YAŞAR UNIVERSITY
GRADUATE SCHOOL

MASTER THESIS

# IMPLEMENTATION OF FUZZY INFERENCE SYSTEM AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR ANALYSIS OF WIND TURBINE EFFICIENCY

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We certify that, as the jury, we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science /Master of Arts/ the Doctor of Philosophy/Proficiency in Art.

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## ABSTRACT

IMPLEMENTATION OF FUZZY INFERENCE SYSTEM AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR ANALYSIS OF WIND TURBINE EFFICIENCY



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This master thesis proposes the use of a fuzzy inference system (FIS) and an adaptive neuro-fuzzy inference system (ANFIS) to evaluate the performance of wind turbines. Key factors influencing wind turbine performance, such as wind speed, blade length and distance to other turbines are identified through data analysis. Understanding these factors allows for informed decision-making regarding turbine operation and design, contributing to improved overall efficiency and cost-effectiveness. Wind turbines are complex systems with multiple inputs and outputs, which makes traditional analysis methods insufficient to provide accurate results. The FIS and ANFIS are designed to model the uncertainty and imprecision in wind turbine data and provide a more accurate assessment of turbine efficiency. This study demonstrates the effectiveness of the approach by using real-world data from a wind farm in Turkey. The paper concludes that the FIS is a promising tool for analyzing wind turbine efficiency and has the potential to improve the performance of wind farms. Our main motivation in working on this subject is the request of the customer to replace two turbines as they will produce more energy. Although we cannot express this situation mathematically due to lack of data, valuable information to be used in this decision has been shared.



**Keywords**: wind turbine, fuzzy inference system, adaptive neuro fuzzy inference system, renewable energy, efficiency

# ÖZ

## RÜZGAR TÜRBİNİ VERİMLİLİĞİNİN ANALİZİ İÇİN BULANIK ÇIKARIM SİSTEMİ VE UYARLAMALI AĞ TABANLI BULANIK ÇIKARIM SISTEMININ UYGULANMASI

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Bu çalışma rüzgar türbinlerinin performansını değerlendirmek için bir bulanık çıkarım sistemi (FIS) ve uyarlanabilir bir nöro-bulanık çıkarım sistemi (ANFIS) kullanılmasını önermektedir. Rüzgar hızı, kanat uzunluğu ve diğer türbinlere olan mesafe gibi rüzgar türbini performansını etkileyen temel faktörler, veri analizi yoluyla belirlenir. Bu faktörlerin anlaşılması, türbin işletimi ve tasarımına ilişkin bilinçli karar vermeye olanak tanıyarak genel verimliliğin ve maliyet etkinliğinin iyileştirilmesine katkıda bulunur. Yazarlar, rüzgar türbinlerinin birden çok girdi ve çıktıya sahip karmaşık sistemler olduğunu ve bunun da geleneksel analiz yöntemlerini doğru sonuçlar vermede yetersiz kıldığını ileri sürüyorlar. FIS ve ANFIS, rüzgar türbini verilerindeki belirsizliği modellemek ve türbin verimliliğinin daha doğru bir şekilde değerlendirilmesini sağlamak için tasarlanmıştır. Bu çalışma, yaklaşımın etkinliğini Türkiye'deki bir rüzgar santralinden gerçek dünya verilerini kullanarak göstermektedir. Çalışma sonucunda FIS'in rüzgar türbini verimliliğini analiz etmek için umut verici bir araç olduğu ve rüzgar türbini sahalarının performansını iyileştirme potansiyeline sahip olduğu sonucuna varılıyor. Bu konuda çalışmamızdaki temel motivasyonumuz, müşterinin iki türbini daha fazla enerji üreteceği için değiştirme talebidir. Veri eksikliğinden dolayı bu durumu matematiksel olarak ifade edemesek de bu kararda kullanılacak değerli bilgiler paylaşılmıştır.

