

**ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL**

**DEEP LEARNING FOR WIND ENERGY SYSTEMS USING THE HURST  
EXPONENT AND STATISTICAL PARAMETERS**



**M.Sc. THESIS**

**Behnaz ALAFI**

**Department of Electrical Engineering**

**Electrical Engineering Programme**

**AUGUST 2021**



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**Behnaz ALAFI  
(504181008)**

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**Thesis Advisor: Prof. Dr. Şahin Serhat ŞEKER**

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**İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ**

**HURST ÜSLÜ VE İSTATİSTİKSEL PARAMETRELERİ KULLANARAK  
RÜZGAR ENERJİSİ SİSTEMLERİ İÇİN DERİN ÖĞRENME**



**YÜKSEK LİSANS TEZİ**

**Behnaz ALAFİ  
(504181008)**

**Elektrik Mühendisliği Ana Bilim Dalı**

**Elektrik Mühendisliği Programı**

**Tez Danışmanı: Prof. Dr. Şahin Serhat ŞEKER**

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Behnaz ALAFI, a M.Sc student of ITU Graduate School student ID 504181008, successfully defended the thesis entitled “DEEP LEARNING FOR WIND ENERGY SYSTEMS USING THE HURST EXPONENT AND STATISTICAL PARAMETERS”, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

**Thesis Advisor :**      **Prof. Dr. Şahin Serhat ŞEKER** .....  
Istanbul Technical University

**Jury Members :**      **Prof. Dr. Şahin Serhat ŞEKER** .....  
Istanbul Technical University

**Prof. Dr. Emine AYAZ** .....  
Istanbul Technical University

**Prof. Dr. Osman Nuri UÇAN** .....  
Altınbaş University

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*To my dear family, beloved friends,*



## FOREWORD

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Behnaz ALAFI  
(Electrical Engineer)



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## ABBREVIATIONS

|             |                                |
|-------------|--------------------------------|
| <b>ANN</b>  | : Artificial Neural Network    |
| <b>BP</b>   | : Back-Propagation             |
| <b>WS</b>   | : Wind Speed                   |
| <b>P</b>    | : Pressure                     |
| <b>H</b>    | : Humidity                     |
| <b>NN</b>   | : Neural Network               |
| <b>ANN</b>  | : Artificial Neural Network    |
| <b>AI</b>   | : Artificial Intelligence      |
| <b>DNN</b>  | : Deep Neural Network          |
| <b>DL</b>   | : Deep learning                |
| <b>CNN</b>  | : Convolutional Neural Network |
| <b>RNN</b>  | : Recurrent Neural Network     |
| <b>LSTM</b> | : Long Short Term Memory       |
| <b>MLP</b>  | : MultiLayer Perceptron        |
| <b>MSE</b>  | : Mean Square Error            |
| <b>RMSE</b> | : Root Mean Square Error       |
| <b>HE</b>   | : Hurst Exponent               |
| <b>PDF</b>  | : Probability Density Function |
| <b>CDF</b>  | : Cumulative Density Function  |
| <b>D</b>    | : Dimension                    |



## SYMBOLS

|           |                                  |
|-----------|----------------------------------|
| $v$       | : Wind speed                     |
| $H$       | : Hurst exponent                 |
| $f(v)$    | : Weibull density function       |
| $F(v)$    | : Weibull cumulative function    |
| $k$       | : Shape parameter of Weibull PDF |
| $c$       | : Scale parameter of Weibull PDF |
| $P_m$     | : Wind power density             |
| $P_w$     | : Theoretical wind power density |
| $\rho$    | : Air density                    |
| $D$       | : Fractal dimension              |
| $R$       | : Rescaled range of variation    |
| $S$       | : Standard deviation             |
| $w_i$     | : Weight value                   |
| $i_i$     | : Input value                    |
| $o_i$     | : Output value                   |
| $t_i$     | : Target value                   |
| $e$       | : Error                          |
| $F^i$     | : $i^{\text{th}}$ Hidden layer   |
| $R_i$     | : Recurrent weight value         |
| $b_i$     | : Bias weight value              |
| $h_i$     | : Hidden state value             |
| $f$       | : Forget gate                    |
| $g$       | : Cell candidate                 |
| $\sigma$  | : Activation function            |
| $A$       | : Turbine blade Area             |
| $t$       | : Time                           |
| $\varphi$ | : Activation function            |
| $R$       | : Regression factor              |
| $y_t$     | : Time series                    |

$T_t$  : Trend of Time series  
 $S_t$  : Seasonal component of Time series  
 $I_t$  : Irregular component of Time series



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# DEEP LEARNING FOR WIND ENERGY SYSTEMS USING THE HURST EXPONENT AND STATISTICAL PARAMETERS

## SUMMARY

As we all know, energy demand is continuously increasing because of population growth and developing technology. As a result of this increasing demand, energy shortages and environmental pollution will occur. Besides, because of the growing crisis and other critical issues around energy, renewable energy is taking countries' attention and becoming important in various parts of the entire world. Wind energy, solar power, tidal energy, geothermal energy, etc. as renewable energy sources have been used to solve these issues. Among these alternative sources of energy, wind and solar energy have got the most attention recently. Since wind power has less pollution, shorter construction time, less occupation, and flexible investment, it has become one of the most effective sources of energy. And in this study, the information is about wind data. But the wind is unstable and mainly affected by meteorological and navigational conditions and the principle for its implementation changes from one place to another. These changes in the meteorological measurement cause uncertainty in wind farms' generated power that affects power supply and quality. Also, because it is impossible to generate every power amount by wind energy or store electrical energy, there is a limitation on the amount of output power. Therefore, An accurate prediction can cause the cost of power generation reduction, less winding reserve capacity of the grid, and more reliable operation of the grid. Because of aforesaid reasons, prediction in wind energy systems is a very important issue. Nowadays, deep neural networks have been considering for prediction problems. In this study, the convolutional neural network(CNN) as a deep neural network is used to do predictions in wind energy systems based on meteorological data of one station. Since the Hurst exponent  $H$  is used to determine the predictability degree of a set of data, it gives some information about data that is useful in developing predictive models both theoretical and computational in nature. We first aim to apply the Hurst exponent method on wind energy data and then execute a deep neural network on data to train data through that deep neural network.

Work steps: this literature study on the yearly meteorological features of one station applies deep learning methods to it. First of all, we gathered reported data for wind speed, air pressure, and relative humidity as the inputs of one deep neural network to train that network for predicting wind speed data. Since the power of one turbine is related to wind speed value, studying the wind speed behavior of one location leads to the study of the power capacity of that location. Before training a neural network, it is better to study the behavior of wind speed and find its statistical model and predictability degree, so before entering meteorological data into a deep neural network we studied statistical parameters of wind speed and find probability density of it and then we found Hurst exponent, as the factor for predictability degree, and, then, all data is entered to one CNN to train that network and predict wind speed data.

# HURST ÜSLÜ VE İSTATİSTİKSEL PARAMETRELERİ KULLANARAK RÜZGAR ENERJİSİ SİSTEMLERİ İÇİN DERİN ÖĞRENME

## ÖZET

Hepimizin bildiği gibi, günümüzde nüfus artışı ve gelişen teknoloji nedeniyle enerji talebi sürekli artmaktadır. Artan bu talep sonucunda enerji kıtlığı ve çevre kirliliği oluşacaktır. Ayrıca, artan kriz ve enerji ile ilgili diğer kritik konular nedeniyle yenilenebilir enerji, ülkelerin dikkatini çekmekte ve dünyanın çeşitli yerlerinde önem kazanmaktadır. Bu sorunları çözmek için rüzgar enerjisi, güneş enerjisi, gelgit enerjisi, jeotermal enerji vb. yenilenebilir enerji kaynakları olarak kullanılmaktadır. Ancak her birinin bazı olumlu ve olumsuz yanları vardır. Sonuç olarak, son zamanlarda en fazla ilgiyi rüzgar ve güneş enerjisi almaktadır. Rüzgar enerjisi daha az kirlilik, daha kısa inşaat süresi, daha az işgal ve esnek yatırıma sahip olduğundan, en etkili enerji kaynaklarından biri haline gelmiştir. Daha önce de belirtildiği gibi, rüzgarı enerji kaynağı olarak kullanmanın kendi sınırlamaları vardır. Rüzgar çok dengesizdir ve esas olarak meteorolojik ve seyir koşullarından etkilenir ve uygulama prensibi bir yerden başka bir yere değişir. Meteorolojik ölçümdeki bu değişiklikler, güç kaynağı ve kaliteyi etkileyen rüzgar çiftliklerinin ürettiği güçte belirsizliğe neden olur. Ve her güç miktarını rüzgar enerjisi ile üretmek mümkün olmadığından, çıkış gücü miktarı için bir sınırlama vardır. Örneğin, bir rüzgar santrali bir şebekeye bağlandığında, şebeke benzeri stabilite, dağıtım, pik yük, kompanzasyon, sevk, frekans gibi her parametre bu bağlantıdan etkilenecektir. Uçucu rüzgar çiftlikleri ne kadar güçlü olursa, şebeke parametreleri üzerinde o kadar fazla etki olur. Rüzgar türbinlerinde üretilen güç, rüzgar hızından doğrudan etkilendiğinden, üretilen gücün doğru bir şekilde tahmin edilmesi için rüzgar hızı tahmini uygun bir yaklaşım olabilir. Doğru bir tahmin, elektrik üretiminin maliyetinin düşmesine, şebekenin daha az sarım rezerv kapasitesine ve şebekenin daha güvenilir çalışmasına neden olabilir. Yukarıda bahsedilen tüm nedenlerden dolayı rüzgar hızı tahmini çok önemli ve tartışmalı bir konudur. Genel olarak, tahmin iki ana kategoriye ayrılabilir; kısa vadeli ve uzun vadeli tahmin ve bazen üç kategoriye genişletilebilir; kısa vadeli, orta kısa vadeli ve uzun vadeli. Rüzgar dinamiğinin sürekli değişen davranışıyla ilgili maliyeti belirlemek için yapay operasyonel tahminler gereklidir. Uzun vadede üretilen rüzgarın ortalama değeri, belirli bir konumdan rüzgar ve gücü tahmin etmede önemli bir parametredir. Ancak daha yakın vadeli veya kısa vadeli yapay tahminler, rüzgar üretim miktarını takip eden önemli bir unsur olarak rezerv ön koşullarının belirlenmesi için zorunludur. Son yıllarda, rüzgar hızı tahmini için stokastik zaman serisi modeli, destek vektör regresyonu, dalgacık analizi, Kalman filtreleri, uzaysal-zamansal modeller ve AI modelleri olarak bilinen Yapay Zeka gibi birçok yöntem uygulanmaktadır. Rüzgar hızı, kontrol sistemi verilerini ve karşılaştırılabilir önceki verileri çıkaran istatistiksel bir öğrenme yaklaşımı kullanılarak tahmin edilir. Tahmin için genellikle bir zaman serisi modeli kullanılır ve parametreleri tahmin etmek için veri kümesindeki yinelemeler kullanılır. Veri madenciliği teknikleri, çeşitli araştırma türlerinde tahmin için de kullanılmıştır. Veri madenciliği, yapay sinir ağlarında kullanılanlara benzer öğrenme teknikleri kullanır. İki nedenden dolayı istatistiksel öğrenme yaklaşımları önerilir: oluşturması kolay ve mükemmel kısa vadeli tahmin doğruluğuna sahip tahmin modelleri. Rüzgar tahmini, fiziksel sistemlere dayalı modellerden de yararlanabilir. Bu yaklaşımlar sayısal hava tahminleri için kullanılır ve bir dizi diferansiyel denklemden oluşur. Daha kapsamlı bilgi gerektiren uzun vadeli sistemler bu fiziksel tekniklerden

yararlanabilir. Ayrıca bu fiziksel sistemler istatistiksel öğrenme yaklaşımlarına dayalı tahminlerle karşılaştırıldığında başarı oranları daha düşüktür. Bununla birlikte, hem istatistiksel hem de fiziksel teorileri birleştiren yöntemler vardır. Bunlar hibrit model yaklaşımları olarak bilinir ve sayısal meteorolojik veri tahminini çözmek için istatistiksel modellerin uygulanmasını içerir. Rüzgar hızı, hava basıncı ve diğer meteorolojik veriler gibi çok girişli veriler, tahmin algoritmalarına girdi olarak yaygın olarak kullanılır. Doğrusal olmayan özellikleri haritalama kapasitesi nedeniyle, AI prosedürü mükemmel sonuçlar verir. AI tekniklerinin birincil faydası, önceden belirlenmiş bir matematiksel modele ihtiyaç duymadan olası rüzgar hızı serilerini tahmin edebilmeleridir. Araştırmacılar şu anda rüzgar hızını tek bir AI yaklaşımı olarak tahmin etmek için yapay sinir ağlarını (YSA) kullanıyor. YSA yöntemi, insan beynindeki nöronlar gibi bir düğüm ağı aracılığıyla öğrendiği, düzenlediği ve kendini uyarladığı için tahmin için daha etkilidir. Rüzgar hızı serilerinin daha kapsamlı özelliklerini ortaya çıkarmak için standart sinir ağları üzerinden derin öğrenme teknikleri önerilir. Derin öğrenme algoritmaları, çeşitli makine algılama, görme, konuşma ve sinyal işleme uygulamalarında mükemmel sonuçlar üretir. Rüzgar hızı verilerinin karmaşık özellikleri, derin bir öğrenme yaklaşımı kullanılarak ortaya çıkarıldı. Günümüzde derin öğrenme algoritmaları, tahmin etmek için en güvenilir ve uygulanabilir yöntemlerdir. Rüzgar hızı tahmini araştırmalarında, doğrudan ham rüzgar hızı verilerinden tahmin edilen rüzgar hızı değerlerini üreten birçok araştırma, rüzgar hızı serisinin durağan olmayan etkilerini görmezden geldi. Derin öğrenme, makine öğreniminin bir alt kümesi olan bir tür makine öğrenimidir. Derin sinir ağları veya derin sinir öğrenimi, büyük miktarda yapılandırılmamış ve etiketlenmemiş veriden (denetimsiz kategoride büyük veri olarak bilinir) öğrenebilir çünkü büyük miktarda yapılandırılmamış ve etiketlenmemiş veriden öğrenme imkana sahiptir. Büyük veri olarak adlandırılan dünyanın her yerinden gelen veri patlamasına yanıt olarak derin öğrenme istikrarlı bir şekilde tamamlandı. Dünyanın her yerindeki diğer kaynaklardan büyük verilerin toplanması ve analizi uzun bir zaman, belki de on yıllar alacaktır. Derin öğrenme, bu büyük hacimli yapılandırılmamış ve etiketlenmemiş verileri öğrenmek için kullanılır. Sonuç olarak, bu araştırmada İstanbul Göztepe için rüzgar hızı dağılımlarının istatistiksel uyumları yapılmıştır. meteorolojik veriler yıllık olarak toplanmaktadır. Saatlik, mevsimlik ve yıllık ortalama rüzgar hızı verileri, uygun frekanslar kümesine sıkıştırılmıştır. Grafiksel yöntem, rüzgar hızı olasılık dağılımının en iyi modeli olarak Weibull dağılımının iki temel parametresini belirlemek için kullanılır: Weibull ölçek faktörü "c" ve Weibull şekil faktörü "k". İdeal türbinin rüzgar gücü yoğunluğu ve elektrik enerjisi çıkışı Weibull faktörleri kullanılarak ölçülmüştür. Daha sonra rüzgar hızı verilerinin Hurst üssü ile tahmin edilebilirliği incelenmiştir. Rüzgar enerjisi rüzgar hızına bağlı olduğundan rüzgar hızı tahmin edilebilir ise üretilen enerji de tahmin edilebilir olacaktır. Son adımda, bunun öngörülebilirlik derecesi faktörü olarak Derin Öğrenme yöntemi kullanılarak rüzgar hızı tahmini yapıldı ve ardından tüm veriler tek bir CNN'ye girilerek o ağı rüzgar hızı verilerini tahmin etmek için tarandı.

Çalışma adımları: Bir istasyonun yıllık meteorolojik özelliklerine ilişkin bu literatür çalışması, ona derin öğrenme yöntemlerini uygular. Her şeyden önce, rüzgar hızı verilerini tahmin etmek için bu ağı eğitmek için bir derin sinir ağının girdileri olarak rüzgar hızı, hava basıncı ve bağıl nem için raporlanmış verileri topladık. Bir türbinin gücü, rüzgar hızı değeri ile ilgili olduğundan, bir konumun rüzgar hızı davranışını incelemek, o konumun güç kapasitesinin incelenmesine yol açar. Bir sinir ağını eğitmeden önce, rüzgar hızının davranışını incelemek ve istatistiksel modelini ve tahmin edilebilirlik derecesini bulmak daha iyidir, bu nedenle meteorolojik verileri

derin bir sinir ağına girmeden önce rüzgar hızının istatistiksel parametrelerini inceledik ve olasılık yoğunluğunu bulduk ve sonra tahmin edilebilirlik derecesi faktörü olarak Hurst üssünü bulduk ve ardından, tüm veriler bu ağı taramak ve rüzgar hızı verilerini tahmin etmek için bir CNN'ye girildi.







## 1. INTRODUCTION

Today, energy demand is continuously increasing because of population growth and developing technology. As a result of this increasing demand, energy shortages and environmental pollution will occur. Besides, because of the growing crisis and other critical issues around energy, renewable energy is taking countries' attention and becoming important in various parts of the entire world. To solve these issues, wind energy, solar power, tidal energy, geothermal energy, etc. as renewable energy sources have been using. However, each of them has some positive and negative sides. As a consequence, wind and solar energy have got the most attention recently. Since wind power has less pollution, shorter construction time, less occupation, and flexible investment, it has become one of the most effective sources of energy. As aforementioned, using wind as a source for energy supply has its own limitations (Filik, 2017; Zhu et al, 2017). The wind is so unstable and mainly affected by meteorological and navigational conditions and the principle for its implementation changes from one place to another place. These changes in the meteorological measurement cause uncertainty in generated power by these wind farms that it affects power supply and quality. And there is a limitation for the amount of output power because it is not possible to generate every power amount by wind energy. For example, when a wind farm is connected to a grid, every parameter in the grid like stability, distribution, peak load, compensation, dispatching, the frequency will be affected by this connection. The stronger the volatile wind farms, the more effect on grid parameters. Since the generated power in wind turbines directly is affected by wind speed, wind speed prediction can be an appropriate approach to correctly estimate the generated power. An accurate prediction can cause the cost of power generation reduction, less winding reserve capacity of the grid, and more reliable operation of the grid (Filik, 2017; Zhu et al, 2017). Because of all the aforementioned reasons, wind speed prediction is a crucial and controversial issue. Generally, prediction can be divided into two main categories; short-term, and long-term prediction, and sometimes it can be extended to three categories; short-term, mid-short-term, and long-term. To determine the cost related to the continuously changing behavior of wind dynamics, artificial operational predictions are required. The average

value of generated wind in the long term is an essential parameter in predicting wind and power from a specific location. But closer term or short-term artificial predictions are imperatives to deciding reserve prerequisites, as a prominent element following wind generation amount (Dragoon, 2010). In recent decades, a lot of methods are implemented for wind speed prediction like the stochastic time series model, the support vector regression, wavelet analysis, Kalman filters, spatial-temporal models, and Artificial Intelligence known as AI models (Zhu et al, 2017). Wind speed is estimated using a statistical learning approach that subtracts control system data and comparable previous data (Y. Jiang, et al, 2013). A time series model is typically used for prediction, and iterations on the dataset are used to estimate parameters. Data mining techniques have also been utilized for prediction in several types of research. Data mining employs learning techniques that are similar to those employed in artificial neural networks (Y. Jiang, et al, 2013; E. Cadenas and W. Rivera, 2010; Kusiak, et al, 2009). For two reasons statistical learning approaches are recommended: prediction models that are simple to construct and have excellent short-term forecast accuracy. Wind forecasting can also benefit from models based on physical systems. These approaches are used for numerical weather predictions and consist of a set of differential equations (Y. Jiang, et al, 2013). Long-term systems that require more comprehensive information might benefit from these physical techniques. Furthermore, when these physical systems are compared to estimates based on statistical learning approaches, the success rates are lower. There are, however, methods that combine both statistical and physical theories. These are known as hybrid model approaches, and they include applying statistical models to solve numerical meteorological data forecast. Multi-input data such as wind speed, air pressure, and other meteorological data are commonly utilized as inputs to prediction algorithms (I. Colak, et al, 2015; J. Zhang, and B. M. Hodge, 2014; E. Yatiyana et al, 2019; G. W. Chang, et al, 2016). Because of its capacity to map nonlinear characteristics, the AI approach produces excellent results. The primary benefit of AI techniques is that they can predict probable wind speed series without the need for a predetermined mathematical model. Researchers are presently using artificial neural networks (ANN) to predict wind speed as one AI approach (S. S. Sanz, et al, 2008; D. Reddy, and S. Ramasamy, 2019). Since the ANN method learns, organizes, and adapts itself through a network of nodes – like neurons inside the human brain – is more effective for prediction. To disclose more comprehensive characteristics of wind speed series, deep

learning techniques are recommended over standard neural networks. Deep learning algorithms produce excellent outcomes in a variety of machine sensing, sight, and speech, and signal processing applications (K. F. Abdulraheem and G. Al-Kindi, 2018). The intricate characteristics of wind speed data were revealed using a deep learning approach (K. Wang, et al, 2018; A. T. Sergio and T. B. Ludermit, 2015; R. Y. Kazakova, et al, 2016). Today, Deep learning algorithms are the most reliable and applicable methods to predict. Many investigations in wind speed prediction research, which generated predicted wind speed values directly from raw wind speed data, ignored the non-stationary effects of the wind speed series. Deep learning is a type of machine learning that is a subset of machine learning (H. D. Wehle, 2019). Deep neural networks or deep neural learning can learn from a large quantity of unstructured and unlabeled data – known as big data in the unsupervised category – because it can learn from a large quantity of unstructured and unlabeled data. Deep learning has been steadily completed in response to the explosion of data from every part of the globe, which is referred to as big data. The collection and analysis of large data from other sources throughout the world would take a long time, perhaps decades. Deep learning is used to learn this massive volume of unstructured and unlabeled data (Alafi, B. 2019). To conclude, in this research, the statistical fits of wind speed distributions for Goztepe in Istanbul were carried out. meteorological data has been gathered annually. Hourly, seasonally, and yearly mean wind speed data have been condensed in a series of suitable frequencies. The graphical method is used to determine two essential parameters of Weibull distribution as the best model of wind speed probability distribution: Weibull scale factor "c" And Weibull shape factor "k". The ideal turbine's wind power density, availability factor, and electrical energy output were measured using the Weibull factors. (Azad, Kalam, et al, 2014). Then predictability of wind speed data via Hurst Exponent (HE) is studied. Since wind energy depends on wind speed, if the wind speed is predictable, generated energy will be predictable as well. At the end step, wind speed prediction has been done using the Deep Learning method as the factor for predictability degree of it, and, then, all data has been entered to one CNN to train that network to predict wind speed data.



