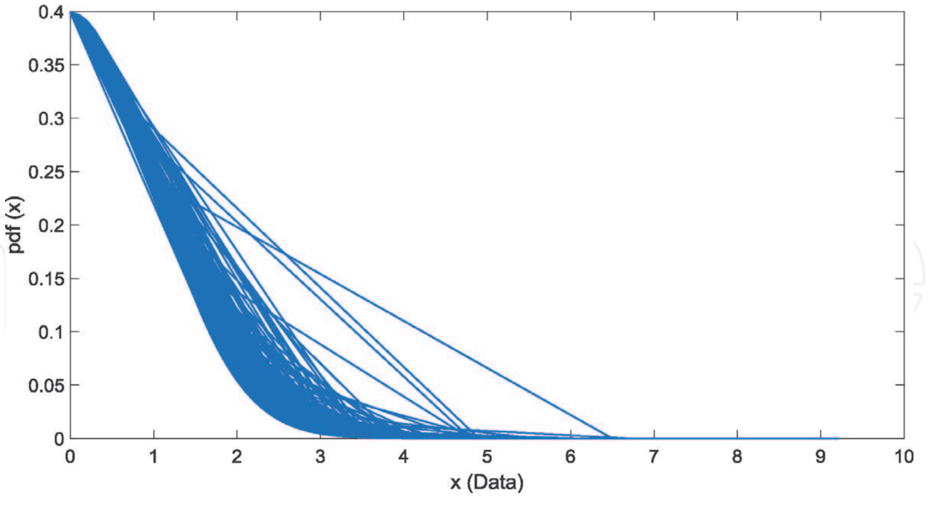

Figure 9.
Probability density function graph.

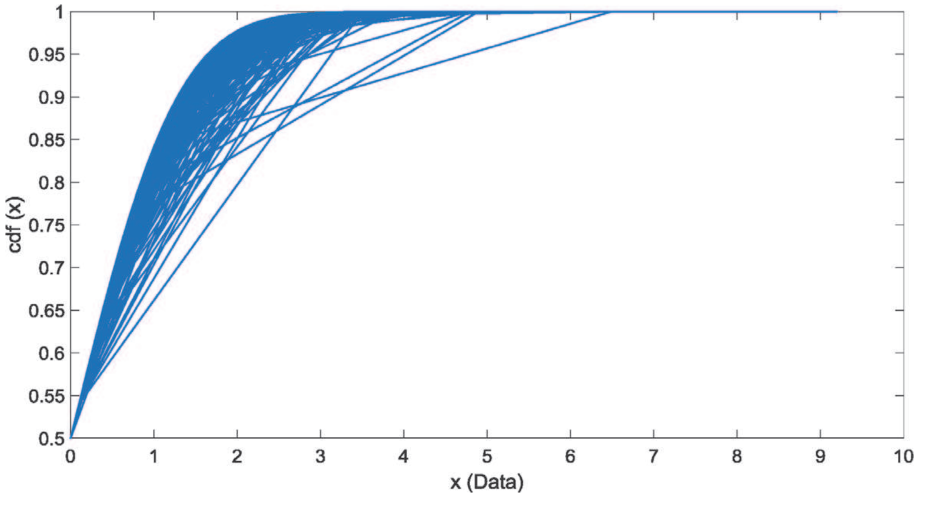

Figure 10.
Graph of probability distribution function of wind speed.

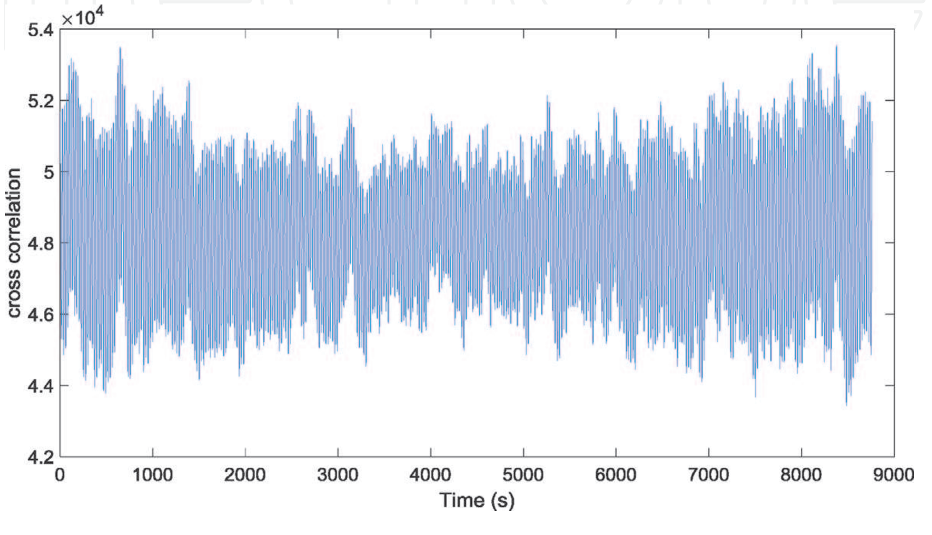

Figure 11.
Cross-relationship chart (2014–2015).

In **Figures 9** and **10**, when the probability distribution and density function are evaluated together, they are concentrated especially in 1–3 regions of the information signals.

When **Figure 11** is examined, it is seen that the cross-relationship is maximum in the first months and last months of the year (the season with the highest wind speeds).

4. Conclusions

In this study, Istanbul wind speed data were used. The data were obtained hourly from the national meteorological station. In the study, the seasonal variation of wind can be observed clearly from the time-amplitude graph of the wind speed. In addition, the wind speed data were analyzed using signal processing methods. These analyses are STFT, reassigned spectrogram, frequency power analysis, bi-spectral in-phase surface, and probability density function. In addition, cross-relationships and histogram between 2014 and 2015 were obtained by statistical analysis. In signal processing analyses, the distinction of seasonal transitions during the year can be determined by low- and high-frequency levels. Again in the autumn and winter seasons where the wind speed is higher, the frequency level at which the wind speed has reached can be clearly determined. The results of the statistical analysis of the histogram and cross correlation are quite satisfactory, and the relationship between the wind speed between 2014 and 2015 is quite similar, especially in autumn and winter seasons. Again, the dominant frequency was found to be around 0.04 Hz.

If this study evaluated as spectral analysis, it can be seen that the observed wind profile is a combination of some dominant modes defined by terms such as synoptic or large scale and mesoscale. With thıs assumptıon, these dominant scales are seen as the relative maximum ın power spectral analysis of wind speed. This assumption shows itself as the correct spectrum amplitudes ın this study. It shows consistency in terms of seasonal similarıty in the first months of the year and in the last month of the year, as seen from the cross-relation chart. The symmetrical distribution in **Figure 7** also proves that the wind speed is seasonally similar. Similarly, **Figure 2** energy distribution also proves the seasonal wind speed distribution and the accuracy of the relationshıp between spectral analysis and energy. In this sense, thıs study shows that the analysis of spectral methods is parallel to statistical methods in the analysis of wind speed data.

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