**Keywords**: rüzgar türbini, bulanık çıkarım sistemi, uyarlamalı ağ tabanlı bulanık çıkarım sistemi, yenilenebilir enerji, verimlilik

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Gülcan İncu Özcan
İzmir, 2023

# TEXT OF OATH

I declare and honestly confirm that my study, titled “IMPLEMENTATION OF FUZZY INFERENCE SYSTEM AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR ANALYSIS OF WIND TURBINE EFFICIENCY” and presented as a Master’s Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

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# SYMBOLS AND ABBREVIATIONS

ABBREVIATIONS:

FIS Fuzzy Inference System

ANFIS Adaptive Neuro Fuzzy Inference System

WTG Wind Turbine Generator

FCM Fuzzy C-Means Clustering

# CHAPTER 1
# INTRODUCTION

Energy is defined as the ability to do work in a system. Depending on the application, energy can be classified as electrical energy, mechanical energy, or chemical energy. However, some of the energy resources used in the world are depleted and cannot be reused. In general, the source of this group is fossil fuels. The energy need in our world is increasing by about 4-5% every year. However, the fossil fuel reserves that meet this increase are decreasing more rapidly. Even the most optimistic forecasts show that oil reserves will be depleted largely between 2030 and 2050 at the latest and will not be able to meet the need. The same is true for coal and natural gas. Due to this, it is necessary for humans to shift towards clean sources of energy without delaying until the fossil fuel reserves are entirely depleted. Renewable energy sources like the sun, wind, water, and biomass, which can reproduce themselves indefinitely, will become more significant in a very short period. The development of these technologies is the sole focus of research and development studies conducted by large oil firms, who are aware of this. After the initial investment cost, the unit prices of the systems whose maintenance need is close to zero started to decrease worldwide. As a result, in the very near future, alternative energy source systems will be at the same level as other conventional systems in terms of both efficiency and cost (He et al., 2021).

Turkey's goal is to be self-sufficient in meeting its energy needs in the future. This is an unattainable goal at the moment. Considering that approximately 69% of our current energy production is met from foreign-dependent sources, it is not easy for Turkey to pull this indicator down. Considering that our coal resources are limited, we naturally have alternative energy sources. These are primarily renewable energy sources such as solar, wind, and geothermal. With the current rate of industrialization and growth, it is a fact that we have to make enormous investments to reduce our foreign dependency rate on energy. While doing this, our existing systems also need to be improved (Çıray, 2019).

Every place where a hydroelectric power plant can be established in Turkey has been evaluated or is being evaluated. Since it is affected by seasonal conditions, it cannot be considered as a guaranteed energy source. Again, the gas shortage of natural gas power plants is the best example of foreign dependency. In nuclear energy, however, our dependence will continue due to the lack of sufficient uranium reserves. With the remaining solar, wind, geothermal, and other resources it will be challenging and expensive to respond to the need of the whole country. However, it is also a fact that; We must create a Turkey with energy diversity, where we use all these energy resources. It would not be right to turn to only one source. Nevertheless, we must shift our focus to clean energy, and especially wind. We have to move faster and bring the latest technology, the turbines of the most significant possible power. We should even look for ways to produce them locally. Thus, both new business lines are created, and the country's money does not go out (Yalçın, 2021).

In this study, it is aimed to analyze the efficiency of the wind turbine with the fuzzy reference system. In this context, information about wind energy and wind turbine concept will be given in the second part. In the third chapter, the fuzzy reference system will be discussed. In the fourth part ANFIS is analyzed. In the last section, detailed information about the application will be shared.