## **2. DATA DESCRIPTION**

To get some information about wind energy in one place free from the type of turbines which can be used at those stations, we have to know some hourly, daily, monthly, yearly, or ten yearly meteorological data which is taken precisely. Depends on the type of investigation, a data period may be selected. According to the type of forecasting, these items may make difference. For example, the sampling frequency is less relevant in short-term forecasting. Since you can always toss data away, you'll typically attempt to gather data at the maximum feasible frequency. The higher frequencies, on the other hand, are unlikely to be useful for long-term forecasting. In short-term forecasting, data in small intervals is required, but in long-term forecasting, large buckets or data with large intervals are required to determine the future horizons, which requires multi-year forecasting. In this research, since we want to study meteorological behavior in order to wind energy prediction rather than studying a sustainable condition or future horizons of related wind energy, yearly data in small intervals is perfect for this purpose. Meteorological data which is very essential in wind energy prediction includes wind gust, air pressure, and air density. In this study, wind speed, air pressure, and relative humidity data are measured and recorded sensitively by Göztepe meteorological station in Istanbul. all data is monitored and recorded every hour during the year 2006. Air pressure is considered 1.225 kg/m<sup>3</sup>. The future wind speed will be predicted with a deep learning method through training the system rather than some structures of the system, and then according to that predicted wind speed, power of any type of turbine which is applicable at that site condition can be predicted. All data which is given year is divided by four seasons, and all mathematical and training procedures are done on them.

### **2.1 Data Acquisition And Modeling**

There are three data sets as wind speed data, air pressure data, and relative humidity data. All data sets are recorded hourly during 2006. this information is considered a time series. Totally, we have 8760 hourly records for all of these three items, then we divide them by 4 seasons, approximately 2200 data for each season, to process

meteorological data. In the end, to show more details of the change process of all variables, the first day of January as a sample is represented.

### 2.1.1 Wind speed

Wind Speed data set has 8760 data which is gathered during 2006 in one-hour intervals. This one-year data is divided by four to build four seasonal data set. Figure 2.1 shows all wind speed data during the year 2006; it can be seen that the mean value is around 2.33 m/sec and minimum and maximum values are 0 and 8.3 m/sec respectively. The other figures as 2.2, 2.3, 2.4, and 2.5 represent seasonally wind speed changes. The last figure as figure 2.6 represents wind speed changes for one sample day to represent wind speed changes on a bigger scale with more detail.

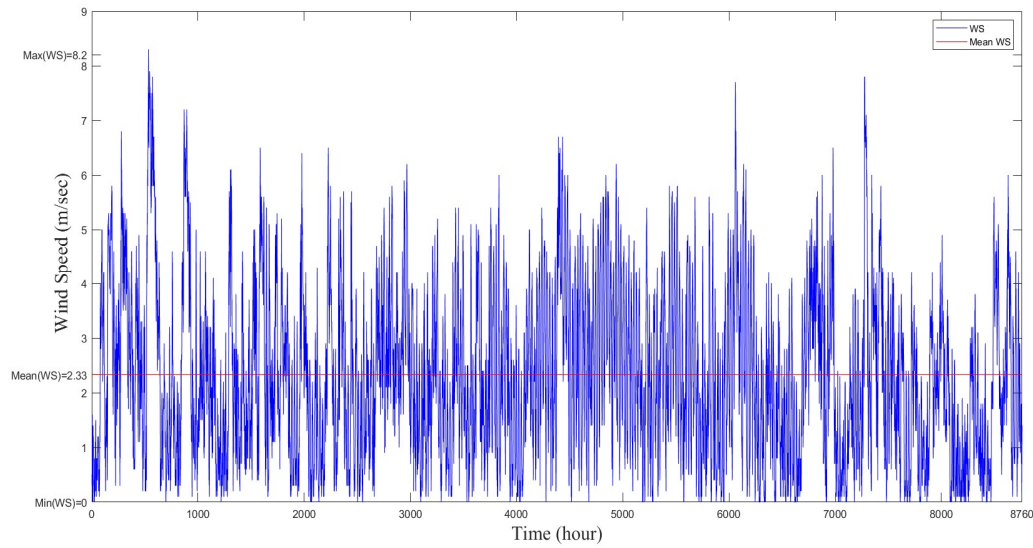


**Figure 2.1:** Yearly changes of wind speed (m/sec).

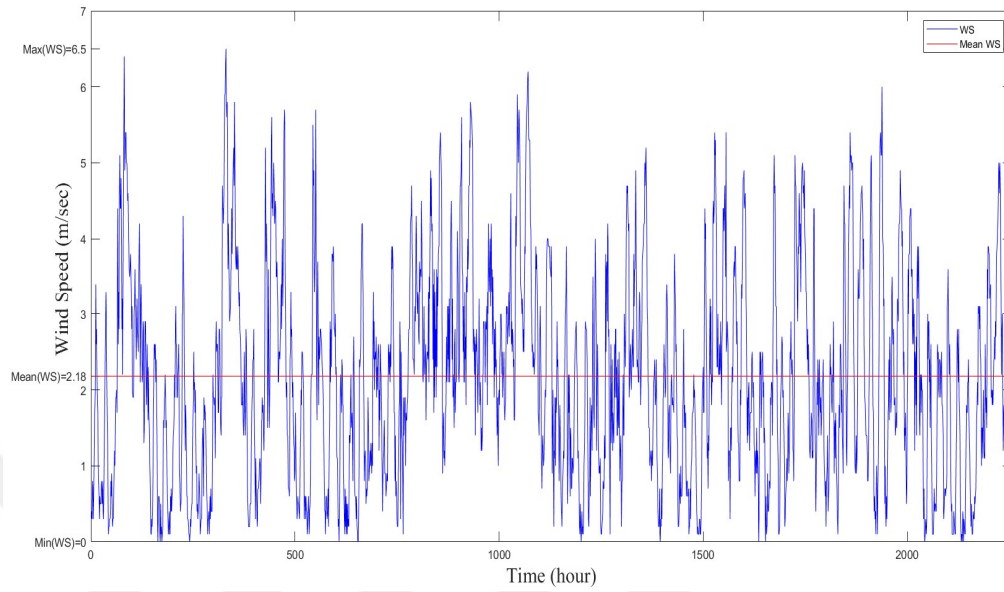


**Figure 2.2:** Wind speed changes during spring (m/sec).

Figure 2.2 shows changes in wind speed during spring from 21st March to 21st June with 2256 wind speed data which is gathered hourly. Wind speed changes between 0 and 6.5 m/sec with a mean value of 2.18 m/sec.

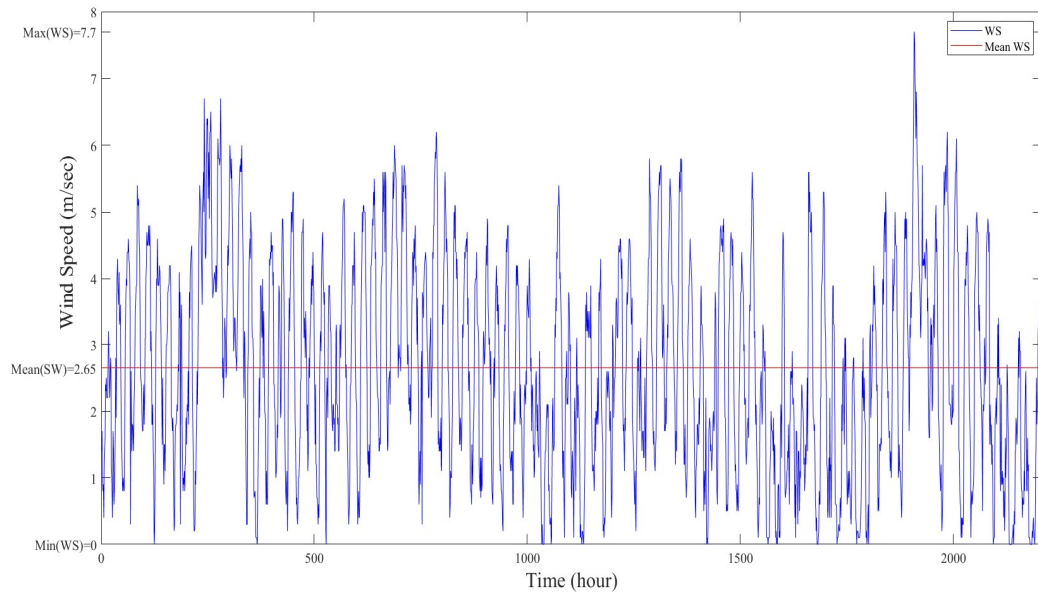


**Figure 2.3:** Wind speed changes during summer (m/sec).

Figure 2.3 Represents changes in wind speed during summer from 22nd June to 22nd September with 2208 wind speed data which is gathered hourly. Wind speed changes between 0 and 7.7 m/sec with a mean value of 2.65 m/sec.

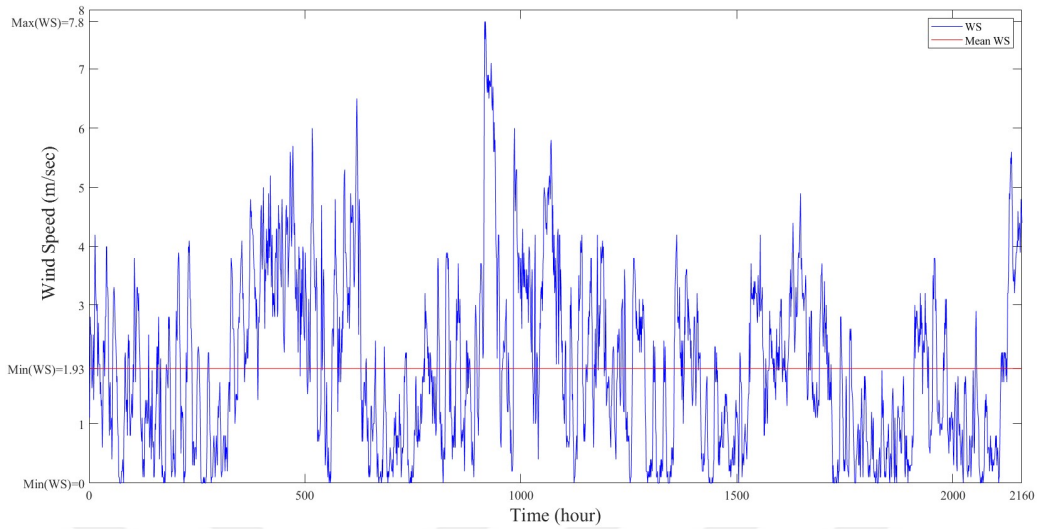


**Figure 2.4:** Wind speed changes during autumn (m/sec).

Figure 2.4 Represents changes in wind speed during autumn from 23rd September to 21st December with 2160 wind speed data which is gathered hourly. Wind speed changes between 0 and 7.8 m/sec with a mean value of 1.93 m/sec.

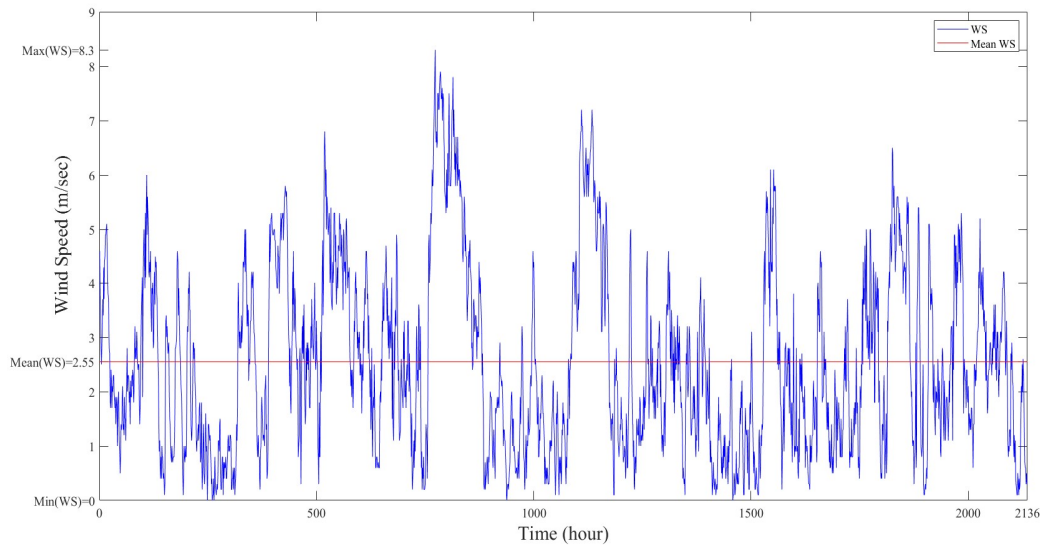


**Figure 2.5:** Wind speed changes during winter (m/sec).

Figure 2.5 Represents changes in wind speed during winter from 22nd December to 20th March with 2136 wind speed data which is gathered hourly. Wind speed changes between 0 and 8.3 m/sec with a mean value of 2.55 m/sec.

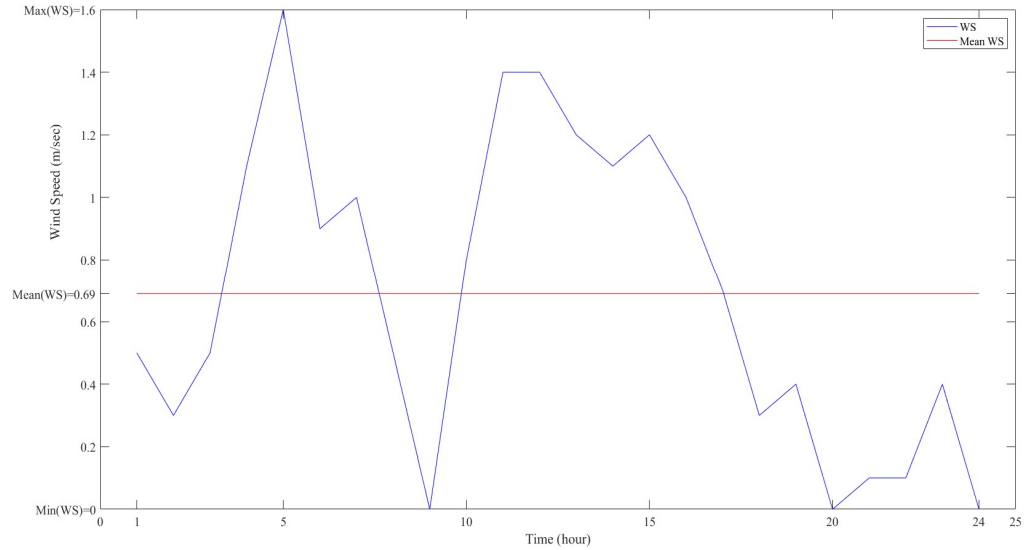


**Figure 2.6:** Wind speed changes on 1st January (m/sec).

Figure 2.6 Represents changes of wind speed on 1<sup>st</sup> January with 24 wind speed data which is gathered hourly. Wind speed changes between 0 and 1.6 m/sec with mean value 0.69 m/sec. Without any trial, it is obvious from the figures that one-day data is not enough to study wind speed changes and predict it followingly.

### 2.1.2 Air pressure

Air pressure data set has 8760 data which is gathered during 2006 in one-hour intervals. This one-year data is divided by four to build four seasonal data set. Figure 2.7 shows all air pressure data during the year 2006; it can be seen that the mean value is around 1010.55 mb while air pressure value changes between 992.7 mb and 1033 mb. The other figures as 2.8, 2.9, 2.10, and 2.11 represent seasonally air pressure changes. The last figure as figure 2.12 represents air pressure changes for one day as a pattern to represent wind speed changes on a bigger scale with more detail.

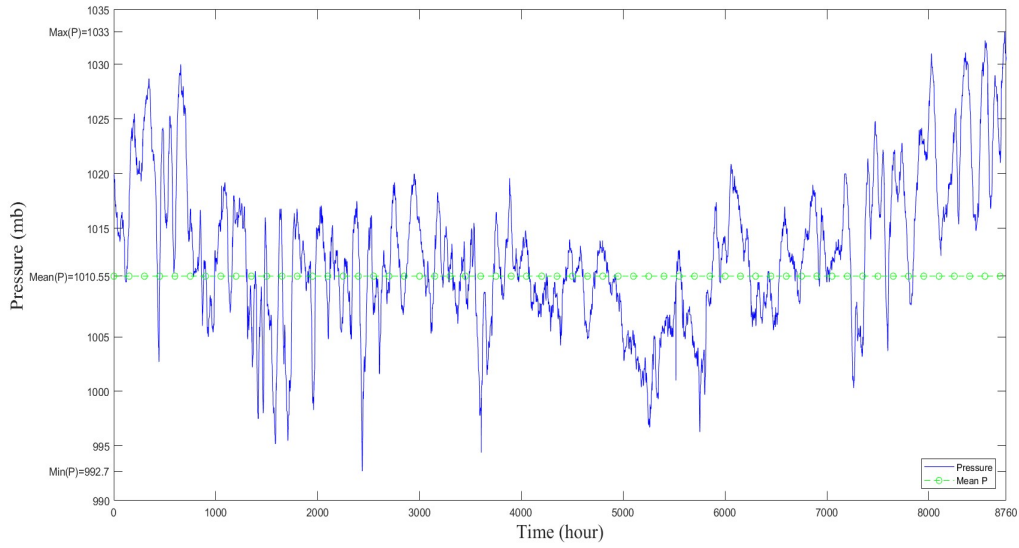


**Figure 2.7: Yearly changes of air pressure (mb).**

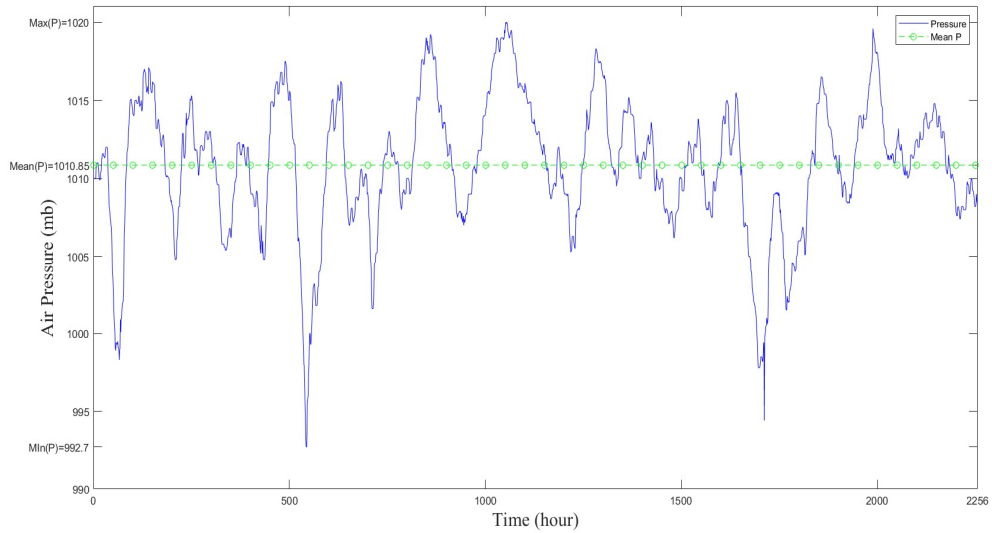


**Figure 2.8: Air pressure changes during spring (mb).**

Figure 2.8 represents changes in air pressure during spring from 21st March to 21st June with 2256 air pressure data which is gathered hourly. The mean air pressure value is 1010.85 mb while it changes between 992.7 mb and 1020 mb which is represented in the picture.

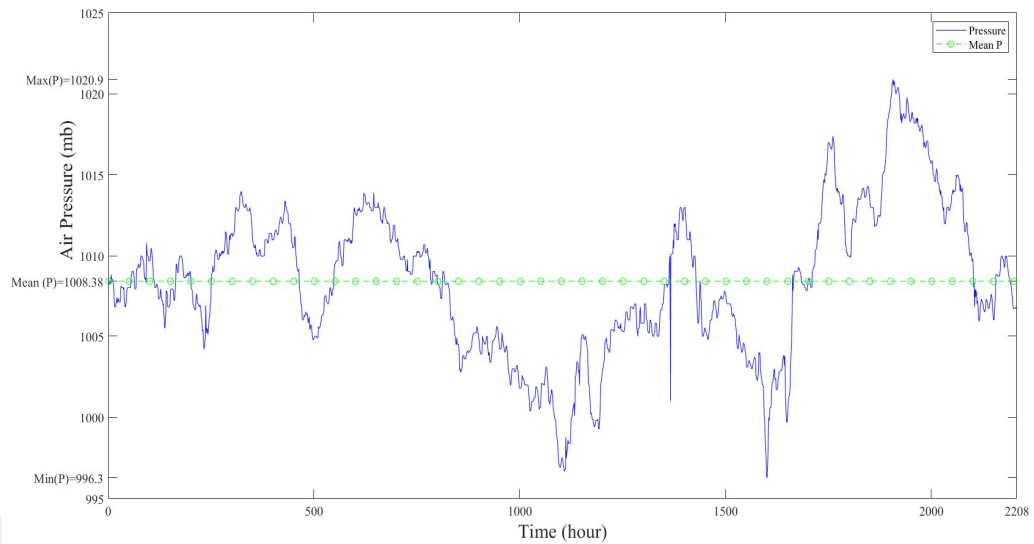


**Figure 2.9:** Air pressure changes during summer (mb).

Figure 2.9 shows changes in air pressure during summer from 22nd June to 22nd September with 2208 air pressure data which is gathered hourly. The mean air pressure value is 1008.38 mb while it changes between 996.3 mb and 1020.9 mb which is represented in the picture.