# CHAPTER 2

# WIND ENERGY AND WIND TURBINE CONCEPT

While developed countries have been utilizing a large part of their renewable energy resources potential in recent years, these studies are just beginning in Turkey. Utilization of these resources is very important for Turkey. In this way, some of the energy needed by Turkey will be met from our own resources, and the foreign currency paid to foreign countries for energy will remain in our country and turn into an investment. In addition, thanks to the employment provided during the establishment and operation of the facilities established in this area, more people will be employed, and a double contribution will be made to the country's economy. There is a rapid development in the field of wind energy, one of the renewable energy sources. Wind energy is generally used by converting it to electrical energy or converting it to mechanical energy. Systems that produce electrical energy from wind energy are used for the purpose of supplying electricity or feeding the interconnected system in units (such as television, radio, meteorology, and communication stations) in settlements, islands, rural areas, forested and mountainous areas where there is no electricity network (Buldur et al., 2020).

Wind turbines are manufactured in a modular manner that can be easily mounted to the desired location, and sometimes tens or hundreds of them are installed together to form wind farms. Today, wind farms are installed in the sea as well as on land. The transition from land to sea was achieved in the technical field with the first applications and commercial applications were also realized. However, R&D studies continue for more advanced systems. The first studies on offshore wind energy started towards the end of the 1970s in Denmark, the Netherlands, Sweden and the USA. In the early 1980s, these studies were carried out within the International Energy Agency (IEA) (Köse, 2004).

In 1992, the Turkish Wind Energy Association was established and affiliated to the European Wind Energy Association. This union is composed of many public and private sector participant members. As a result of the effective work of the Ministry of Energy and especially this union, for the first time by private companies, wind turbines with a total power of 7.2 MW were installed by the ARES Power Union company in Izmir-Çeşme Alaçatı in 1998, and electricity generation was started (Aras, 2003).

In this section, information about renewable energy sources, wind energy, wind turbines, and wind turbine efficiency will be given.

### 2.1. Renewable Energy Sources and Wind Energy

Energy is responsible for numerous events that occur around us. There are several primary types of energy, including heat energy, chemical energy, nuclear energy, electrical energy, potential energy, and kinetic energy. Renewable energy resources encompass energy sources derived from natural or naturally occurring materials such as hydro, wind, solar, wave, geothermal, and biomass. These resources are continuously replenished or renewed, ensuring their sustainability for as long as our world exists. Hydrogen energy obtained from water is also one of the renewable energy sources. Nuclear energy is an event related to the nucleus of the atom and is obtained in two ways. The first of these is fission (fission) of a large nucleus. The second is the fusion (merging, fusion) of two small nuclei. With the heat energy released from both reactions, steam can be obtained, and electricity can be produced as in thermal power plants. Conventional energy sources have been around for a while and are widely used energy sources today. These are classical biomass (biomass), fuel wood obtained from conventional forests, fuels consisting of plant and animal residues, fossil fuels such as coal, oil and natural gas, hydraulic energy (hydroelectric), nuclear fuels consisting of fission elements such as uranium and thorium (Walker, 2014).

The common and important features of conventional energy sources enable production levels to be kept under control according to demand, a production that can be produced continuously and does not require the storage of the produced energy. However, renewable energy sources cannot provide these features. In general terms, wind is the movement of air in the atmosphere. The sun's rays fall on the pieces of land and water that make up the earth and warm them. Air over land heats up faster than air over water. Warm air over land begins to rise, and cold air above water moves toward land, displacing rising air. As a result of this event, wind is formed. Heating of the air causes the heated mass to expand, thus moving and rising. However, since the rising air mass cannot get out of the atmosphere, it first moves vertically and then horizontally. At this point, the heating and mass displacement of the air causes the pressure to build up. However, the pressure exerted by the atmosphere is not the same all over the world, because it varies depending on gravity, temperature, and altitude. In this way, high and low-pressure centers are formed. High-pressure areas in the atmosphere can be compared to hills and low-pressure areas can be compared to troughs. Since the air is fluid, it moves from high pressure areas to low pressure areas under the influence of gravity, as if water flows from the slopes and creates winds (Karadağ, 2009).