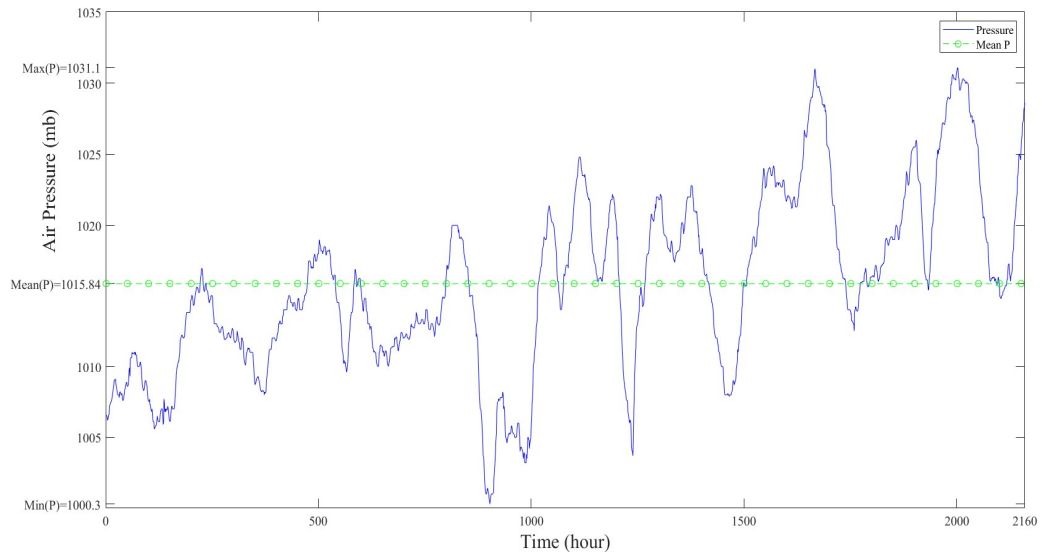


**Figure 2.10:** Air pressure changes during autumn (mb)

Figure 2.10 shows changes in air pressure during Autumn from 23rd September to 21st December with 2160 air pressure data which is gathered hourly. The mean air pressure

value is 1015.84 mb while it changes between 1000.3 mb and 1031.1 mb which is represented in the picture.

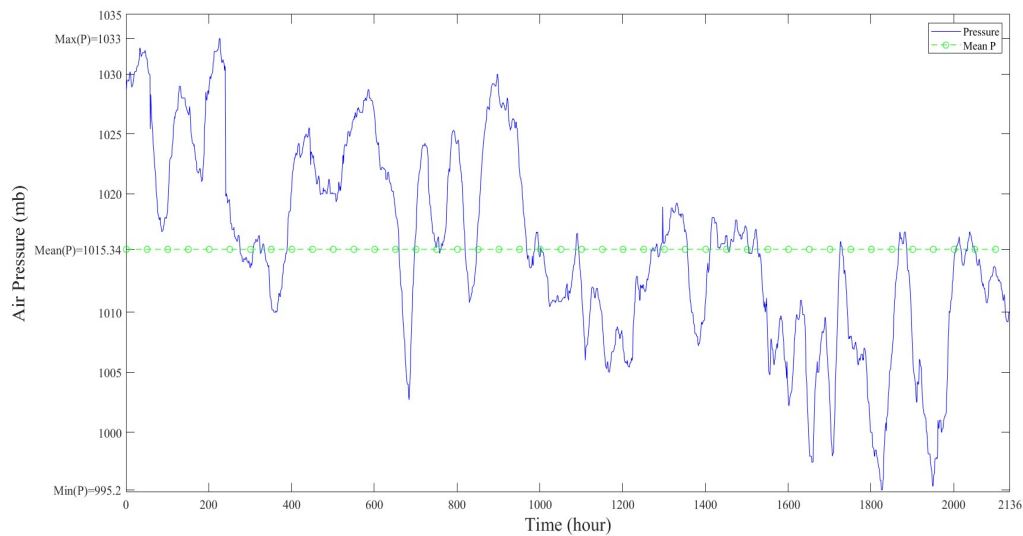


**Figure 2.11:** Air pressure changes during winter (mb).

Figure 2.11 shows changes in air pressure during winter from 22nd December to 20th March with 2136 air pressure data which is gathered hourly. The mean air pressure value is 1015.34 mb while it changes between 995.2 mb and 1033 mb which is represented in the picture.

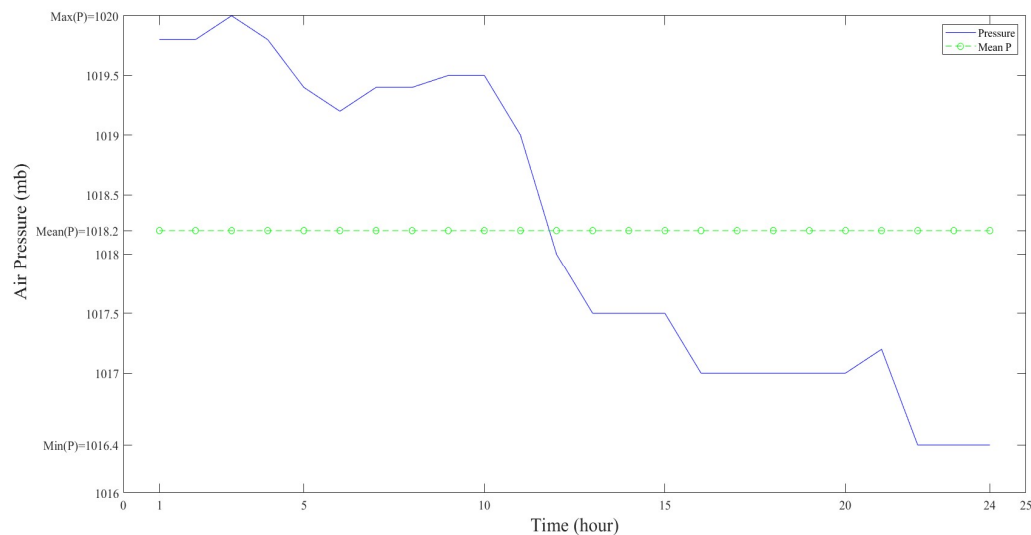


**Figure 2.12:** Air Pressure changes on 1st January (mb).

Figure 2.12 represents changes of air pressure on 1st January with 24 air pressure data which is gathered hourly. The mean air pressure value is 1018.2 mb while it changes between 1016.4 mb and 1020 mb which is represented in the picture.

### 2.1.3 Relative humidity

Relative Humidity is another data that is supposed to use as input data to predict wind speed, so we need its raw data. Its data set also has 8760 data which is gathered during 2006 in one-hour intervals. This one-year data is divided by four to build four sets of 2190 data which is considered seasonal data. Figure 2.13 shows all data during the year 2006; it can be seen that the mean relative humidity for one year is around 69.75% while its value changes between 17.5% and 100%. Other figures as 2.14, 2.15, 2.16, and 2.17 represent seasonal changes. The last figure as figure 2.18 represents humidity changes for one day as a pattern to represent humidity changes on a bigger scale with more detail.

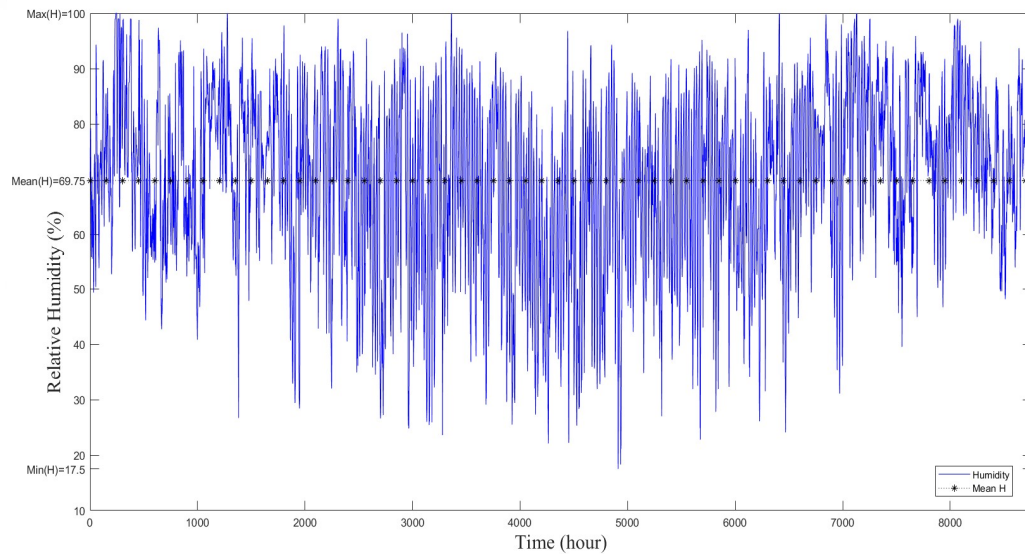


**Figure 2.13:** Yearly changes of relative humidity (%).

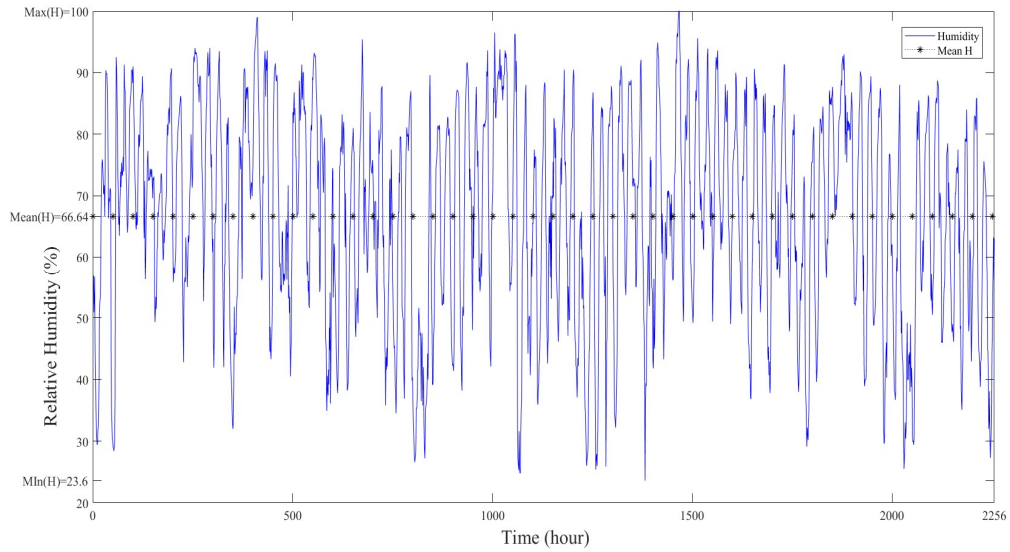


**Figure 2.14:** Relative humidity changes during spring (%).

Figure 2.14 represents changes of humidity in the air during spring from 21st March to 21st June with 2256 relative humidity data which is gathered hourly. The mean humidity value is 66.64% while it changes between 23.6% and 100% which is represented on the picture.

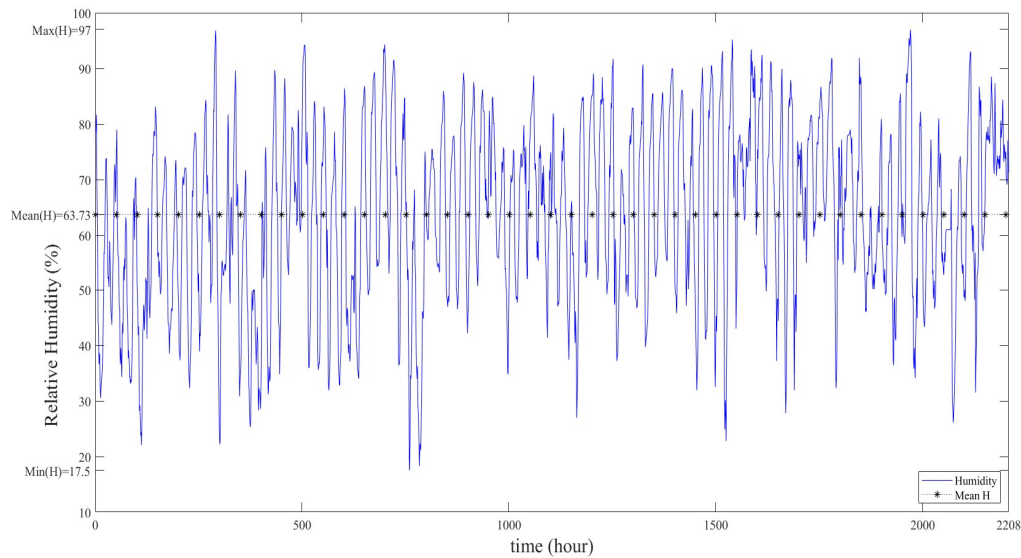


**Figure 2.15:** Relative humidity changes during summer (%).

Figure 2.15 represents changes of humidity in the air during summer from 22<sup>nd</sup> June to 22<sup>nd</sup> September with 2208 relative humidity data which is gathered hourly. The mean humidity value is 63.73% while it changes between 17.5% and 97% which is represented on the picture.

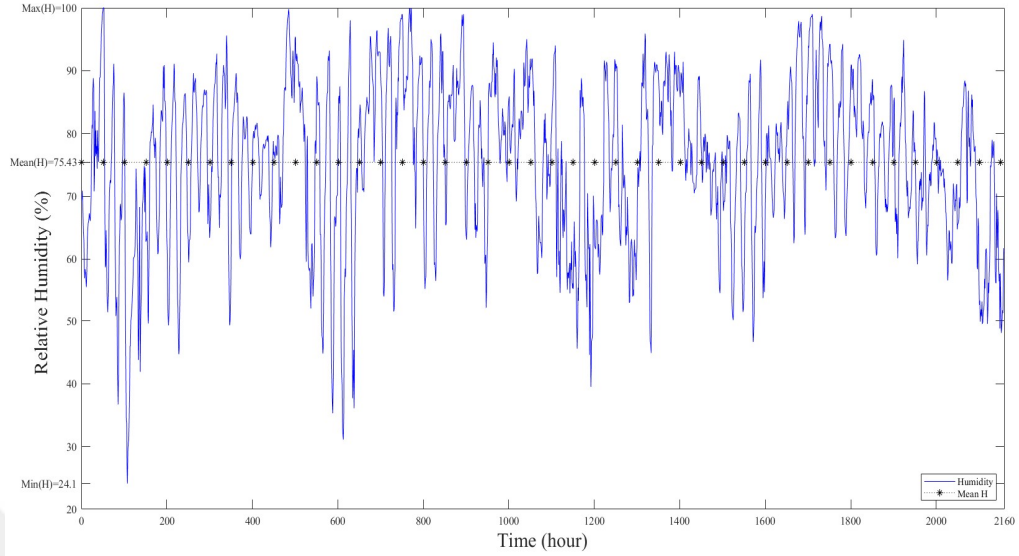


**Figure 2.16:** Relative humidity changes during autumn (%).

Figure 2.16 represents changes of humidity in the air during autumn from 23<sup>rd</sup> September to 21<sup>st</sup> December with 2160 relative humidity data which is gathered hourly. The mean humidity value is 75.43% while it changes between 24.1% and 100% which is represented on the picture.

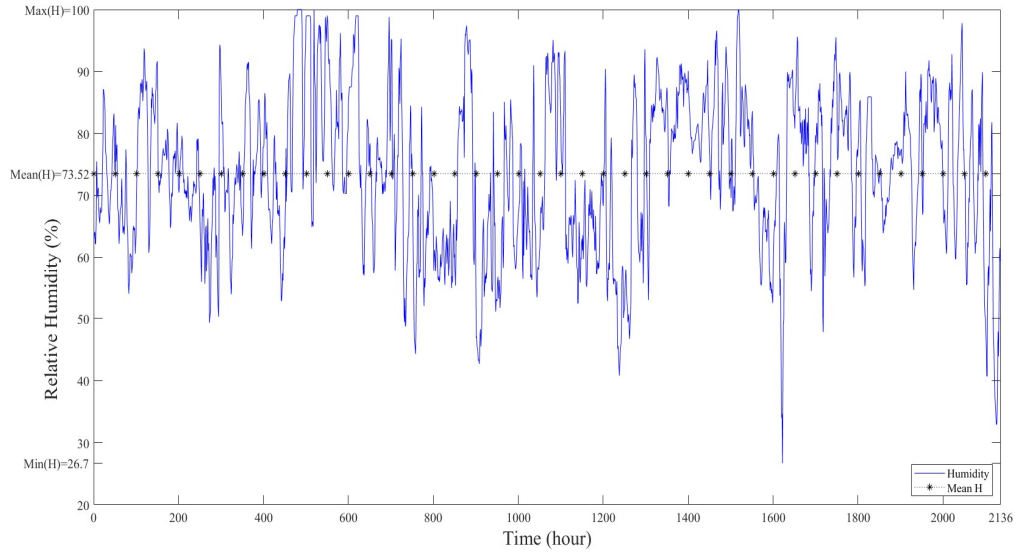


**Figure 2.17:** Relative humidity changes during winter (%).

Figure 2.17 represents changes of humidity in the air during winter from 22<sup>nd</sup> December to 20<sup>th</sup> March with 2136 relative humidity data which is gathered hourly. The mean humidity value is 73.52% while it changes between 26.7% and 100% which is represented on the picture.

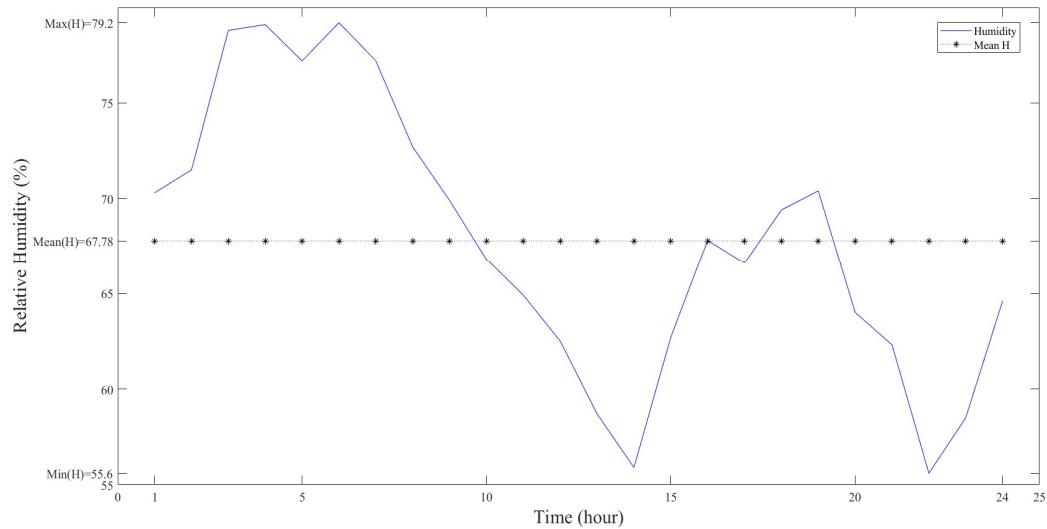


**Figure 2.18:** Relative humidity changes on 1st January (mb).

Figure 2.18 Represents changes of relative humidity on 1<sup>st</sup> January with 24 air humidity data which is gathered hourly. The mean humidity in the air is 67.78% while it changes between 55.6% and 79.2% which is represented on the picture. All information which is aforementioned is summarized in below table:

**Table 2.1:** wind speed, air pressure, and relative humidity properties.

| Time                                 |                      | Mean    | Min    | Max    | STD  |
|--------------------------------------|----------------------|---------|--------|--------|------|
| <b>2006</b><br><b>(8760 hours)</b>   | Wind Speed(m/sec)    | 2.33    | 0      | 8.2    | 1.56 |
|                                      | Air Pressure(mb)     | 1010.55 | 992.7  | 1033   | -    |
|                                      | Relative Humidity(%) | 69.75   | 17.5   | 100    | -    |
| <b>Spring</b><br><b>(2256 hours)</b> | Wind Speed(m/sec)    | 2.18    | 0      | 6.5    | 1.38 |
|                                      | Air Pressure(mb)     | 1010.85 | 992.7  | 1020   | -    |
|                                      | Relative Humidity(%) | 66.64   | 23.6   | 100    | -    |
| <b>Summer</b><br><b>(2208 hours)</b> | Wind Speed(m/sec)    | 2.65    | 0      | 7.7    | 1.58 |
|                                      | Air Pressure(mb)     | 1008.38 | 996.3  | 1020.9 | -    |
|                                      | Relative Humidity(%) | 63.73   | 17.5   | 97     | -    |
| <b>Autumn</b><br><b>(2160 hours)</b> | Wind Speed(m/sec)    | 1.93    | 0      | 7.8    | 1.45 |
|                                      | Air Pressure(mb)     | 1015.84 | 1000.3 | 1031.1 | -    |
|                                      | Relative Humidity(%) | 100     | 24.1   | 75.43  | -    |
| <b>Winter (2136 hours)</b>           | Wind Speed(m/sec)    | 2.55    | 0      | 8.3    | 1.76 |
|                                      | Air Pressure(mb)     | 1015.34 | 995.2  | 1033   | -    |

|                                              |                      |        |        |       |   |
|----------------------------------------------|----------------------|--------|--------|-------|---|
|                                              | Relative Humidity(%) | 100    | 26.7   | 73.52 | - |
| <b>1<sup>st</sup> January<br/>(24 Hours)</b> | Wind Speed(m/sec)    | 0.69   | 0      | 1.6   | - |
|                                              | Air Pressure(mb)     | 1018.2 | 1016.4 | 1020  | - |
|                                              | Relative Humidity(%) | 79.3   | 55.6   | 67.78 | - |





### **3. STATISTICAL ANALYSIS**

The study of gathering data and identifying patterns and trends is known as statistical analysis. It's merely a fancy way of expressing "statistics." After gathering data, analyzing these data starts. In the first step, a summary of the information is made through some pie charts, tables, or any graphs. Secondly, primary location indicators are found. For example, the mean gives information about the average (or "middle") number in the data set. Then, spread tests illustrate if the data is closely clustered or more dispersed. The standard deviation is a widely used indicator of spread that indicates how spread-out data is around the mean. Finally, predictions for the future are made based on previous actions. The theory of an experiment should be tested. Data collected from an experiment only reveals a story as it is analyzed. The null hypothesis (the widely accepted theory) is either proven or disproven in this aspect of mathematical research, which is officially referred to as "hypothesis testing." Statistical interpretation is widely used in research, ranging from physics to sociology. In addition to evaluating hypotheses, statistics may offer an estimate for an unknown that is challenging or hard to calculate. Quantum field theory, for example, has proven difficult to experiment with and quantify empirically, despite its theoretical popularity. Some social science subjects, such as the study of consciousness or preference, are almost impossible to quantify; mathematical research may reveal the most plausible and least likely scenarios. For data of this project which is given based on time, we deal with a data set called time series.

#### **3.1 Time Series**

As in all statistical analysis time series data is collected from the real-life thing that we are interested in the data is analyzed using a computer to give graphic and numeric output; the output of the analysis tells us more about real life condition. It can be used to make and find predictions of future values. A time series is state of numerical measurements of the same entity taken an equally spaced intervals overtime. Time series data can be collected yearly, quarterly, monthly, weekly, daily, or even early.

Here are some examples of time series, average monthly temperature, annual profit from a company, daily Petrol price at the pump, hourly electricity consumption in the home, daily takings in restaurant takeaways, quarterly Haas sales. Time series data has four aspects of behavior: trend, seasonality, cycles, and unexplained variations; they can also be irregularities or outliers in the data which can be related to real world occurrences. Trend is the overall long-term direction of a series; economic series usually go up except when they do not. Some series have no this trend. Seasonality occurs when there is repeated behavior in the data which occurs in a regular endeavor. Seasonality is related to seasonal natural or human behavior. Cycles occur when a series follows an up-and-down pattern which is not seasonal; the cycle can be a varying length which makes them more difficult to detect than seasonality. We need to distinguish between seasonal and cyclic patterns as very different type of times series models are used in each case. To summarize, seasonal patterns have constant length but cyclic ones have variable length. If both exist together, the average length of cyclic pattern is longer than that of seasonal one. The magnitude of the cycles tends to be more variable than magnitude of seasonal fluctuations. As a result, it is much harder that predict cyclic data than seasonal data. In all data there is random variation, sometimes series are very regular which with little random variations. sometimes there is strange dips or jumps in a series, these can be usual one-off event such as an ash cloud disrupting air travel or an anticipated change in the range of sales tax. There are many computer packages that make it very easy to do the mechanics of time series analysis. It is really important to relate the mathematical aspects of the series to the real-life application; this is what makes time series analysis so interesting and practical. Time series as  $y_t$  can be represented as an additive decomposition of its trend  $T_t$ , seasonal  $S_t$ , and irregular components  $I_t$  as follow:

$$y_t = T_t + S_t + I_t \quad (3.1)$$

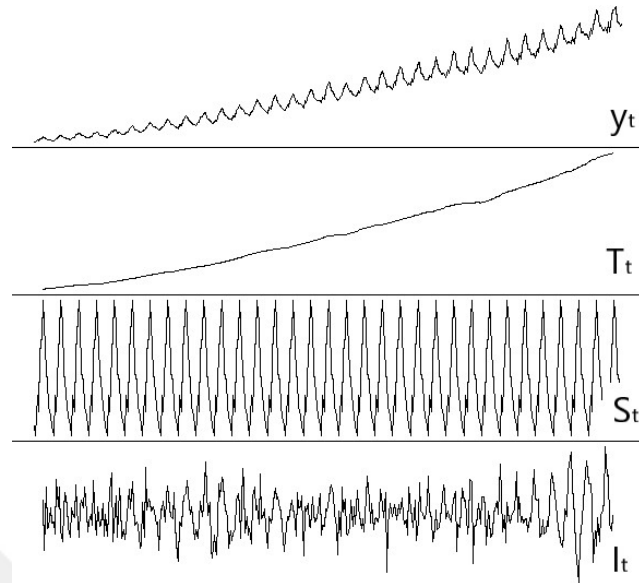


**Figure 3.1:** Time series aspects of behavior

### 3.1.1 Time series analysis

The form of analysis that works with time series data is known as time series analysis. In time series analysis, a variety of concepts are employed. A random or stochastic process is an example of such a process. This is a set of random variables that have been arranged according to time. For example, if  $Y$  is a random variable, it will be denoted as  $Y(t)$  in the case of continuous nature and  $Y(t)$  in the case of discrete nature.

It is critical for the analyst to understand that before undertaking time series analysis, the stochastic process must be rendered stationary. A stationary process is defined as one in which the mean and variance remain constant throughout time and the magnitude of the covariance between two time periods is mostly determined by the distance between them. In time series analysis, it is critical for the analyst to understand why stationary stochastic processes exist. The reason for this is that computing the mean and the variance for each time period is impractical. The mean and variance for that particular time series will be calculated if the time series is not stationary. In time series analysis, a stochastic process is said to be entirely random if the mean is zero and the variance is constant. It also has to be serially uncorrelated. Differencing is a time series analysis technique that transforms a volatile time series into a stationary one. There are several different orders. Consider the case when the data's volatility isn't decreased after first order differencing. In this Procedure, the analyst can attain stationarity by using second-order differencing. The exponential smoothing approach

predicts the future period value based on the previous and current values in time series analysis. This strategy is used in time series analysis to create short-term forecasts regarding commodities or stock exchanges. The various models are used in accordance with the pattern that appears in the data and its time-series behavior like trend, seasonality, cycles, and irregular fluctuations. The parameters Alpha, Gamma, Phi, and Delta are used to estimate the influence of time series data. When there is no seasonality in the data, alpha is applied. When the data in a series shows specific tendencies, gamma is employed. When there are seasonality cycles in the data, Delta is utilized. The main purpose of time series analysis is to match the data to the model that is being considered. In time series analysis, some assumptions are established. The following are the assumptions:

- The series should be stationary, according to the first assumption. In other words, the series is normally distributed in time series analysis, and the mean and variance are constant during that time span.
- The error term is considered to be randomly distributed, with the mean and variance remaining constant throughout time. In time series analysis, mistakes are supposed to be unrelated to one another.
- There is no outlier in the series, it is presumed. The existence of outliers has an impact on data inference in time series analysis, resulting in erroneous conclusions. Shocks are considered to be randomly distributed with a mean zero and constant variance if they appear in the time series analysis.

The temporal sequencing of time series data is natural. This distinguishes time series analysis from cross-sectional analysis, in which the observations are not naturally ordered (for example, explaining people's incomes by reference to their relative educational degrees, where the individuals' data might be put in any order). Time series analysis differs from spatial data analysis in that the observations are usually related to geographic places (For example, taking into consideration both the location and the inherent attributes of the properties when calculating property values). In general, a probability distribution for a time series will represent the reality that data near together in time are more tightly connected than observations far away. Furthermore, time series models frequently employ the natural one-way sequence of time, with values for a particular period derived in some way from previous values rather than

future values. There are two types of time series analysis approaches frequency-domain approaches and time-domain approaches. Spectral and wavelet analysis are examples of the former, whereas auto-correlation and cross-correlation analysis are examples of the latter. Scaled correlation can be used to perform filter-like correlation and analysis in the time domain, eliminating the requirement to work in the frequency domain. Furthermore, time series analysis methodologies can be classified as parametric or non-parametric. The parametric techniques presume that the underlying stationary stochastic process has a structure that can be characterized with a few parameters. The goal of these methods is to estimate the model's parameters that describe the stochastic process. Non-parametric techniques, on the other hand, directly estimate the covariance or spectrum of the process without presuming any specific structure. All data analysis methods can be divided into linear and non-linear, as well as univariate and multivariate.

### **3.1.2 Time series forecasting**

The deployment of a model to predict future values based on the previously observed values is called time series forecasting. While regression analysis is frequently used to examine correlations between several sets of time series, this form of analysis is not typically called "time series analysis," which refers to correlations between distinct points in time within a single series. Interrupted time series analysis is used to find changes in a time series' evolution from before to after some action that may affect the basic variables. Many traditional forecasting models require the time series to be stationary, which makes analysis more straightforward, but modern approaches work with data without pre-processing for stationary properties. Prediction is a type of statistical inference in statistics. The predictive inference is one method for making such inferences, although the prediction can be made using any of the several statistical inference methods. In fact, one definition of statistics is that it allows for the transfer of information from a sample of a population to the entire population and other related populations, which is not the same as prediction over time. Forecasting is the act of transferring knowledge across time, frequently to precise periods in time. (Bivona S et al, 2003). Prediction is a concept very similar to forecasting but is broader. Risk and uncertainty are fundamental to forecasting and prediction, and indicating the degree of uncertainty attached to projections is widely regarded as good practice. In any event, in order for the forecast to be as precise as possible, the data must be current. In certain

circumstances, the data used to predict the variable of interest is forecasted as well (Weisser D. A. 2003). Today, the Artificial intelligence method is the most updated method which is employed to do prediction which is frequently carried out by specialized programs that are generally characterized, data mining, machine learning, pattern recognition. There are some other forecasting methods such as Naïve approaches seasonal and simple, Relational methods, Judgmental methods, extrapolation and interpolation methods with the prediction of error, and some other time series methods.

### **3.2 Statistical Calculations And Probability Distribution**

Researchers working on renewable energy projects can now benefit greatly from wind analysis. Wind energy has the potential to dramatically cut fossil fuel burning and carbon dioxide emissions. Due to the current energy crisis and rising environmental consciousness, supplementing our energy base with clean and renewable sources of energy has become critical. The statistical characteristics of wind speed must be understood in order to estimate the energy output of a wind generator. Due to the significant variability of wind energy in location and time, it is critical to ensure that the analysis technique used to gather wind data yields estimated energy that is near to the actual energy obtained. Many efforts have been undertaken in recent years to develop an appropriate model for the wind speed probability distribution (Weisser D. A. 2003; Sathyajith et al, 2002; Bivona S et al, 2003). One of the wind characteristics, wind speed distribution, is critical not only for structural and environmental design and analysis but also for assessing the wind energy potential and the performance of wind energy conversion systems. Many studies have been conducted over the last two decades in order to build an acceptable statistical model to characterize wind speed frequency distribution. For fitting the observed wind speed probability distribution, the Weibull, Rayleigh, and Lognormal functions are widely employed (Meishen Li and Xianguo Li. 2005). The weibull probability density function is the function that has been widely using for wind speed (Buhairi, Mahyoub, 2006).

### 3.2.1 Weibull distribution

The Weibull distribution is a good approximation to several natural phenomenon' probability rules. For a long time, it has been used to depict wind speed distributions for use in wind load research. This technique has received a lot of interest in recent years for wind energy applications, not only because of its additional adaptability and simplicity, but also because it may provide an excellent match to observed measurements. For more than a century, statisticians working on theory and techniques and many other disciplines of statistics have been inspired by the Weibull distribution. The Weibull distribution is one the most common statistics models (Zaharim et al, 2009; Xiao et al, 2006). Because of its numerous unique characteristics and its ability to fit data from a wide range of fields, including meteorological data, business, management, and financial measurements, biochemistry, social science, hydrology, engineering, and biology, it is one of the most interested statistical approaches (Akpinar, E.K. and S. Akpinar, 2004; Akpinar, E.K. and S. Akpinar, 2005; Azad, Kalam et al, 2014). The probability density function and the cumulative distribution function are two functions that may be used to represent wind speed (H. Jiang et al, 2017; W. Weibull, 1941). Two parameter Weibull distribution function for wind speed is represented as follows:

$$f(v) = \left(\frac{k}{c}\right) \left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right] \quad (3.2)$$

And cumulative distribution function is:

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right] \quad (3.3)$$

k and c are two parameters of Weibull distribution. Where v represents wind speed, k is considered as shape parameter and c is considered as scale parameter. The scale parameter, c, indicates how 'windy' a surveyed wind area is, while the shape parameter, k, indicates how overhead the wind distribution is (i.e., if wind speeds are extremely close to a certain number, the distribution has a high k value and is very peaked) (D. A Weisser, 2003). There are several numerical methods to estimate these two parameters of Weibull distribution such as Moment Method (MM), Standard Deviation Method (SDM), Graphic Method (GM), Energy Pattern Factor Method (EPFM), and Empirical Method of Justus (EMJ). According to data which is available

in this study, GM will be used according to following mathematical approach which is based on cumulative distribution function:

$$\ln[-\ln[1 - F(v)]] = k \ln v - k \ln c \quad (3.4)$$

According to this equation, which a double logarithmic transformation is taken of cumulative distribution Eq. (3.3), if the values of  $\ln[-\ln[1 - F(v)]]$  and  $\ln v$  are considered as y and x respectively, we can rewrite Eq. (3.4) as follows:

$$y = k x - k \ln c \quad (3.5)$$

According to above linear relationship between y and x, if y is plotted versus x, k will be slope of line and  $-k \ln c$  will be the y-intercept of the line. GM by considering straight line equation as follows:

$$y = ax + b \quad (3.6)$$

Values of k and c will be:

$$k = a \quad (3.7)$$

$$c = \exp\left(-\frac{b}{a}\right) \quad (3.8)$$

In the case that k is 2, distribution function will be a Rayleigh distribution.

### 3.2.2 Wind power density function

For wind power density there are two equations related to actual wind speed data represented by  $P_m$  (W/m<sup>2</sup>) and the other one based on the theoretical wind speed density function represented by  $P_w$  (W/m<sup>2</sup>), which their relationships are represented as follows [gm]:

$$P_m = \frac{1}{2} \rho \overline{v^3} \quad (3.8)$$

Where,  $\rho$  is air density which is assumed to be 1.225 kg/m<sup>3</sup>, and  $\overline{v^3}$  is the mean of wind speed cubes in (m/sec)<sup>3</sup>, which is assumed to be calculated as follows:

$$\overline{v^3} = \frac{1}{n} \sum_{i=1}^n v_i^3 \quad (3.9)$$

Where,  $v_i$  is the  $i^{\text{th}}$  data of wind speed data, and n is the number of observed wind speed data or the number of data in the wind speed time series.

The relationship for  $P_w$  is represented as follows:

$$P_W = \int_0^{\infty} \frac{1}{2} \rho v^3 f(v) dv = \frac{1}{2} \rho c^3 \Gamma(1 + \frac{3}{k}) \quad (3.10)$$

Where,  $c$  and  $k$  are parameters of Weibull distribution, and  $\Gamma$  is Gamma function; Standard formula of gamma function of  $x$  is calculated as follows (Weisser D.A. 2003):

$$\Gamma(x) = \int_0^{\infty} e^{-u} u^{x-1} du \quad (3.11)$$

### 3.3 Hurst Exponent

The Hurst exponent is a measure of time series long-term memory. In other words, it is used to estimate stochasticity level of series. It has to do with time series autocorrelations and the pace at which they drop as the interval between pairs of values grows. The Hurst exponent was first used in hydrology to determine the best dam size for the Nile River's fluctuating rain and dry periods, which had been studied over a lengthy period of time (Hurst, H.E. 1951; Hurst, H.E.; Black, R.P.; Simaika, Y.M. 1965). The name "Hurst exponent" or "Hurst coefficient" comes from the primary researcher in these investigations, Harold Edwin Hurst (1880–1978); the usage of the standardized notation  $H$  for the coefficient is likewise related to his name. Hurst was tasked with researching Nile spills in order to construct a storage large enough that the inhabitants would not require water during dry years. He should have studied the mechanics of the Nile's ebb and flow for this. For a long time, the flow of water was thought to be a random variable, a stochastic process. The occurrences under investigation were to be unrelated and have the same likelihood. The Nile overflows revealed patterns to Hurst. He discovered that spills that were greater than usual caused even more spills. Thereafter, the process flipped and the spills at the level below the average were replaced by even smaller ones (Nazarychev et al 2019). The generalized Hurst exponent has been designated as  $H$  or  $H_q$  in fractal geometry by Benoît Mandelbrot (1924–2010) in honor of both Harold Edwin Hurst and Ludwig Otto Hölder (1859–1937).  $H$  is a measure of a data series' "mild" or "wild" unpredictability and is directly connected to fractal dimension,  $D$  (Mandelbrot, Benoît B. 1968). The "index of dependency" or "index of long-range reliance" is the name given to the Hurst exponent. It measures a time series' tendency to regress substantially to the mean or

cluster in a certain direction (Torsten Kleinow 2002). This exponent's value ranges from 0 to 1. A time series with a value H in the range 0.5–1 has long-term positive autocorrelation, which means that a high value in the series will almost certainly be followed by another high value, and that the values in the future will likewise tend to be high. After that, the value will likely to be high, with the tendency to flip between high and low levels persisting for a long period. H=0.5 may appear to be the value for a totally uncorrelated series, but it is really the value for series in which the autocorrelations at small time delays might be positive or negative, but the absolute magnitude of the autocorrelations decreases exponentially to zero. This is in contrast to the power law decline in time series with  $0.5 < H < 1$  and  $0 < H < 0.5$ . The longer the long-term memory, the more different it is from 0.5. As a result, processes with a large memory are processes that take a long time to complete. [11] All aforementioned facts around the relationship between time series properties and Hurst Exponent value are shown in table 3.1.

**Table 3.1:** Time series properties for different HE values.

| Hurst Exponent                     | $0 < H < 0.5$   | $H \approx 0.5$ | $0.5 < H < 1$ |
|------------------------------------|-----------------|-----------------|---------------|
| Stochasticity level of time series | anti-persistent | Random          | Persistent    |

### 3.3.1 Calculation of Hurst coefficient

Albert Einstein's work on Brownian motion, which is essentially a model of random walk of a particle, served as the foundation for the statistical Hurst model. The theory states that the distance R over which a particle travels grows in proportion to the square root of time T:

$$R = T^{0.5} \quad (3.12)$$

Hurst broadened Einstein's equation, making it more general:

$$\frac{R}{S} = c \cdot n^H \quad (3.13)$$

Where, R is rescaled range of variation; S is standard deviation; C is constant number; n is number of sample elements, and H will be the Hurst exponent or Hurst index which indicates how stochastic is a time series. Furthermore, The Hurst formula contains principles relating to the fractality of time series, which were found by Benoit Mandelbrot, the pioneer of fractal geometry. The following relationship exists between the Hurst exponent and the Hausdorff-Bezikovich dimension (Mandelbrot B 2002; Mandelbrot B 2004):

$$D = 2 - H \quad (3.14)$$

Where, D is Fractal Dimension. The Hurst exponent can be calculated in a variety of ways and methods in both time and frequency domain, such as R/S analysis, Period gram regression, variance-time analysis, detrended fluctuation analysis (DFA), local Whittle's estimator, and wavelet-based estimation (Kirichenko et al, 2011). Among these methods, R/S analysis or rescaled range analysis is that method which was pioneered by Mandelbrot and Wallis and based on prior Hurst hydrological discoveries, is the oldest and most well-known one.

### 3.3.2 R/S analysis algorithm

Rescaled range analysis examines a data series to see whether it has any persistence or mean-reverting tendencies. This empirical method suggested by H.E. Hurst, which is used to calculate the Hurst exponent to predict a future value or average based on the data, is still one of the most often used approaches for studying fractal series of various kinds. According to this method for the time series  $X(t)$  with the length of  $N$ , HE can be calculated by R/S analysis through follow calculation steps based on statistical parameters: (Nazarychev et al, 2019; ian, Bo & Rasheed, Khaled, 2004)

1. The smallest factor of time series length  $N$  is found as  $nk=N$ , which  $n$  represents the number of elements in each group, and  $k$  is the number of groups or samples to split time series  $X(t)$ ; elements of each group are represented by  $X_i$ .

2. Mean value calculation for each group as  $\mu$ :

$$\mu_t = \frac{1}{n} \sum_{i=(t-1)n+1}^{tn} X_i \quad ; t = 1, 2, \dots, k \quad (3.15)$$

3. Standard deviation calculation for each group as  $S$ :

$$S_t = \sqrt{\frac{1}{n} \sum_{i=(t-1)n+1}^{tn} (X_i - \mu_t)^2} \quad ; t = 1, 2, \dots, k \quad (3.16)$$

4. Mean-adjusted series creation for each group as  $Y$ :

$$Y_i = X_i - \mu_t \quad ; i = (t-1)n + 1, \dots, tn \text{ \& } t = 1, 2, \dots, k \quad (3.17)$$

5. Cumulative deviate series calculation for each group as  $Z$ :

$$Z_i = \sum_{i=1}^n Y_i \quad ; i = (t-1)n + 1, \dots, tn \text{ \& } t = 1, 2, \dots, k \quad (3.18)$$

6. Range calculation on  $Z$  series for each group as  $R$ :

$$R_t = \max(Z_i) - \min(Z_i) \quad ; \quad i = (t-1)n + 1, \dots, tn \quad \& \quad t = 1, 2, \dots, k \quad (3.19)$$

7. Rescaled range calculation for each group as  $\frac{R_t}{S_t}$ .

8. The average range of variation for any step of splitting time series calculation as  $E[R/S]$ :

$$E[R/S] = \frac{1}{k} \sum_{t=1}^k \frac{R_t}{S_t} \quad (3.20)$$

9. By repeating aforesaid procedure for all possible divisors of time series length as  $N$ , it can be written that for any step of iteration shown as  $j$ , expect value of rescaled range value will be represented as  $E[R/S]_j$ , and the value of  $k, n$  corresponds to the divisor numbers of  $N$  in iteration  $j$ .

$$E[R/S]_j = \frac{1}{k} \sum_{t=1}^k \frac{R_t}{S_t} \quad (3.21)$$

10. Estimation of the mean of  $(\frac{R}{S})_n$  of statistics  $\frac{R_t}{S_t}$ :

$$(\frac{R}{S})_n = \frac{1}{k} \sum_{t=1}^k \frac{R_t}{S_t} \quad (3.22)$$

11. Hurst exponent calculation Through rescaled range as  $H$ :

$$(\frac{R}{S})_n = C n^H \quad (3.23)$$

Using this relationship to estimate the value of  $H$  comes up with below relationship:

$$\log(\frac{R}{S})_n = H * \log n + \log C \quad ; \quad C \text{ is constant} \quad (3.24)$$

$C$  is constant, and  $n$  is that variable which depends on divisor selection and changes from one iteration to another iteration, so if  $\log(\frac{R}{S})_n$  is plotted versus  $\log n$ , the slope of the regression line will represent  $H$  as Hurst Exponent (HE).

We may use the Hurst exponent to assist data selection before predicting since it gives a measure of predictability. Before attempting to design a prediction model, we can find time series with significant Hurst exponents. We can also concentrate on eras with big Hurst exponents. This can save time and effort while also improving predicting accuracy.