Breeze, which is one of the short-term winds arising from the warming and pressure difference between the lands and the seas and seen in the hot season, is one of the winds that affect the temperature. At noon, when the air temperature is high, the pressure drops because the land gets too hot. In this way, the wind blowing from the sea, which is the high-pressure center, towards the land, which is the low-pressure center, cools the air. At night, the air is already cool, so it doesn't need to be cooled any further. Therefore, the mechanism works in reverse. The imbat blowing in the summer months in İzmir, located on the Aegean coast of our country, is a typical example of this wind. Some winds are warmer than where they come from. The most well-known ones in this group are the winds called "Fhön". These winds are formed when the rising air mass passes over a mountain and descends on the other slope. During this descending movement, it heats up by 1$^{o}$C every 100 m. It is interesting that these winds, which descend on the other slope as hot and dry, blow on the northern slopes of the Swiss Alps and the sea-facing parts of the Eastern Black Sea and Taurus Mountains of our country, and mountain areas with similar conditions, in other words, in the cooler parts of the world, and soften the harsh, cold climate conditions here.

We can explain how the wind is formed and its definition from different sources as follows.

In the atmosphere, which can be described as a heat engine that takes its necessary energy from the sun; Air masses with thermal potential differences move from a cooler and higher-pressure area to a warmer and lower pressure area. The air mass movement in this natural event, where heat energy is transformed into kinetic energy, is called wind (Özdamar, 2000). In other words, winds are air currents formed by balancing pressure and temperature differences caused by different solar heat distribution on the earth. While the air, land, and sea warm in one part of the world, cooling occurs on the other surface. With the daily rotation of the earth, this warming and cooling continues periodically. The variation of the tilt of the earth's solar axis according to the seasons causes the daily distribution of thermal energy to differ from season to season (Avşar et al., 2001).

The conversion of potential energy into kinetic energy under the effect of pressure forces results in the conversion of the entire amount of energy in the atmosphere, which is split into kinetic and potential energy. Hot and humid air in contact with the ground around the equator rises by convection, cools as it rises, rises to colder northern latitudes after rising to a certain level, and descends towards the earth again when it approaches 30º North latitudes. Here, the relatively colder and drier air tends towards the equator. This is called the 'Hadley Circulation'. Since the movement of the air is deflected to the right of the direction of movement due to the 'Coriolis Force' that occurs with the rotation of the earth, the winds formed on the earth's surface between 0º-30º latitudes are basically of North-East character. It takes place between 30º- 90º latitudes in a circulation that has a similar structure, but this time exhibits a characteristic in the form of waves, and we call the 'Rossby Circulation'. As a result of this circulation, South-Western winds occur between 30º-60º latitudes and North-Eastern winds between 60º-90º latitudes. Winds can be examined in two groups according to their continuity as continuous winds blowing all year round and discontinuous winds blowing at certain times, such as hurricanes, typhoons, tornadoes, and eddies. That is, when the wind speed is 0.3-1.5 m/s, the smoke rises with a light breeze, the wind direction is uncertain, the wind speed is between 1.6 and 3.3 m/s, the breeze is felt on the human face, the leaves and thin It can be observed that the branches move at 3.4-5.4 m/s wind speeds. In addition, thin branch movements, paper and dust are seen to rise in breezes called 5.5-7.9 m/s medium wind speed. It is seen that open conductors shake at speeds, umbrella control becomes difficult, and walking becomes difficult at 13.9-17.1 m/s. In addition, it is observed that at speeds of 17.2 -20.7 m/s, thin branches are broken on the trees and walking becomes difficult, and at 20.8-24.4 m/s, roof tiles fly off and light building damage occurs. It is observed that large trees are uprooted at 24.5-28.4 m/s, large-scale damages occur at 28.5-32.6 m/s, and extreme damage occurs at speeds greater than 32.7 m/s (Özgener, 2002).