### 3.4 Deep Learning

Deep Neural Network (DNN) which is known as Deep Learning (DL) is an approach of Artificial Intelligence (AI). Artificial intelligence is an area of computer science that aims to duplicate or imitate human behavior on a machine, to allow machines to do activities that would otherwise need the use of a human talents and brain. Some capabilities of AI systems such as organizing, remembering, understanding, problem-solving, and decision-making are programmable functions. Artificial intelligence systems are supported by algorithms that use techniques like machine learning, deep learning, and applicable logics. Learning algorithms use statistical algorithms to manage data and prepare them for using in AI systems. Learning procedures improve AI systems without special planning (Alafi, B .2019). AI overarch machine learning and deep learning as it is shown in Alafi (2019) as follosw figure 3.2:

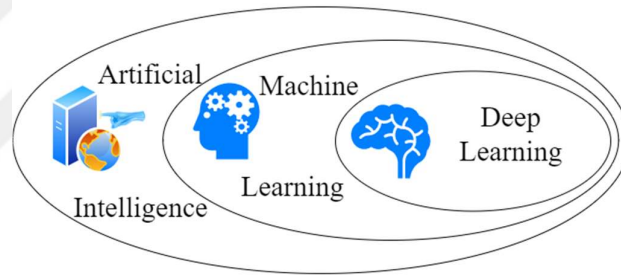


**Figure 3.2:** AI and learning interconnection.

Machine learning (ML) is a kind of interface between human and machine which provide intelligence of system and makes them to learn from human and act like them without defining any special mathematical programming. Deep learning is a part of techniques in machine learning. It is characterized as a deep neural network or deep neural learning because it can learn from a huge quantity of unorganized and unidentified data – known as big data – in the unsupervised category. Deep learning has progressively completed in response to the data explosion that has occurred in every sector of the world today, which is termed as the big data. Gathering and analyzing huge data from other sources throughout the world would take a human a long time, perhaps decades. Deep learning is used to learn this massive volume of unstructured and unlabeled data. Regression and classification are two tasks of deep learning; regression is that kind of prediction where the predicted aspect is a quantity and value of one variable, while classification is that kind of prediction where the

predicted aspect is a class or category of that variable. The most known three algorithms of deep learning are Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). The basic and classical model of DL is MLP. MLP has the basic model of neural network with one input layer, one or more hidden layer, and one output layer which is suitable for mapping from input to output. The architecture of one simple MLP as a neural network is represented as follows:

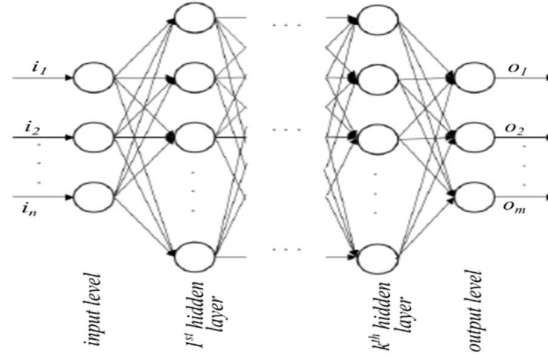


**Figure 3.3:** Neural network architecture.

In all deep learning models, there are two training steps: feed-forward and back-propagation (BP). The learning method in deep learning is carried out by modifying the weight values. As it is mentioned in Goodfellow et al, 2016, BP often is known as "backward error propagation" is a technique for updating weights and training multiple neural networks or deep neural networks. The errors are transmitted to hidden layers in the backpropagation process to train the network. if the error is not properly trained and does not reach the hidden layers, weight cannot be modified. There is an activation function in route of any neuron which can help with the training problem. In general, the mathematical procedure of neural network can be represented as follow:

First step - weight initializing.

Second step - error calculation as (e), which can be by the mean squared error (MSE).

$$e = \frac{1}{N} \sum_{i=1}^N [t_i - o_i]^2 \quad (3.25)$$

Third step – reducing error by adjusting weights as follow:

$$w(n) = -\eta \frac{\partial e}{\partial w} + \alpha w(n-1) \quad (3.26)$$

$$\Delta w = -\eta \frac{\partial e}{\partial w} \quad (3.27)$$

Where,  $w$  stands for weight and  $\eta$  and  $\alpha$  are constant. The weight is adjusted according to the difference between waited value and network output, specified as error. All above mentioned procedures are common neural network steps. According to model which is selected the other steps will be affected. Structure of weight adjustment as BP procedure, which is one of the important parts of neural network, is represented as follows:

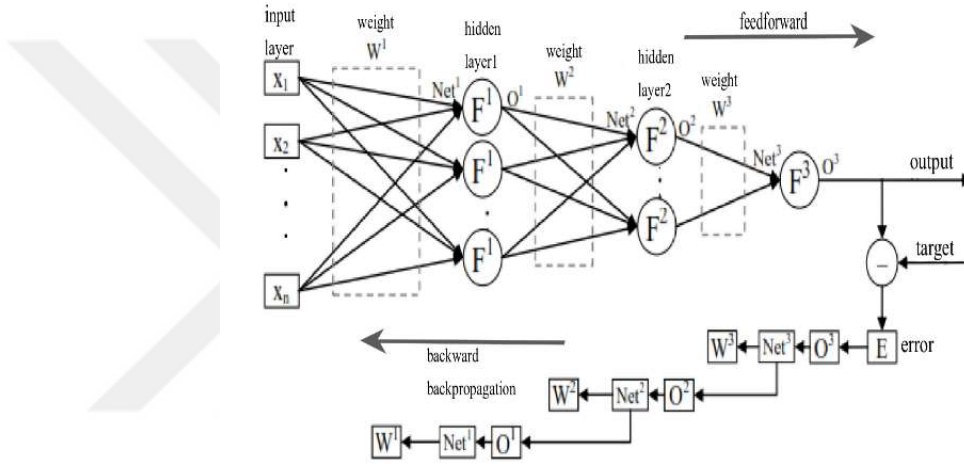


**Figure 3.4:** Back Propagation procedure.

### 3.4.1 RNN

The other model is recurrent neural network (RNN). This model has a neural network structure with this difference that during BP process, feedback is taken from output of network or hidden layers to hidden layers. On the broad way, feedback is from output of RNN network to input of RNN. The structure of RNN is the same as MLP structure with a loop from RNN to itself and it is in represented as follow (Ahmat et al, 2015):

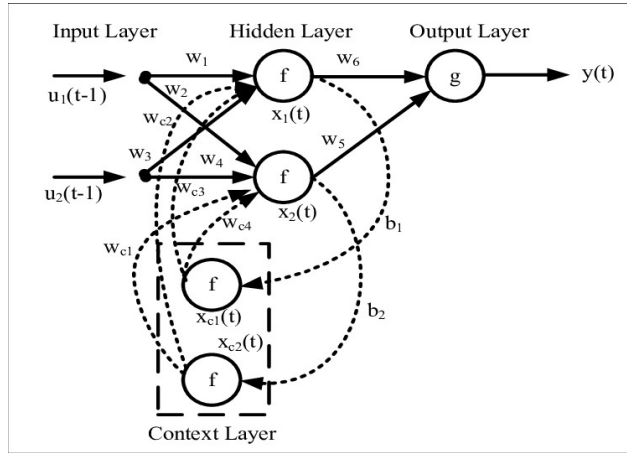


**Figure 3.5:** Normal RNN structure.

Elman and Jordan are the most known traditional RNN approaches. Modern type of RNN is Long Short Term Memory (LSTM) which can overcome some problems of traditional RNNs with long data because of vanishing gradient term. The weight update which is done on a specific layer in a typical feed-forward neural network is a product of error from the previous layer, learning rate, and input, so the error term for a given layer is simply a product of the mistakes of all preceding levels. When working with activation functions like the sigmoid, the tiny values of its derivatives -found in the error function- are multiplied several times when it goes closer to the beginning layers. As a result, the gradient practically becomes smaller and smaller and finally vanishes, and makes it impossible to train following layers. RNNs follow a similar structure and face the same issue. RNN only remembers things for short periods of time, thus if we require the knowledge in a short period of time, it may be repeatable, but if a large number of items are put in, it gets lost. A slightly altered form of RNNs, LSTM, can be used to overcome these type of issues. LSTM by multiplications and adds makes little changes to the data and can active recall or forget state during the learning process. There are three main gates in LSTM, input gate, forget gate, and output gate. The data flow through one cell of LSTM is illustrated as follows:

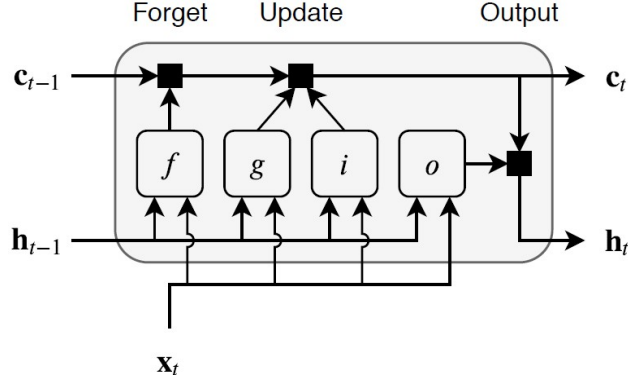


**Figure 3.6:** LSTM structure.

where the input gate, forget gate, cell candidate, and output gate are indicated by  $i$ ,  $f$ ,  $g$ , and  $o$ , respectively. By considering input weights as matrix  $W$ , recurrent weight as matrix  $R$ , and bias weight as matrix  $b$  respectively, the formula of input, forget, cell candidate, output components at any specified time  $t$  is represented as follows:

$$\begin{bmatrix} i_t \\ f_t \\ g_t \\ o_t \end{bmatrix} = \begin{bmatrix} \sigma_g & 0 & 0 & 0 \\ 0 & \sigma_g & 0 & 0 \\ 0 & 0 & \sigma_c & 0 \\ 0 & 0 & \sigma_g & 0 \end{bmatrix} \begin{bmatrix} W_i & R_i & b_i \\ W_f & R_f & b_f \\ W_g & R_g & b_g \\ W_o & R_o & b_o \end{bmatrix} \begin{bmatrix} x_t \\ h_{t-1} \\ 1 \end{bmatrix} \quad (3.28)$$

Where  $\sigma$  represents activation function,  $\sigma_g$  is gate activation function and  $\sigma_c$  is state activation function which are selected, by default, as sigmoid function and hyperbolic tangent function respectively.

$$\sigma_g(x) = \frac{1}{1 + e^{-x}} \quad (3.29)$$

$$\sigma_c(x) = \tanh(x) \quad (3.30)$$

$c_t$  is the cell state at time  $t$  or the next cell memory is written as follows:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad (3.31)$$

Where  $\odot$  indicates element-wise multiplication of vectors, known as Hadamard product. And  $h_t$  is the hidden state at time  $t$  which is written as follows:

$$h_t = o_t \odot \sigma_c(c_t) \quad (3.32)$$

Cell state and hidden state are two outputs of one memory for passing to other cells in LSTM network. For deep networks with multiple units, each of the gates has parameters for its weights and biases, resulting in a huge number of parameters. During the network's training, the weights of these connections are learnt or modified (Tahmina et al, 2018). In general, RNN and in particular LSTM are the most successful approaches in dealing with time series.

### 3.4.2 CNN

There is another important and applicable deep learning algorithm known as Convolutional Neural Network (CNN). Convolution is an operation in mathematics which shifts a function along its dimensions according to follow definition:

$$x[n] * h[n] = \sum_{k=-\infty}^{+\infty} x[n-k].h[k] = \sum_{k=-\infty}^{+\infty} x[n].h[n-k] \quad (3.33)$$

$$(x * h)(t) = \int_{-\infty}^{+\infty} f(\tau)g(t-\tau)d\tau = \int_0^t f(\tau)g(t-\tau)d\tau \quad (3.34)$$

As there is a convolution operation, a random filter is used to scan a random input according to its dimension and provide this convolution operation. the convolution operation is given as follows:

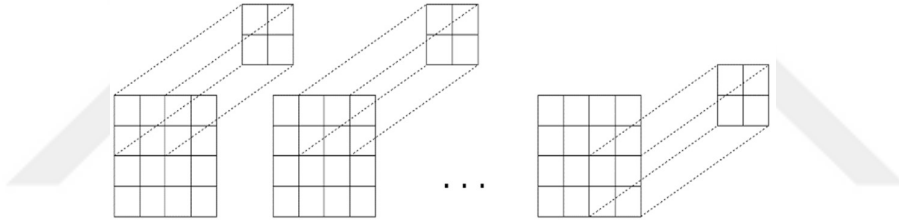


**Figure 3.7:** Convolution operation.

The filter will convolve over each filter and get the spatial feature of data to make the best output. In a CNN, Convolutional layer, pooling layer, and fully linked layer are the three primary layers of CNN. The convolutional layer takes in data, changes it, and then, outputs the modified data to the next layer. A function usually based on the maximum operation is performed across a portion of the input to generate an output during the pooling layer. The output of the pooling layer is dimensionally smaller than the input. Behind the convolution and pooling layers is a fully connected layer with a neural network construction, and features and representations learned from data through the convolutional and pooling layers are fed to this fully connected neural network without being hand-engineered, as is the case with machine learning. A CNN can have one or more convolutions and a pooling layer. In other words, the pooling layer's output represents the artificial neural network's future input. Figure 3.7 illustrates the architecture of a CNN in a simple way (Alafi.B, 2019).

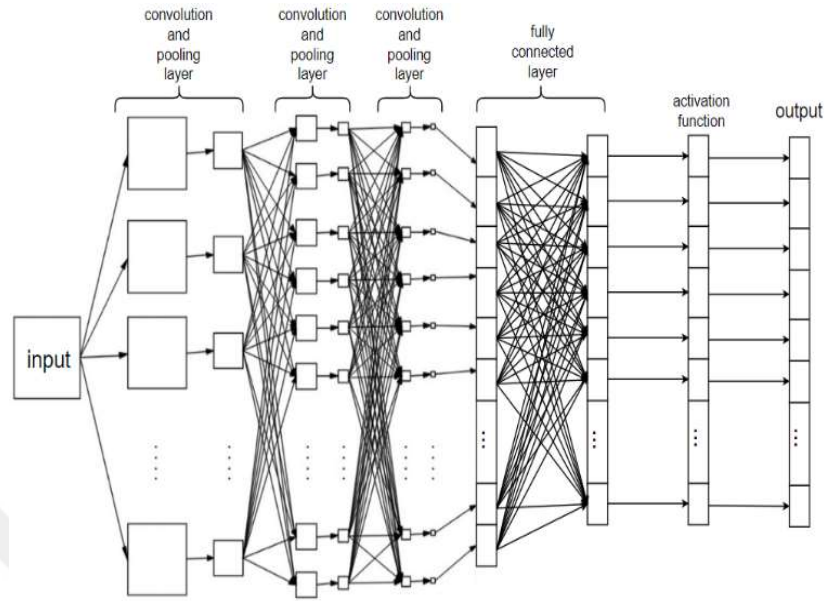


**Figure 3.8:** CNN Architecture.

There are three types of CNN according to its input and output dimensions as one-dimensional (1D), two dimensional (2D), and three dimensional (3D). This category has been made according to dimensions of input data. For time series with as 1D series of data, 1D CNN is used but the CNN layer is two dimensional since CNN will have features of input for as one dimension of its and time step as another dimension of itself. For image data, 2D CNN is used, but with three dimensional CNN layer. For three dimensional images like MRI or CT scan, 3D CNN with four dimensional CNN is used. As this research is about time series and time series are one dimensional data set, we will use 1D CNN, and architecture of proposed 1D CNN is represented in figure 3.8:

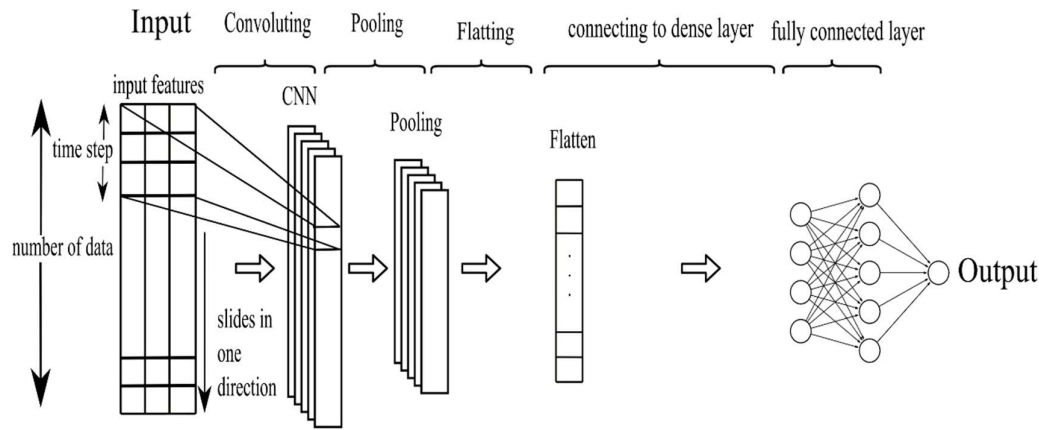


**Figure 3.9:** 1D CNN procedure.

The input is convolved by the filters of convolutional layer first, then, it passes through the pooling layer to be smaller in dimension than the input. Convolution and pooling layers are two-dimensional layers, and one CNN may contain many convolutions and pooling layers. The last pooling layer's output is then flattened. The pooling layer's output is a 2D feature map, whereas the fully connected layer's input is a 1D feature vector which is suitable for taking output as a scalar value. Flattening converts the pooling layer's 2D output to a fully connected layer's 1D input. After that, the learning process is complete, and the processed data is fed into a neural network, and the output is generated as shown in figure 3.8. the important thing in 1D CNN is dimensions of input data. According to the below figure, input is a 2D matrix which features of input data are one dimension and the length of data set is the other dimension. These different features have different values at any specific time, time step specify time steps which is going to be considered together to be sent to CNN layer and slid along time series. After sending each group of data by dimension of features\*time step to CNN layer, CNN gets the main feature of each group through some activation functions like ReLu and some optimizers like adam.

### 3.4.3 Performance estimation

The error of the method, as well as certain other factors that will be discussed, affects the performance of a neural network. As previously stated, there is an error function that describes the difference between the expected output and the computed output during the neural network process. The error term is highly essential in a neural network and is utilized for weight adjustment. A mean squared error (MSE) is a type of error function that has an equation as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2 \quad (3.35)$$

Root mean squared error (RMSE) is another error function which is considered as another performance factor can be stated as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2} = \sqrt{MSE} \quad (3.36)$$

Another parameter is the correlation coefficient, often known as the determination coefficient, which is denoted by the letter R. The correlation between the goal and forecasted value is defined by this parameter. To put it another way, this coefficient expresses the degree to which the actual and anticipated values are linear. The equation is as follows:

$$R = \sqrt{1 - \frac{\sum_{i=1}^N (t_i - y_i)^2}{\sum_{i=1}^N (t_i - \bar{t})^2}} \quad (3.37)$$

In all of the equations above, t represents the goal value or intended output, y represents the calculated or predicted output, and N represents the number of periods of time. RMSE appears to be the square root of MSE. However, there are some practical distinctions between these two numbers. The minimizers are obviously related; if a set of predictions reduces the MSE, it will also minimize the RMSE. However, the difference is in the scale; the error acquired by RMSE is on the same scale as the goal value, and its value provides an acceptable feeling of inaccuracy in the prediction process.



#### **4. APPLICATION USING RAW DATA**

As it has been discussed previously, all wind speed, air pressure, and relative humidity data during year 2006 is recorded and mean, minimum, maximum, and range of it as statistical parameters are calculated and aforementioned. In between wind speed as factor which affects wind energy and specifies wind energy potential of one region has a probability distribution. In this research behavior of wind speed and its predictability degree have been studied through statistical calculation and probability distribution, Hurst Exponent calculation, and training one convolutional neural network to predict the future step of wind speed and energy as the result of it.

##### **4.1 Extraction Of The Statistical Properties From The Raw Data**

Wind speed data for whole year 2006 and four seasons are represented in chapter 2 as a diagram of wind speed raw data with respect to time. To study about behaviour of one time series, it is required to study its frequency diagram. There are several density functions which can be used to describe wind speed frequency behavior. The most common probability density function which has been used here is Weibull function. Since Weibull is a two parameter function, it is more versatile to use than other functions. Weibull function has two parameters as scale factor and shape factor as discussed in chapter 3. To calculate these two factors there are some methods to estimate. For this case Weibull function of raw wind speed data for each season is estimated and its two parameters are calculated through Matlab, and then they are calculated according to GM method, which is explained in chapter 3. The matlab interface which is used in this part is shown in figure 4.1.

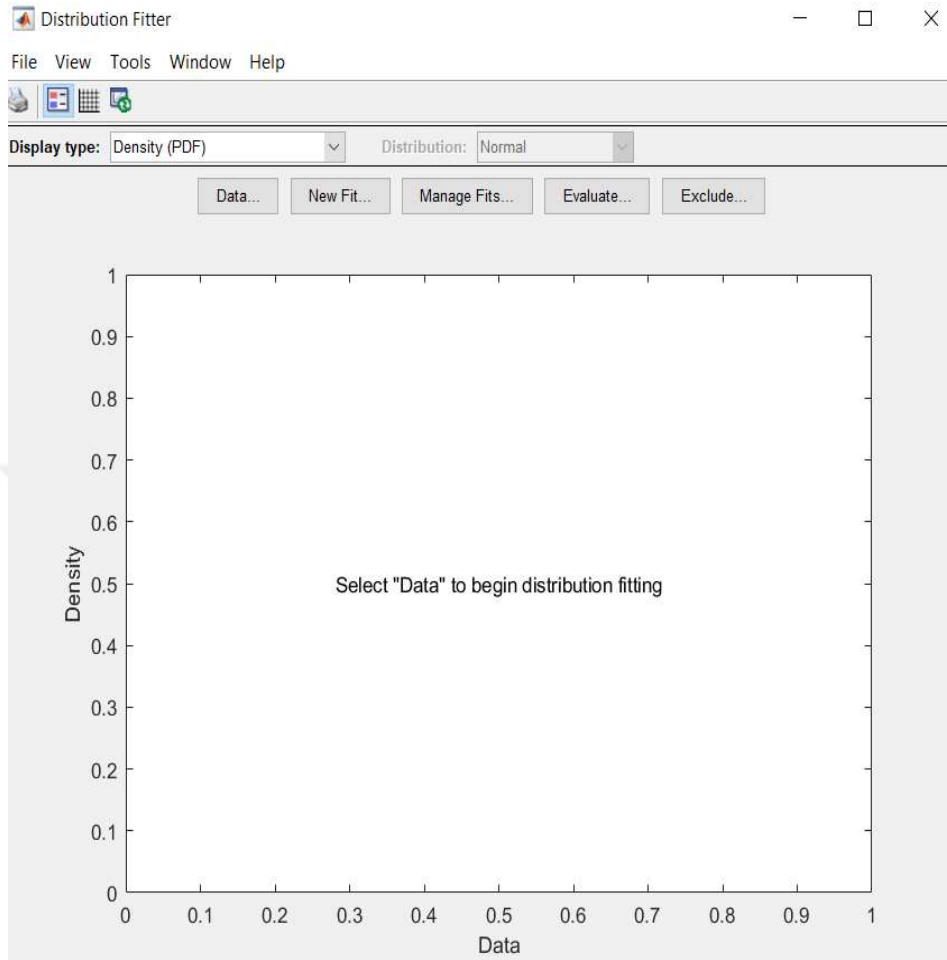


**Figure 4.1:** Matlab Interface to probability distribution.

After importing our raw data to matlab, the fitting tool gives us selection for density function. The important thing in case of wind speed is this point that we sometimes have to underestimate the values at the tails of histogram. After applying some minor changes in data we can import them and get a fit Weibull distribution as shown in figure 4.2.