Apart from these, trades blow from the high-pressure belt above 300 latitudes in the northern and southern hemispheres to the low-pressure belt above the equator every season. Contrasting winds, on the other hand, work in the opposite direction of the 'Trade' winds at the height of the atmosphere and the reason for their formation is that the heated air masses rise at the equator and move away from the equator. Breeze winds are formed due to the fact that the land heats and cools faster than the seas and the mountains get colder than the valleys, and they affect the air masses above them. During the day, sea breezes blow from the seas towards the rapidly warming lands, and at night from the rapidly cooling lands towards the seas. Sea and land breezes are effective up to 40 km inland from the coast. In the same way, valley breezes blow from the valleys to the mountains that heat up quickly during the day, and mountain breezes from the mountains that cool quickly to the valleys at night. The movement of an air mass in motion, colliding with a high mountain, rising by 0.5 $^{o}$C every 100 m, and then descending to the other slope of the mountain by 1 C every 100 m, is called "Föhn" winds (Özgener, 2002).

Wind energy started to be used in the years before Christ, and it has been a power source in many areas from sailing ships to windmills. Wind energy has been utilized for numerous years to fulfill essential requirements like milling grains such as wheat and corn and pumping water. Around 2800 BC, wind energy was first employed in the Middle East. It is believed that wind power was utilized for irrigation purposes in Mesopotamia during the reign of Babylonian King Hammurabi in the 17th century BC. As the need for harnessing wind energy grew, wind turbines were constructed in Denmark in the early 1890s. Paul la Cour, a significant modern aerodynamics engineer, built the first turbine that produced electricity from wind energy in Denmark in 1891. The most crucial aspect of utilizing wind energy is having sufficient wind speed in the area where the wind turbine is intended to be installed. Even in situations of low wind speed, researchers are striving to create sufficient power generation, particularly in small-scale wind turbines. One of these studies is carried out by Professor Andy Knight and his team from the Department of Electrical and Computer Engineering at the University of Alberta. This team develops a system that allows turbines to generate sufficient voltage even in relatively stagnant conditions. In a small-scale wind turbine, the wind turbine rotates, the turbine turns the generator, and the generator produces alternating current (AC) voltage. Nevertheless, due to the fluctuating nature of wind speed, the voltage produced can also vary, and occasionally it may not be adequate to be stored in batteries or supplied to the grid (Akman and Roth, 2005; Varış, 2021).

### 2.1.1. Advantages and Disadvantages of Wind Energy

Among the energy sources, wind energy, which is a clean and renewable energy source, has many advantages and its advantages can be listed as follows (Wang and Wang, 2015):

- "It does not harm the environment as it is a clean and renewable energy source.
- It is an inexhaustible energy source.
- It is in free form in the atmosphere. No processing is required to use.
- It is free to use. No payment is made to anyone or anywhere.
- Its usage area is wide due to its varieties that can work in different conditions.
- By obtaining energy from the wind, the depletion time of energy sources such as fossil fuels, which are in danger of depletion and pollution the environment, can be reduced.
- Power plants can be established and start operating in a short time.
- Since power plants have simple technology, they are easy to operate when their maintenance is done regularly.
- Since the raw material is domestic, it does not create foreign dependency.
- With the developing technology, energy production costs are decreasing, and maintenance and operating costs are very low.
- Energy can be obtained by installing it in places where it is impossible to transport energy.
- It increases employment".

The disadvantages of wind energy are as follows:

- Due to the irregularity of the winds, there are fluctuations in energy production. In addition, turbines may be damaged in regions with strong winds,
- Noisy operation of wind turbines and therefore wind farms should be installed far from residential areas,

- It adversely affects the communication waves in the surrounding area,
- The initial investment (installation) costs are high,
- There is an expensive storage cost during the intensive production period,
- Having a high tower height and high-speed rotation may cause the death of migratory birds and change their flight paths".

### 2.1.2. Usage Areas of Wind Energy

The usage areas of wind energy are quite vast. These are given below (Ajayi, 2009).