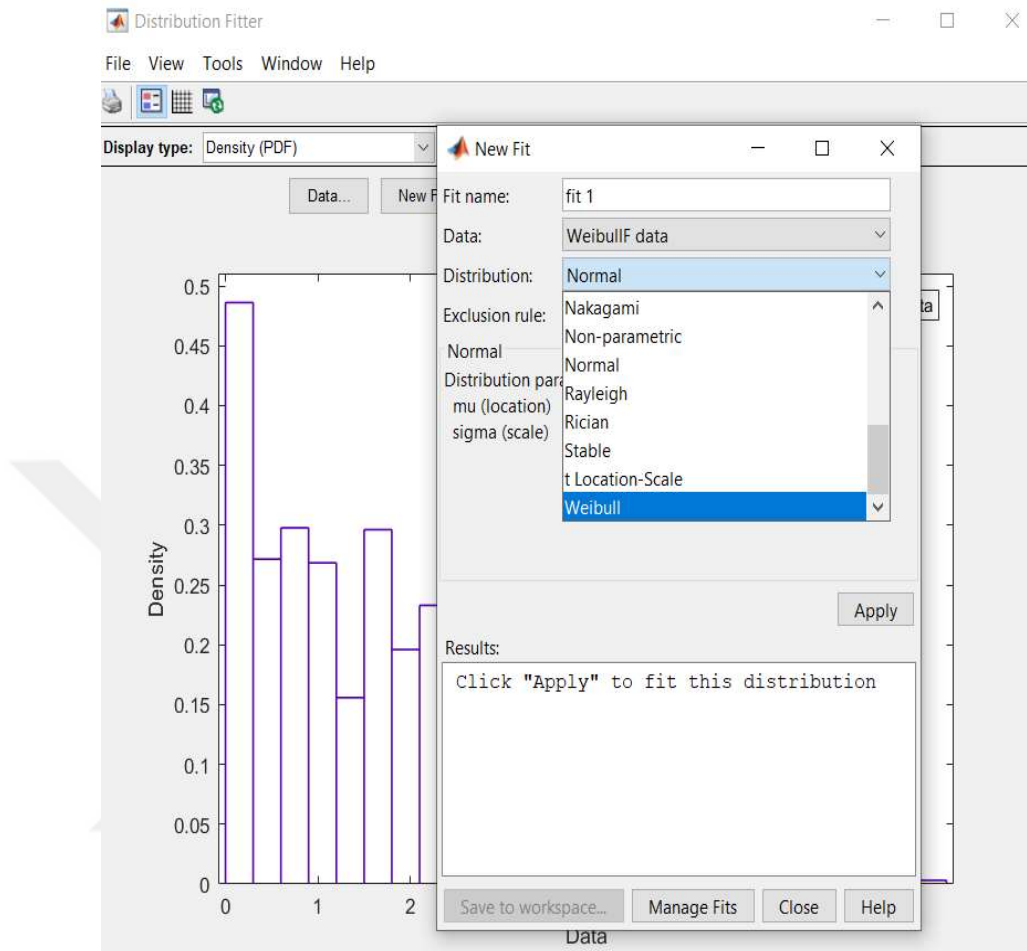


**Figure 4.2:** Distribution function selection in matlab.

The Density function for raw data of wind speed for whole year 2006, and each four season is given in five parts as follows:

### 4.1.1 Year 2006 distribution function

Importing whole year wind speed data to find the appropriate Weibull curves comes up with below figures:

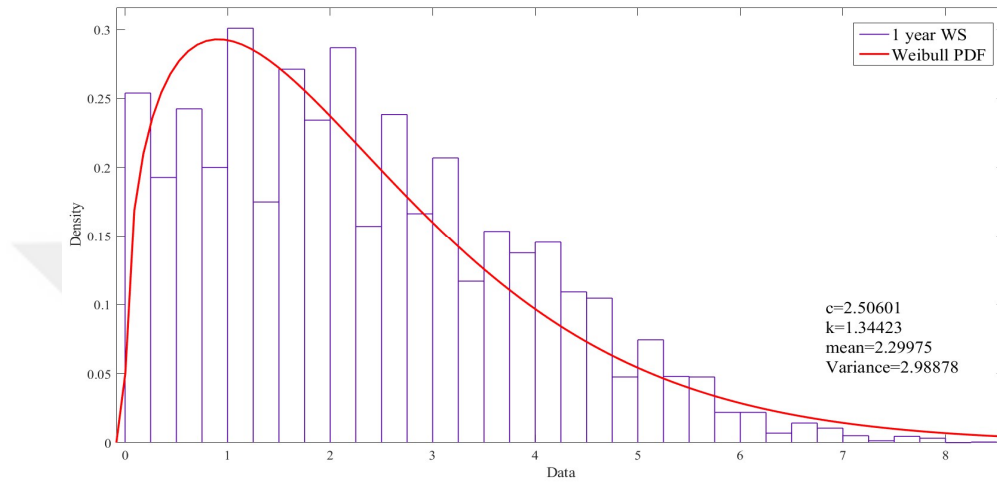


**Figure 4.3:** Weibull probability density curve of wind speed during a year.

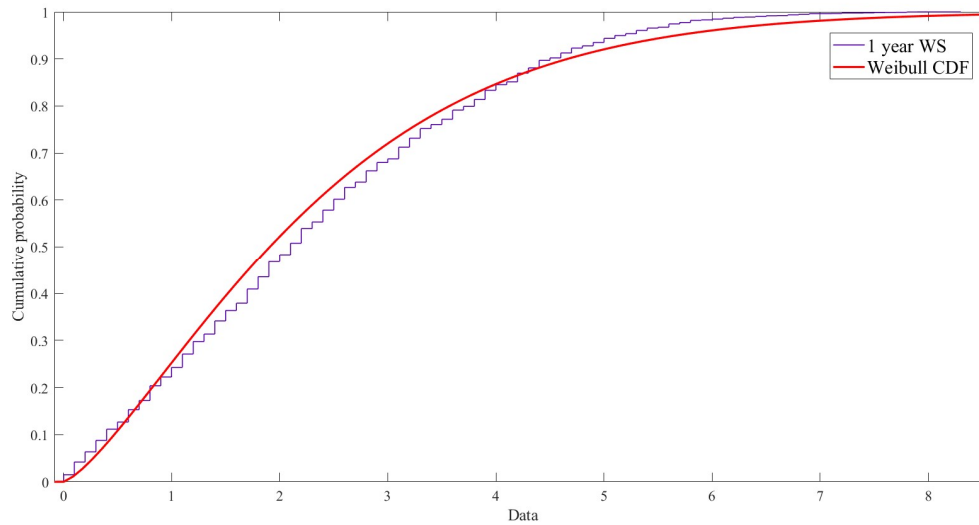


**Figure 4.4:** Weibull cumulative curve of wind speed during a year.

|                                              |                      |             |
|----------------------------------------------|----------------------|-------------|
| Results:                                     |                      |             |
| Distribution:                                | Weibull              |             |
| Log likelihood:                              | -15662.5             |             |
| Domain:                                      | $0 < y < \text{Inf}$ |             |
| Mean:                                        | 2.29975              |             |
| Variance:                                    | 2.98878              |             |
| Parameter                                    | Estimate             | Std. Err.   |
| A                                            | 2.50601              | 0.0207575   |
| B                                            | 1.34423              | 0.0118725   |
| Estimated covariance of parameter estimates: |                      |             |
|                                              | A                    | B           |
| A                                            | 0.000430874          | 6.93066e-05 |
| B                                            | 6.93066e-05          | 0.000140956 |

**Figure 4.5:** Weibull parameters of wind speed during a year.

By considering the equation of cumulative density function which is represented as equation 3.3 in chapter 3, by considering two separate values on  $F(v)$  function as  $F(v_1)$  and  $F(v_2)$ , we can calculate weibull density function parameters. By considering  $F(1)$  and  $F(6)$  we can calculate  $F(1) = 1 - \exp[-(\frac{1}{c})^k]$  and  $F(2) = 1 - \exp[-(\frac{2}{c})^k]$ , and then by some mathematical operation the result will be as follows:

**Table 4.1:** Weibull parameters for one year data.

|                          | Scale parameter | Shape parameter |
|--------------------------|-----------------|-----------------|
|                          | c               | k               |
| <b>Matlab estimation</b> | 2.50601         | 1.34423         |
| <b>CDF graph</b>         | 2.61            | 1.42            |

### 4.1.2 Spring distribution function

Importing spring wind speed data to find the appropriate Weibull curves comes up with below figures:

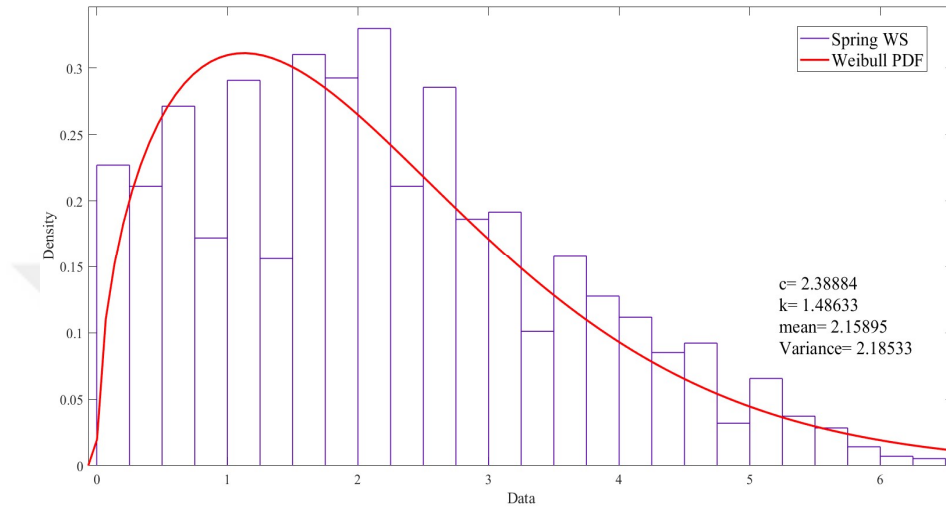


**Figure 4.6:** Weibull probability density curve of spring wind speed.

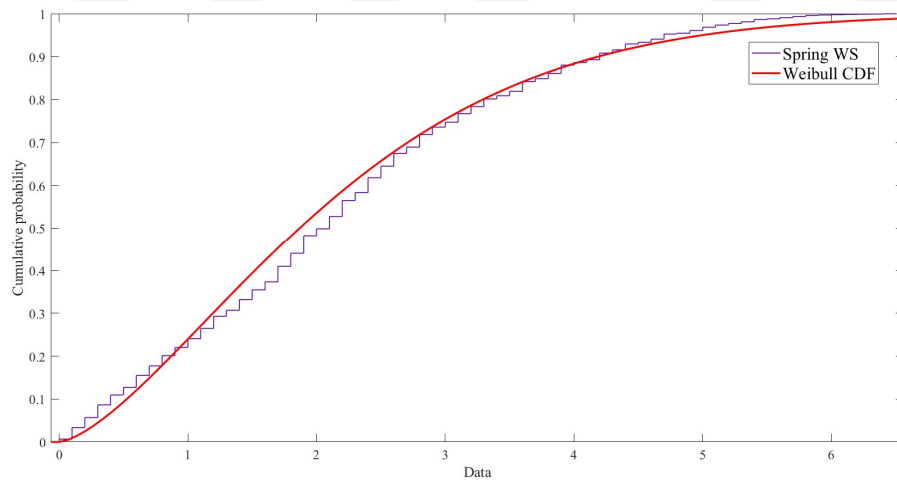


**Figure 4.7:** Weibull cumulative curve of spring wind speed.

```

Results:
Distribution:      Weibull
Log likelihood:   -3793.23
Domain:          0 < y < Inf
Mean:            2.15895
Variance:        2.18533

Parameter  Estimate  Std. Err.
A          2.38884   0.0353488
B          1.48633   0.0257181

Estimated covariance of parameter estimates:
      A          B
A    0.00124954  0.000262959
B    0.000262959  0.000661419

```

**Figure 4.8:** Weibull parameters of spring wind speed.

By applying the same approach described in 4.1.1 on CDF of spring data, weibull parameters will be as follows:

**Table 4.2:** Weibull parameters for spring data.

|                          | Scale parameter | Shape parameter |
|--------------------------|-----------------|-----------------|
|                          | <b>c</b>        | <b>k</b>        |
| <b>Matlab estimation</b> | 2.38884         | 1.48633         |
| <b>CDF graph</b>         | 2.41            | 1.51            |

### 4.1.3 Summer distribution function

Importing summer wind speed data to find the appropriate Weibull curves comes up with below figures:

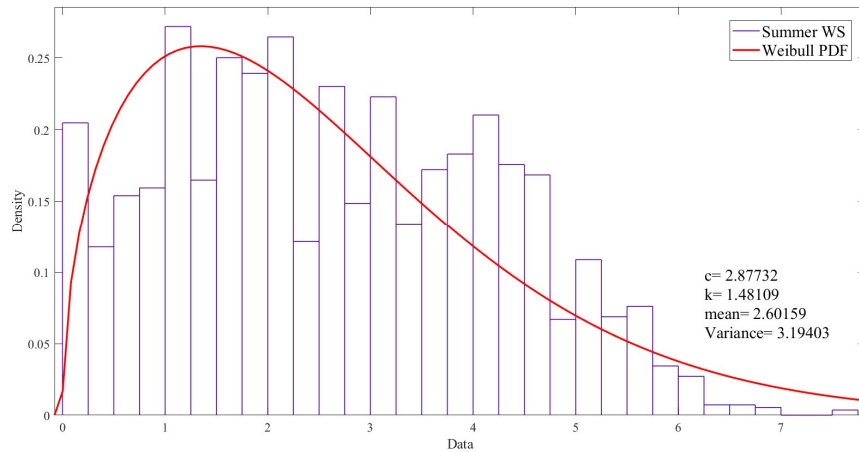


**Figure 4.9:** Weibull probability density curve of summer wind speed.

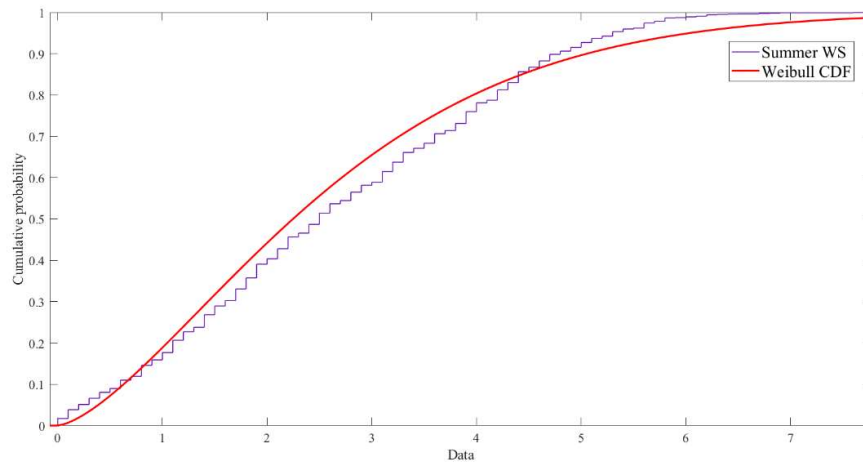


**Figure 4.10:** Weibull cumulative curve of summer wind speed.

|                                              |                      |             |
|----------------------------------------------|----------------------|-------------|
| Results:                                     |                      |             |
| Distribution:                                | Weibull              |             |
| Log likelihood:                              | -4154.07             |             |
| Domain:                                      | $0 < y < \text{Inf}$ |             |
| Mean:                                        | 2.60159              |             |
| Variance:                                    | 3.19403              |             |
| Parameter                                    | Estimate             | Std. Err.   |
| A                                            | 2.87732              | 0.0429083   |
| B                                            | 1.48109              | 0.0265759   |
| Estimated covariance of parameter estimates: |                      |             |
|                                              | A                    | B           |
| A                                            | 0.00184112           | 0.000304248 |
| B                                            | 0.000304248          | 0.000706276 |

**Figure 4.11:** Weibull parameters of spring wind speed.

By applying the same approach described in 4.1.1 on CDF of summer data, weibull parameters will be as follows:

**Table 4.3:** Weibull parameters for summer data.

|                          | Scale parameter | Shape parameter |
|--------------------------|-----------------|-----------------|
|                          | c               | k               |
| <b>Matlab estimation</b> | 2.87732         | 1.48109         |
| <b>CDF graph</b>         | 3.03            | 1.51            |

#### 4.1.4 Autumn distribution function

Importing autumn wind speed data to find the appropriate Weibull curves come up with below figures:

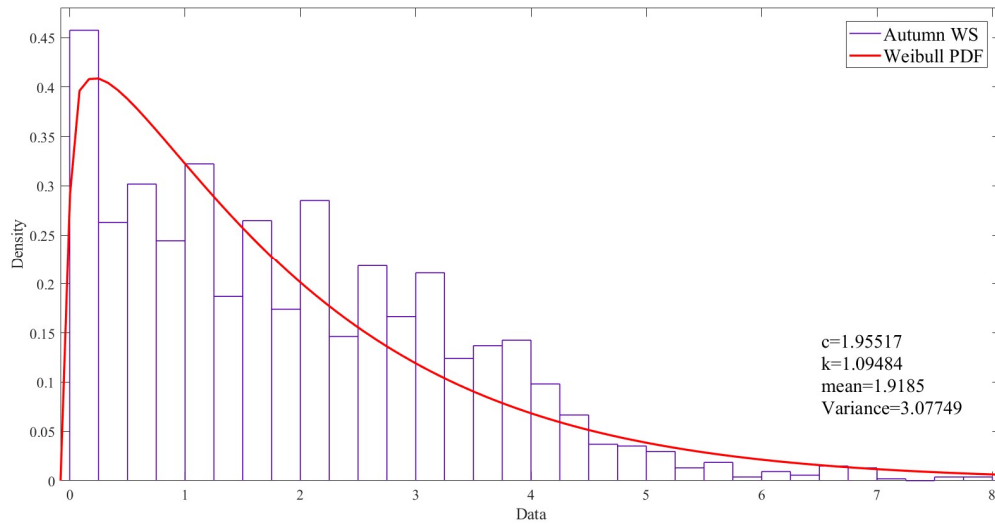


**Figure 4.12:** Weibull probability density curve of autumn wind speed.

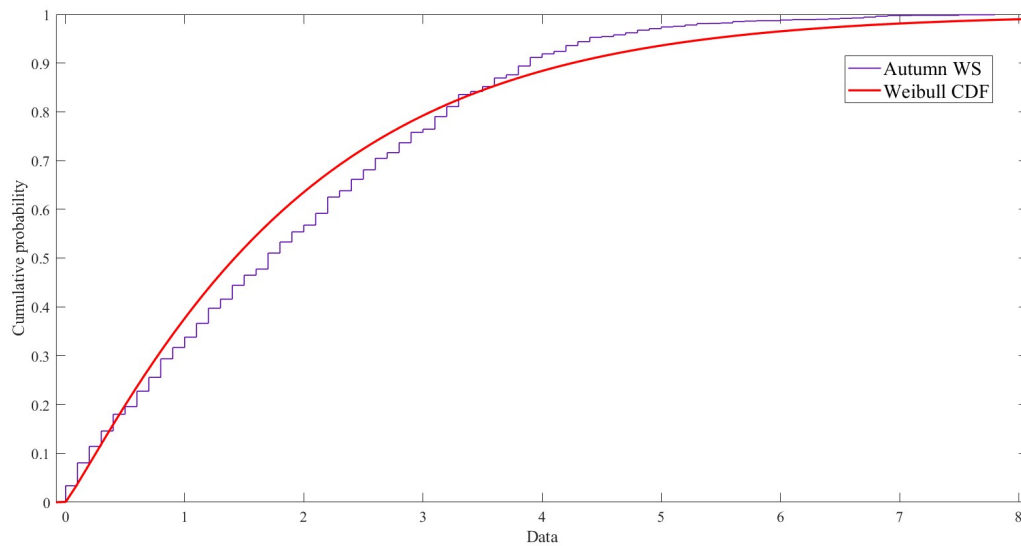


**Figure 4.13:** Weibull cumulative curve of autumn wind speed.

```

Results:
Distribution:    Weibull
Log likelihood: -3570.03
Domain:         0 < y < Inf
Mean:           1.9185
Variance:       3.07749

Parameter  Estimate  Std. Err.
A          1.98517  0.0405216
B          1.09484  0.0198008

Estimated covariance of parameter estimates:
      A          B
A      0.001642  0.000216831
B      0.000216831  0.000392072

```

**Figure 4.14:** Weibull parameters of autumn wind speed data.

By applying the same approach described in 4.1.1 on CDF of Autumn data, weibull parameters will be as follows:

**Table 4.4:** Weibull parameters for Autumn data.

|                          | Scale parameter | Shape parameter |
|--------------------------|-----------------|-----------------|
|                          | <b>c</b>        | <b>k</b>        |
| <b>Matlab estimation</b> | 1.98517         | 1.09584         |
| <b>CDF graph</b>         | 2.07            | 1.14            |

### 4.1.5 Winter distribution function

Importing winter wind speed data to find the appropriate Weibull curves come up with below figures:

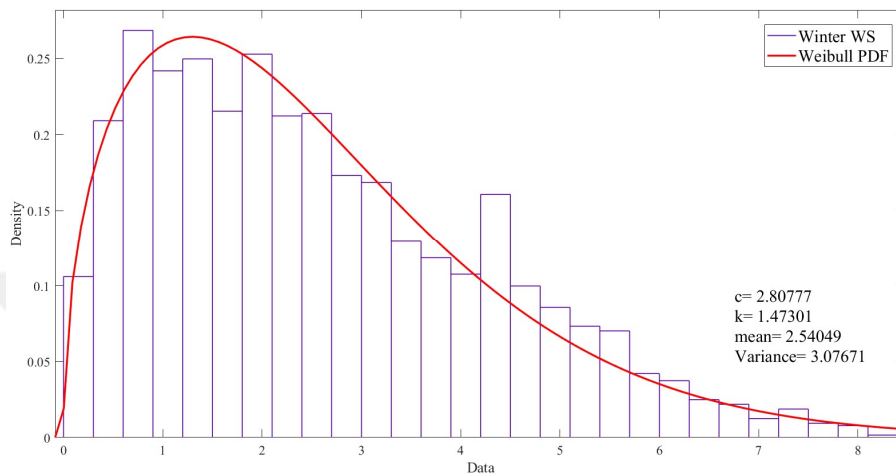


**Figure 4.15:** Weibull probability density curve of winter wind speed.

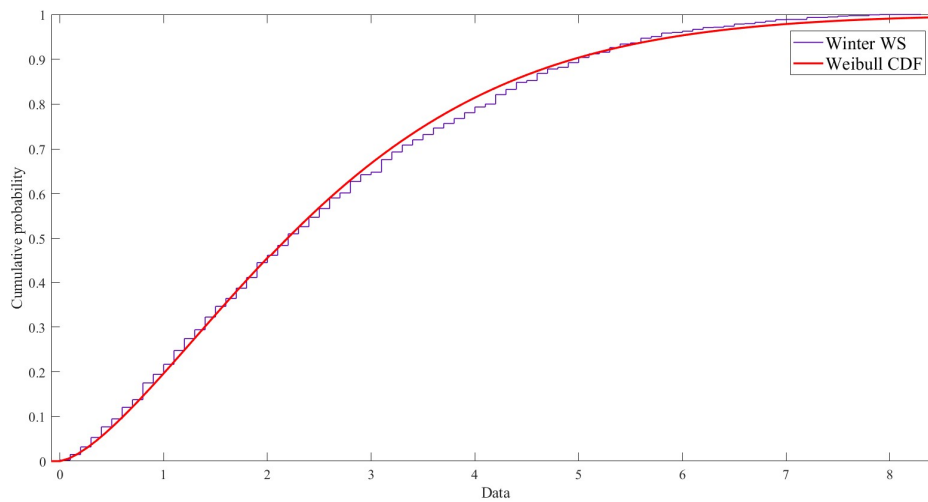


**Figure 4.16:** Weibull cumulative curve of winter wind speed.

```

Results:
Distribution:      Weibull
Log likelihood:   -3924.39
Domain:           0 < y < Inf
Mean:             2.54049
Variance:         3.07671

Parameter  Estimate  Std. Err.
A          2.80777   0.0433263
B          1.47301   0.0255433

Estimated covariance of parameter estimates:
      A          B
A    0.00187717  0.000339006
B    0.000339006  0.000652463

```

**Figure 4.17:** Weibull parameters of winter wind speed data.

By applying the same approach described in 4.1.1 on CDF of winter data, weibull parameters will be as follows:

**Table 4.5:** Weibull parameters for winter data.

|                          | Scale parameter | Shape parameter |
|--------------------------|-----------------|-----------------|
|                          | c               | k               |
| <b>Matlab estimation</b> | 2.80777         | 1.47301         |
| <b>CDF graph</b>         | 2.97            | 1.53            |

## 4.2 Claculation Of Hurst Parameter For Raw Data

To find husrt exponent for each data set including whole data as one year data or seasonally data in this research, one programming code according to the mathematical equations which have been mentioned in chapter 3 is written and run in matlab tool. The base in this code is R/S analysis and the results of this calculations are represented as follows:

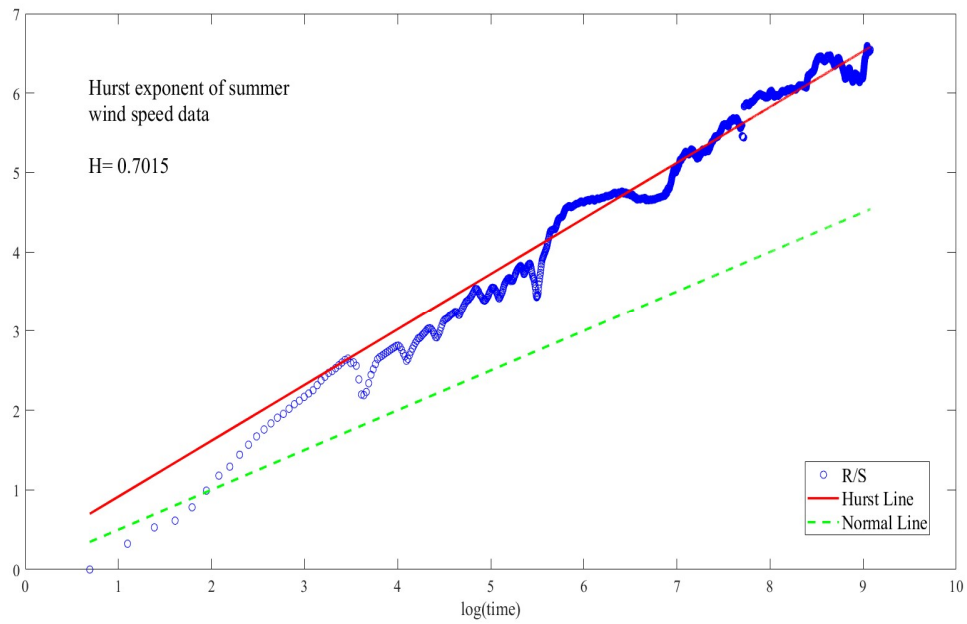


**Figure 4.18:** Hurst exponent of one year.

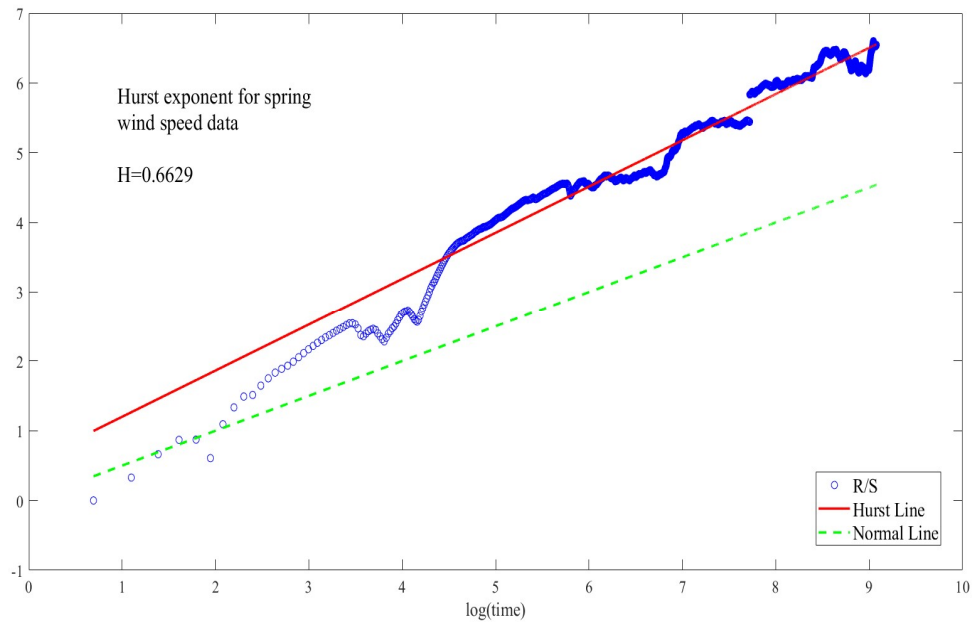


**Figure 4.19:** Hurst exponent of Spring.

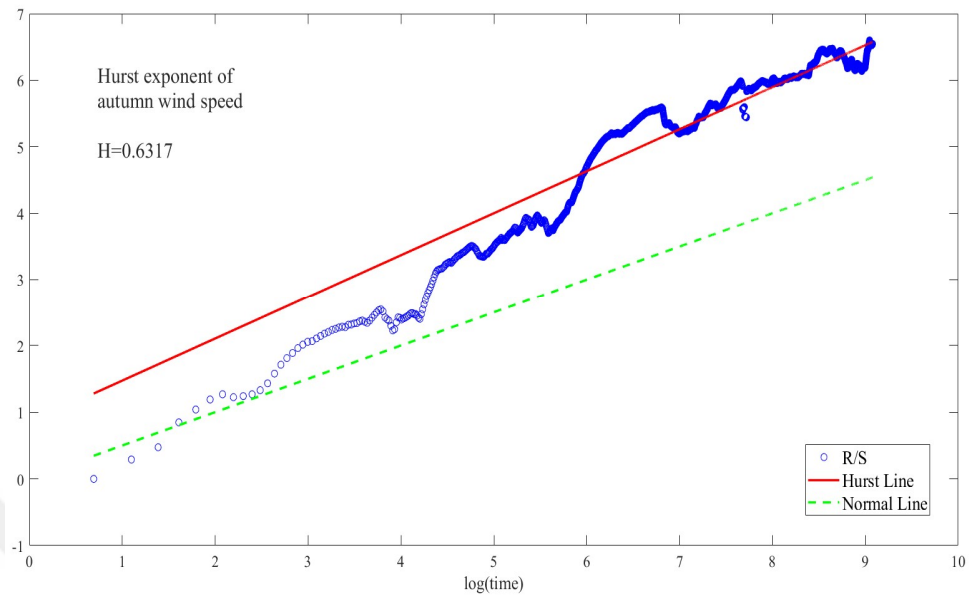


**Figure 4.20: Hurst exponent of Summer.**

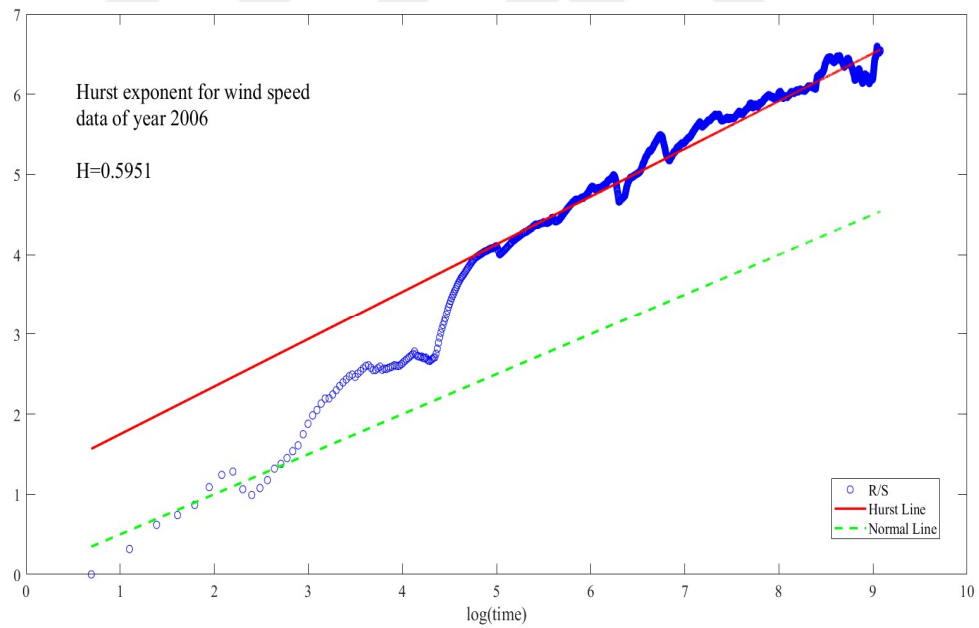


**Figure 4.21: Hurst exponent of Autumn.**

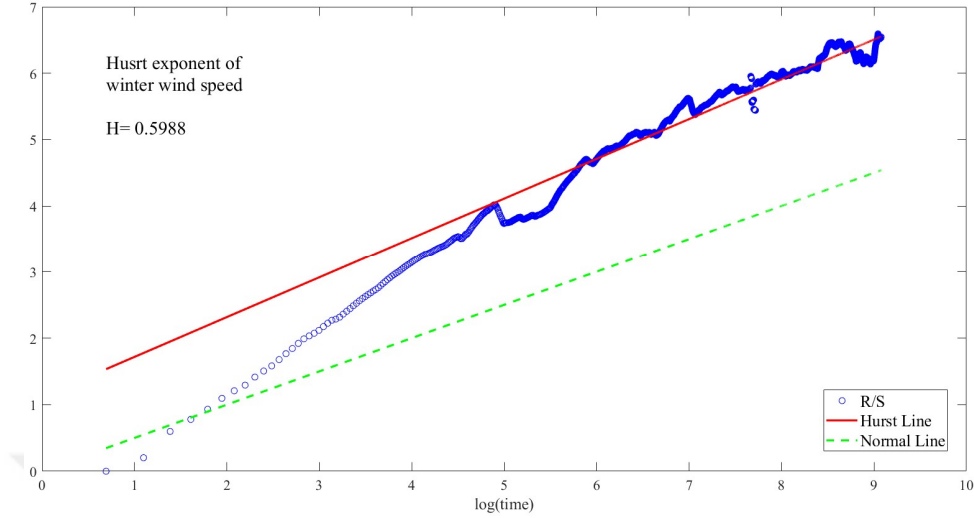


**Figure 4.22:** Hurst exponent of Winter.

The summation of all hurst exponent values is represented as below table for year 2006 and its four seasons.

**Table 4.6:** Hurst exponent value.

| Duration       | 1 year | Spring | Summer | Autumn | Winter |
|----------------|--------|--------|--------|--------|--------|
| Hurst Exponent | 0.5951 | 0.6629 | 0.7015 | 0.6317 | 0.5988 |

According to the result, it can be obtained that degree of predictability in summer is more than the others, and whole year and winter have the least hurst exponent. So according to these data since HE is greater than 0.5, we can do prediction for them, but prediction for summer is more reliable than for others.

### 4.3 Topology For Deep Learning Algorithm And Training Set

As it is discussed in chapter 3, according to type of data we have and final thing that we want to obtain from this network, we will select our deep learning type. In this research we want to find future step wind speed data according to three meteorological data which we have, so it is considered as a prediction problem of time series; we can use LSTM or one dimensional CNN, and also we can use a combination method like CNN-LSTM. Here we used one dimensional CNN to predict. The procedure diagram of the 1D CNN model which is used in this research is as follows:

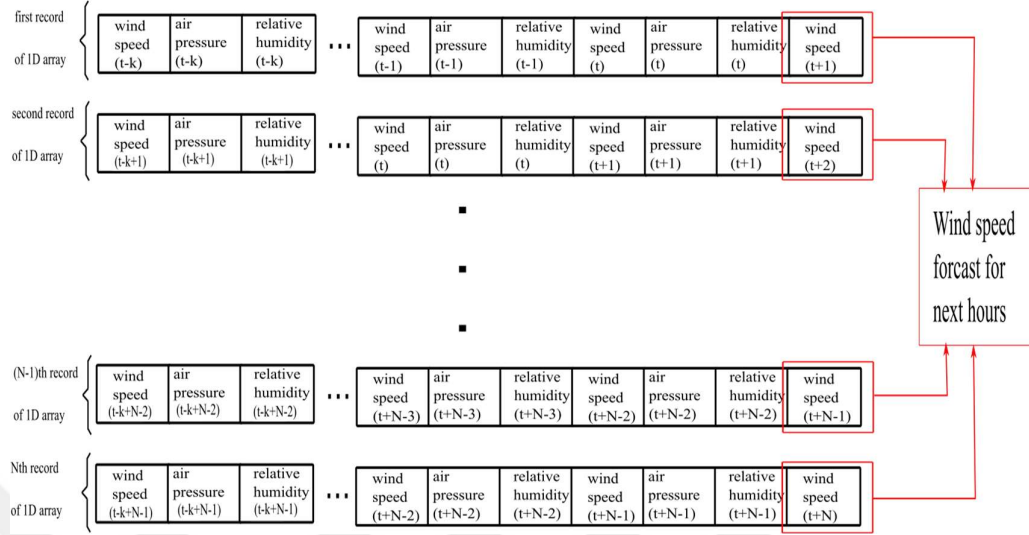


**Figure 4.23:** 1D CNN diagram.

According to number of input data is in hand, we have three input data as wind speed, air pressure, and relative humidity; we should select multi variate CNN type, and consider this different inputs as features of input. After that, we will enter these three inputs under the name of feature of input as columns of two dimensional input matrix, and then, select  $k$  rows of this matrix and apply to CNN layer.  $K$  represents time steps or sampling parameter. Training will be done through this 1D CNN network and finally will learn to find wind speed for step ahead. Now, we have one multivariate 1D CNN. Input data is two dimensional in this CNN, and its dimensions stand for features, which are wind speed, air pressure, and relative humidity, and time steps as sampling time by the meaning of which steps we want to sample from these features. In general, it is like a matrix which number of rows stands for time steps, and the column of it stands for features of input. Rather of having time steps, the data is treated as a sequence over which convolutional read operations may be performed, similar to a one-dimensional image, by the CNN. In order to train the model, we'll have to ignore certain values from the output time series when we don't have values in the input time series at previous time steps. As a result, the number of input time steps chosen has a significant impact on how much of the training data is utilized. After this sampling method from input data and make a two dimensional matrix with these three one dimensional separate time series, sampled data is routed to convolutional and pooling layer, and then flatten layer to reduce the dimension of feature map to one dimensional series or vector to be able to transferred to dense or fully connected layer and after that

be obtained as output. We considered 80% of data for training and the other 20% of it for test of algorithm. All of these procedures is written as an 1D CNN code in Matlab for one-year data and seasonal data separately, and the results under this algorithm is represented as follows:

### 4.3.1 Training results for one year

All data for year 2006 data sets is trained by aforementioned 1D CNN and the results are represented as follow figure:

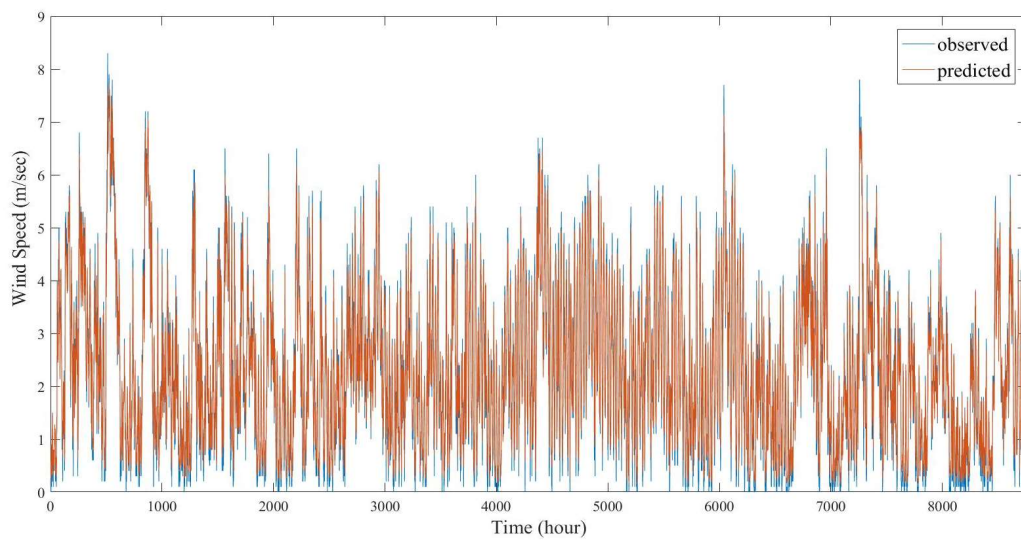


**Figure 4.24:** Observed vs predicted wind speed value for 1-year data

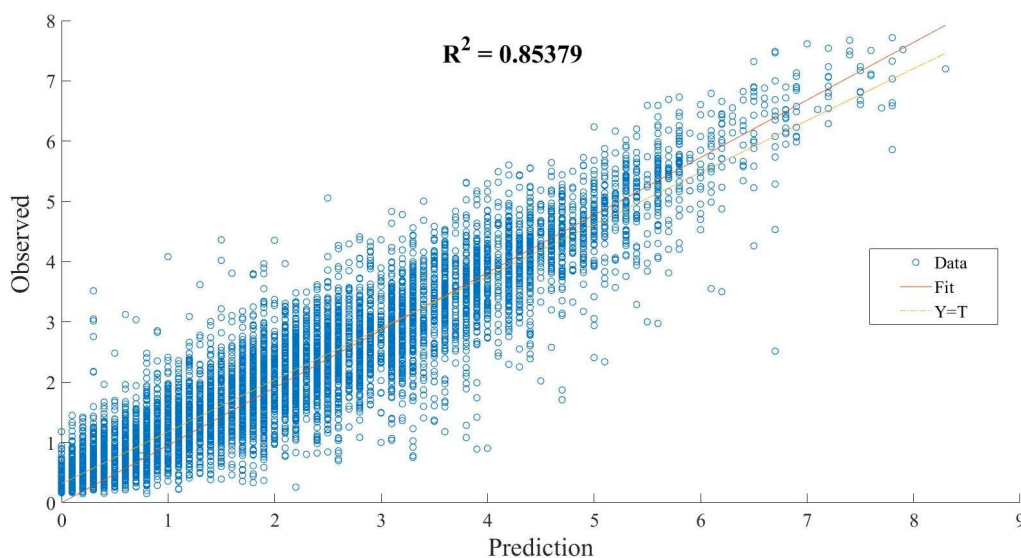


**Figure 4.25:** Regression coefficient for 1-year data.

**Table 4.7:** Performance of one year data.

| <b>MSE</b> | <b>RMSE</b> | <b>R</b> |
|------------|-------------|----------|
| 0.31844    | 0.5643      | 0.924    |