- Energy can be produced by using wind energy in remote settlements where the energy of electricity cannot be transported. By giving the surplus electrical energy to the grid, both a contribution to the economy and national resources are saved.
- It is frequently used in wind thermal application areas. The energy obtained from the wind is converted into thermal energy, and by heating the water, it can be used to meet the needs of hot water as well as heating the campuses.
- Wind energy is used in radar towers, different communication radars, watchtowers, lighthouses, and different units where there is no electricity in mountainous and forested areas.
- Wind energy is used to ventilate various environments and to dry farmers' products.
- In the past, sailing vehicles were used for sports purposes, although they were frequently used in the movement of sea vehicles by using sails".

### 2.1.3. History of Electricity Generation from Wind Energy

Examining the examples of the use of wind energy in history will be a guide in solving the problems that wind energy systems still face today. Wind energy, which has served humanity for thousands of years, contributes to energy production today. Wind energy has shown many technological developments from windmills to modern wind turbines. The fact that petroleum, which is one of the most important and widely used products of non-renewable energy sources, caused an international crisis has served to carry the use of wind energy to the present day (Özdemir, 2021).

Although there is many different information about the use of wind energy in history, human beings who want to meet their needs in the way of civilization have benefited from the opportunities of nature and used wind power for this purpose. It is possible to come across its use, albeit in its primitive form, in valuable works such as moving their boats, pumping water for their lands, grinding their grains. The first and oldest findings on the use of wind energy date back to BC. They are sailing ships depicted in Egyptian ceramics from 4000 BC. Although there are only findings in about those years today, it is thought that the idea of benefiting from the power of the wind, which is one of the beneficial forces of nature, can go back to much earlier dates (Ragheb, 2010).

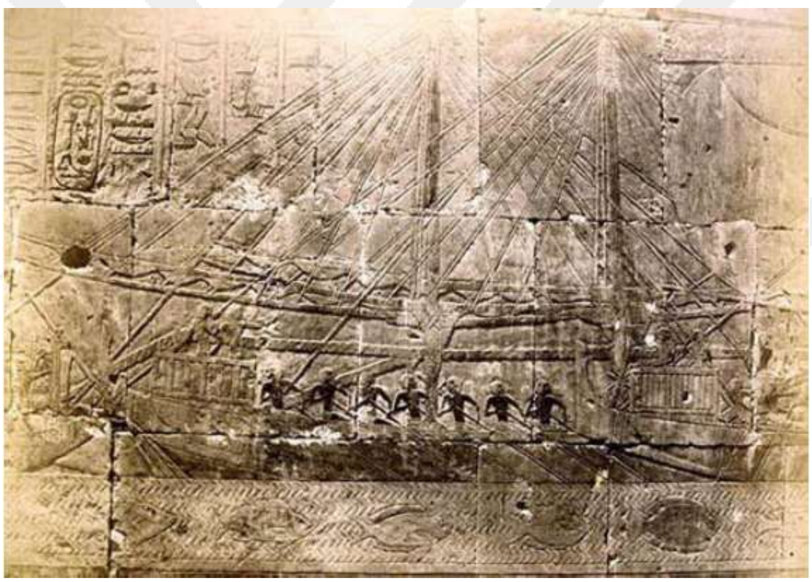

**Figure 2.1.** Relief of double sailboats and boats on the walls of the temple of Queen Hatshepsut in Luxor, Egypt (Ragheb, 2010).

Wind energy applications started in Iran about BC. It appeared as a windmill in the 200s. However, Sistan windmills, known as the first practical windmills, were designed, and used by the Persians with a vertical axis in the 7th century (Tummala et al., 2016). Windmills were used to irrigate rice fields in China in the 8th century AD. Windmills, which are the most common wind energy applications in history, were used for the first time in France in 1105 and in England in 1143, and their use became widespread over time. One of the most significant power sources used before the invention of the steam engine was windmills. Windmills, which were used in agricultural areas such as pumping water and grinding the harvest, were also used in industrial works such as cutting wood. By the 18th century, there were around 10,000 windmills in the Netherlands (Özgener, 2002).