### 4.3.2 Training results for spring:

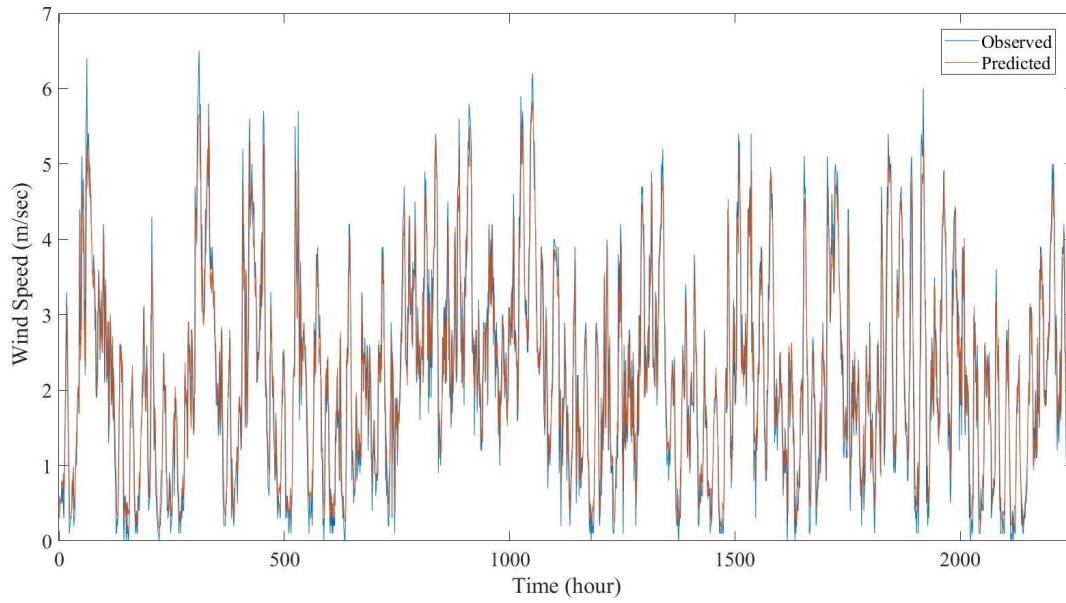


**Figure 4.26:** Observed vs predicted wind speed value for spring data.

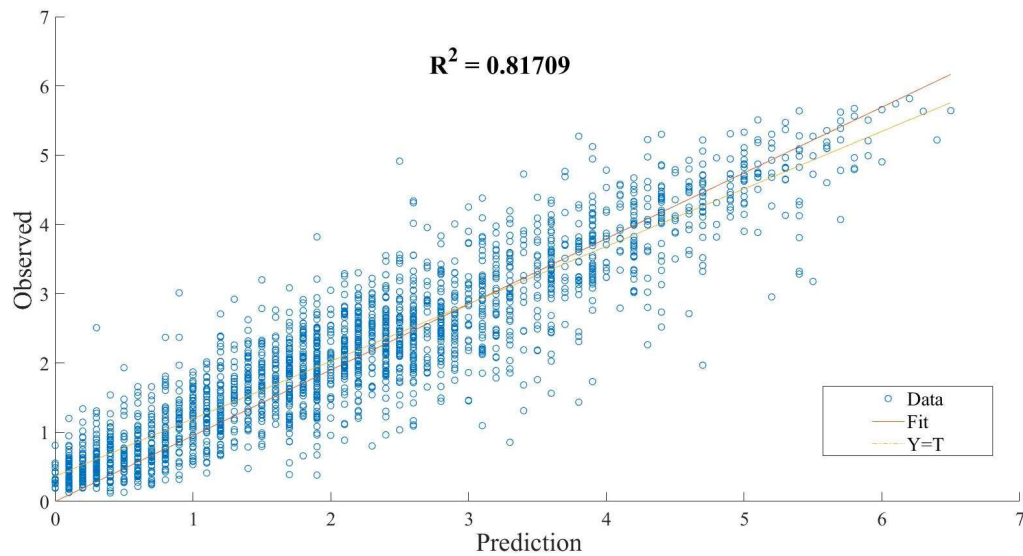


**Figure 4.27:** Regression coefficient for spring data.

**Table 4.8:** Performance of spring data.

| MSE     | RMSE   | R     |
|---------|--------|-------|
| 0.30316 | 0.5506 | 0.904 |

### 4.3.3 Training results for summer

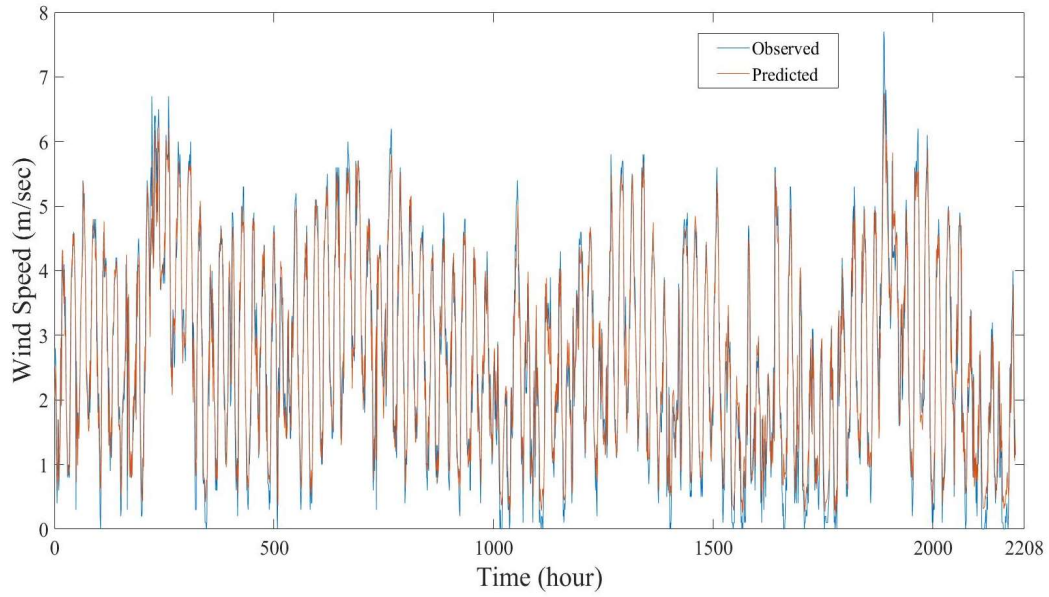


**Figure 4.28:** Observed vs predicted wind speed value for summer data.

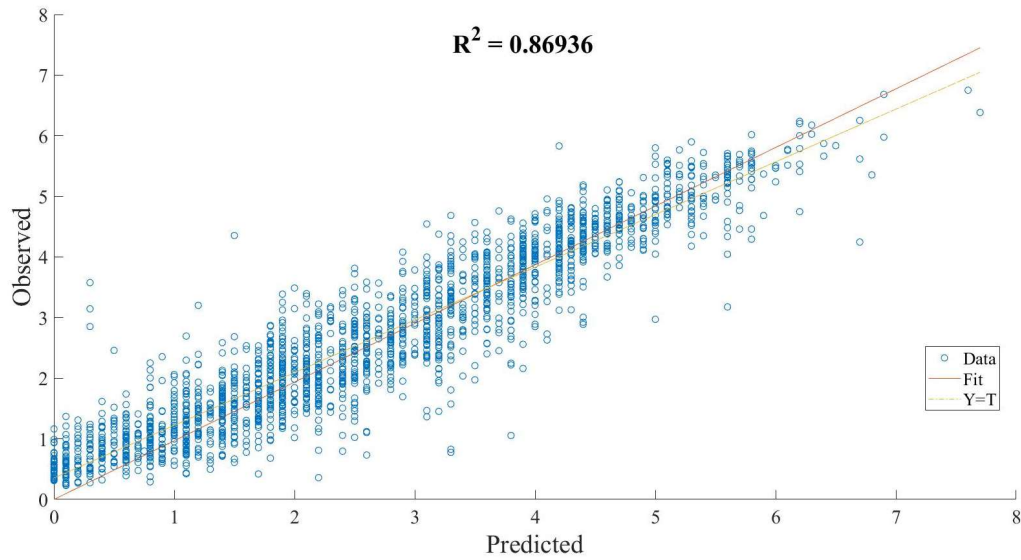


**Figure 4.29:** Regression coefficient for summer data.

**Table 4.9:** Performance of summer data.

| MSE     | RMSE    | R     |
|---------|---------|-------|
| 0.28862 | 0.53714 | 0.932 |

#### 4.3.4 Training results for autumn

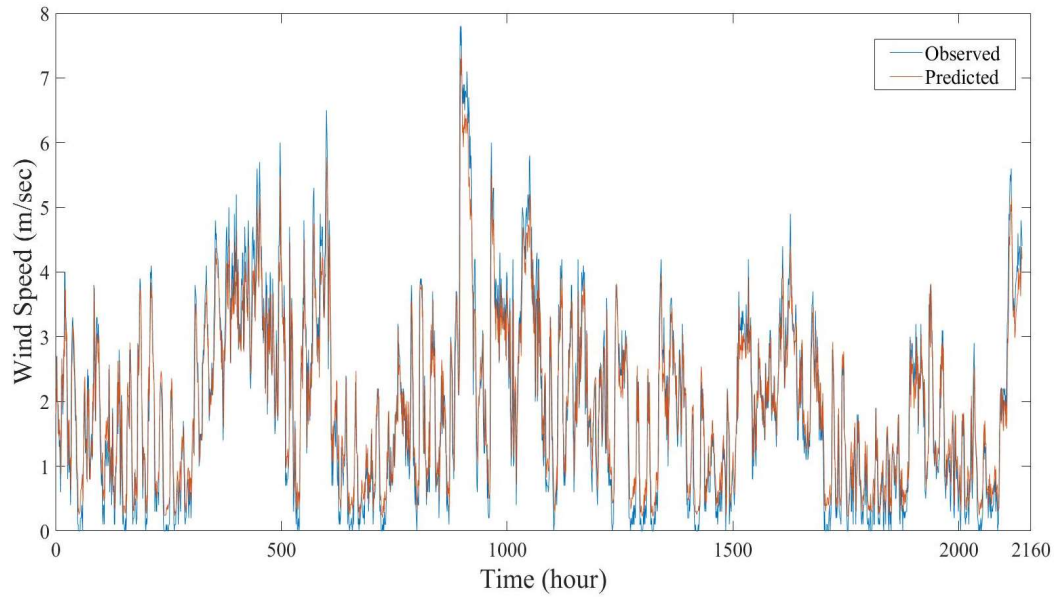


**Figure 4.30:** Observed vs predicted wind speed value for Autumn data.

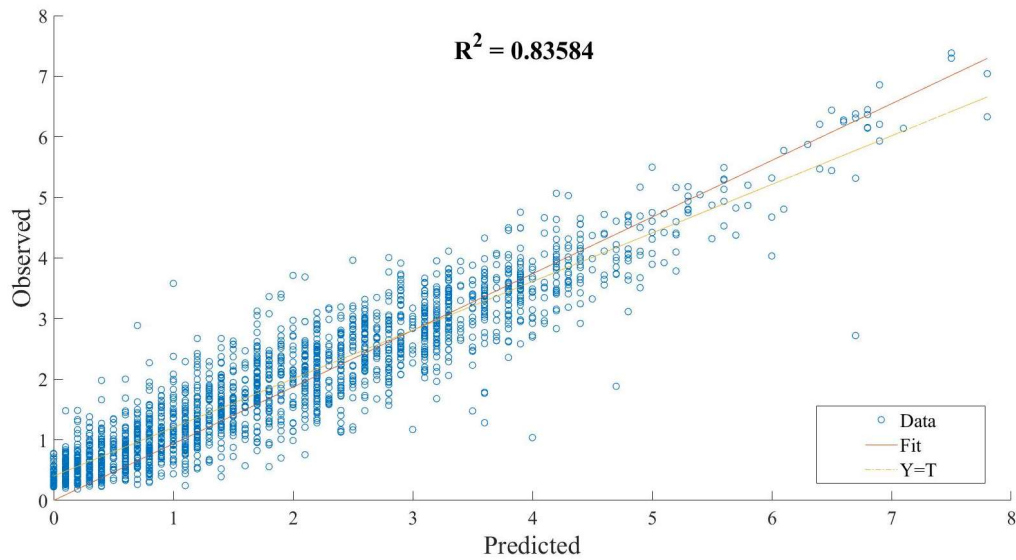


**Figure 4.31:** Regression coefficient for autumn data.

**Table 4.10:** Performance of autumn data.

| MSE     | RMSE    | R     |
|---------|---------|-------|
| 0.28024 | 0.52938 | 0.914 |

#### 4.3.5 Training results for winter

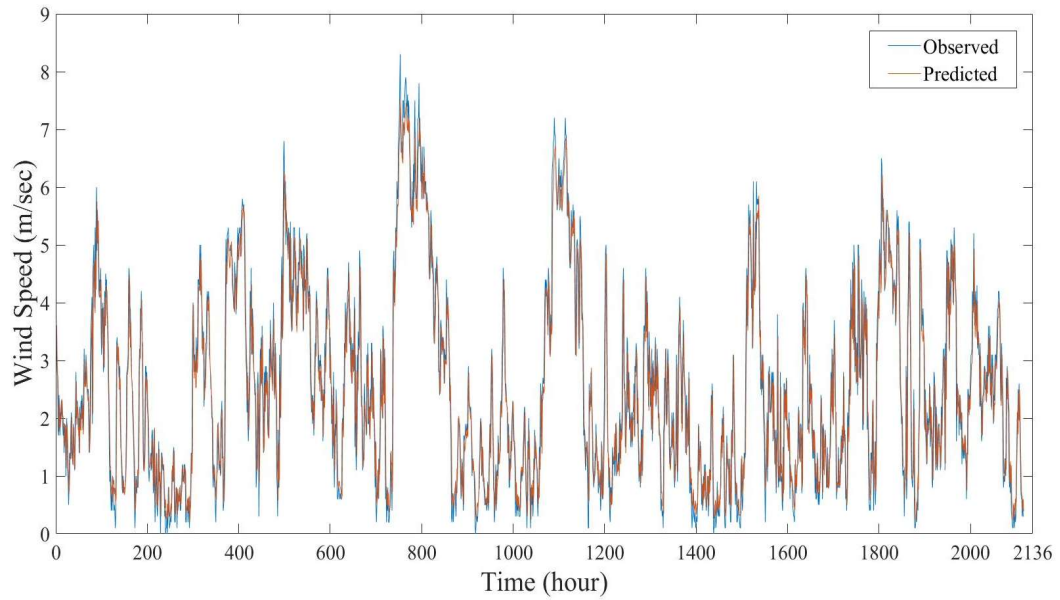


**Figure 4.32:** Observed vs predicted wind speed value for winter data.

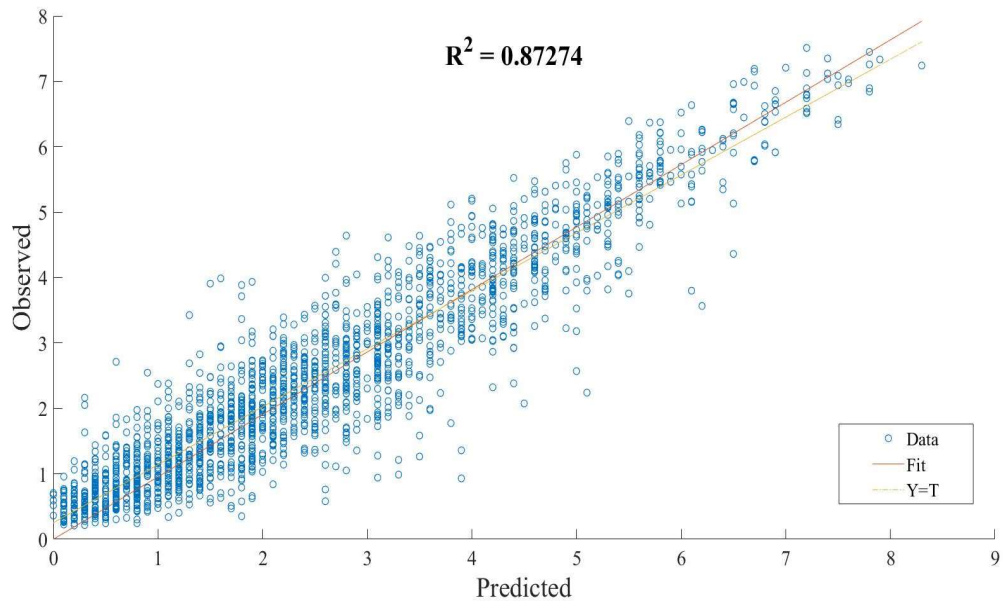


**Figure 4.33:** Regression coefficient for winter data.

**Table 4.11:** Performance of winter data.

| MSE     | RMSE   | R     |
|---------|--------|-------|
| 0.34963 | 0.5913 | 0.934 |



## 5. NUMERICAL RESULTS: INTERPRETATION ON THE RESULTS

According to the results which have been taken from the interface tools and calculations on raw wind speed data, we can summarize results for statistical studies as follows:

**Table 5.1:** Statistical parameters on raw wind speed data.

| Time | 1 year  | Spring  | Summer  | Autumn  | Winter  |
|------|---------|---------|---------|---------|---------|
| PDF  | weibull | weibull | weibull | weibull | weibull |
| k    | 1.34423 | 1.48633 | 1.48109 | 1.09584 | 1.47301 |
| c    | 2.50601 | 2.38884 | 2.87732 | 1.98517 | 2.80777 |

The results represent this fact that despite wind speed data changes without any pattern at first glance, probability density of it follows a model which is named Weibull density function with two parameters. These wind speed data also follow common pattern for some wind speed data which was proven before. we can see that whole year and all seasons have a Weibull density probability which is similar to each other. So we can say that wind speed behaviour during seasons imitate each other. Because each day shows different behaviour, it is very important to have more than one-day data to study about wind speed and meteorological data. The other important usage of Weibull model, which is very important in wind energy systems, is power density function estimation which is obtained from these Weibull parameters. According to what is discussed in chapter 3 around relationship between  $P_w$  as theoretical power density function and wind speed Weibull density function parameters, studying these parameters gives an estimation about power density function as well.

At the second step, we obtained Hurst parameter of wind speed data and the result is represented as follow table:

**Table 5.2:** Hurst Parameter.

| <b>Duration</b> | <b>1 year</b> | <b>Spring</b> | <b>Summer</b> | <b>Autumn</b> | <b>Winter</b> |
|-----------------|---------------|---------------|---------------|---------------|---------------|
| <b>HE</b>       | 0.5951        | 0.6629        | 0.7015        | 0.6317        | 0.5988        |
| <b>HE - 0.5</b> | 0.0951        | 0.1629        | 0.2015        | 0.1317        | 0.0988        |

Hurst parameter illustrates the predictability degree of time series. That series with Hurst parameters between 0.5 and 1 has shows a persistent behavior and has long-term positive autocorrelation, so a high value in these time series will almost certainly be followed by another high value, and future values will follow the same rule. So all studied wind speed data has HE greater than 0.5 and is persistent but their differences from 0.5 are different from each other. The longer the long-term memory, the more different from 0.5. As a result, processes with a large memory are processes that take a long time to complete. Among them, summer data has the greatest Hurst parameter so it has the longest long term memory and is more predictable. According to Hurst parameter value for all case studies, we found that wind speed data is a predictable one, so we can train one neural network to predict it. After applying data to one CNN as DNN, the performance parameters for all cases is written as follow:

**Table 5.3:** CNN performance factor for all data sets.

| <b>Time</b> | <b>1 year</b> | <b>Spring</b> | <b>Summer</b> | <b>Autumn</b> | <b>Winter</b> |
|-------------|---------------|---------------|---------------|---------------|---------------|
| <b>RMSE</b> | 0.5643        | 0.5506        | 0.53714       | 0.52938       | 0.5913        |
| <b>R</b>    | 0.924         | 0.904         | 0.932         | 0.914         | 0.934         |

Here are two parameters which illustrates performance of the network we used. The first one is RMSE based on error, and difference between observed value and predicted value. Smaller RMSE represents more reliable and precise model. We can see that the seasons with high Hurst exponent has less RMSE, so we can say that time series with longer long-term memory can train model better. The other performance parameter is regression or correlation coefficient represents the correlation between actual value and predicted value; the more this parameter approaches 1, the more predicted value approaches to the observed or target value. According to above table winter and summer have the greatest regression value, so predicted wind speed data obtained through training CNN by that data set is closer to observed wind speed data at time duration. According to Hurst exponent, and RMSE values, it is expected that summer has the greatest regression value, and 1 year has the least regression value, but

it doesn't follow that rule. Since the values are near to each other we can not say that this model does not follow the rule, because we can say that one case with great HE and small RMSE has a great regression and is predictable. As the result, wind speed data is predictable and because of relationship between wind speed and wind power density which is discussed in chapter 3, power density of any standard or specified turbine can be predicted. Moreover, the best turbine for that location considering wind speed specification of it can be selected.





## 6. CONCLUSION

The importance of wind energy as renewable energy is clear for everyone. The effects of wind energy on the energy market, air pollution, energy supply is significant and any changes in the amount of production can irreversibly effect on-demand or production side. To overcome some issues around the usage of this source of energy, a study on the behavior of wind speed as an effective parameter on wind energy is necessary. The most important thing in this regard is wind speed behavior. Wind energy is affected by wind features and meteorological data totally, so we used some meteorological data with wind speed data to study the potential energy at the stated location. Hurst exponent as the randomness indicator was calculated for each group of data, following Wind speed statistical model had been estimated and found for a whole year and each season. Weibull density with its coefficients was obtained from statistical studies. The parameters are in the acceptable range for a Weibull probability density function and differed according to the time-series behavior of that case study. Hurst parameter as an index for long-term memory level of time series and a kind of ability of them to be predicted was calculated on raw wind speed data, and, then, deep learning was applied on data sets which were considered to be input. One multivariate 1D CNN was trained to trace and learn wind speed behavior. Performance factors of the implemented network were reported and were at the acceptable range, changes and differences between RMSE and R were also discussed to interpret the numerical results and explain the performance of the network. As the result, this study represents that according to this data, aforesaid CNN can be trained and predict one step ahead wind speed. As a practical result, these results can be introduced to the renewable energy sector as one approach to predict wind speed and wind energy for any standard and appropriate turbine.



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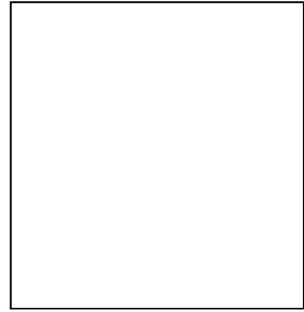
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## **CURRICULUM VITAE**



**Name Surname**

**: Behnaz Alafi**