Although wind energy has been used in every field throughout history, the first attempt to generate electricity from wind energy was made by Charles Brush in the USA in 1888. Known as the world's largest turbine at that time, this turbine, with its 17 m rotor diameter, can generate only 12kW of energy and has served for 20 years (Eriksson et al., 2008).

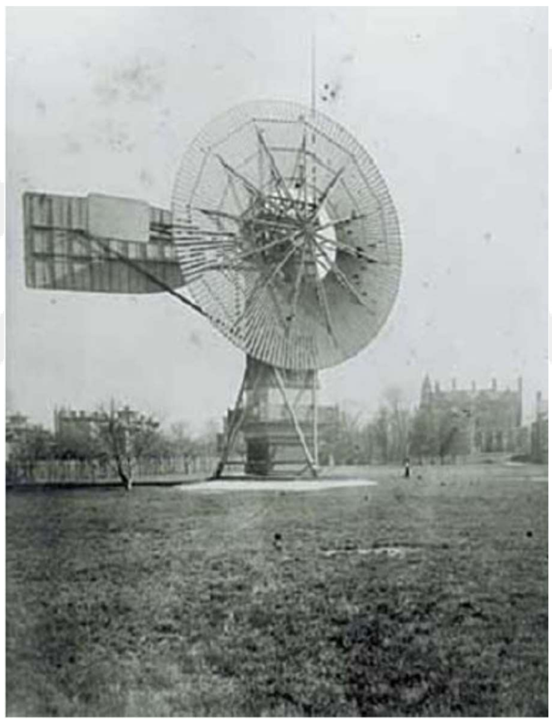

**Figure 2.2.** The first electricity-generating wind turbine was designed by Charles F. Brush (Dismukes et al., 2007).

Danish Paul La Cour, who developed the design after the initiative of Charles F. Brush, obtained direct current with the wind turbine he built in 1891, and managed to store wind energy by obtaining hydrogen gas through electrolysis. It is known as the turning point and pioneer in the transition to modern wind turbines. It is also thought that he was the first person to establish a wind tunnel and test a wind turbine (Özgener, 2002).

Although the use of wind energy in the 20th century declined from time to time with the use of steam engines, the use of wood and coal, and the decline in oil prices, it was the fastest-growing and an essential energy source at the end of the 20th century. The start of modern turbine productions using special sections in Europe and America revitalized the sector and opened the door to important investments. Between 1979 and 1985, more than 4500 state-supported wind farms with a power of 1-25 kW were built. Due to the high unit price of electricity, wind turbines with 55 kW capacity were produced and started to be used in the 1980s. Especially in 1989, with the entry of Germany into wind turbine technology, the development and use of large wind turbines with a capacity of MW became widespread. With this developing technology, it is possible to see wind turbines with a rotor diameter of approximately 200 meters and a power capacity of 2-3 MW. In addition, Wind Power Plants (WPP) are not only land applications, but also electricity is produced from farms built on the sea.

**Figure 2.3.** Wind turbines that produce electricity from the past to the present (Özdemir, 2021).

According to the International Energy Agency (IEA) and the Organization for Economic Cooperation and Development (OECD), it is projected that wind energy will constitute 12% of global electricity production in 2050. Currently, wind turbines generate around 4% of total electricity production. It will be much easier to reach the envisaged scenario when the difficulties in front of the use of wind power such as turbine costs, reverse farm areas and technological limitations in turbines are overcome.

## 2.2. Wind Turbines

Although wind energy has been used in many ways to meet the needs of humanity on the way to civilization, the use of this energy has come from windmills to its modern structure with many technological development processes. In the early days, wind energy was used only by converting it to mechanical energy, but in modern wind turbines, the kinetic energy of the wind is first converted into mechanical energy and then into electrical energy. Wind turbines generally consist of the tower, blades, generator, and electrical-electronic elements together with the rotor shaft and the hub that contains the gearbox that provides the power conversion.

The energy present in wind is transformed into mechanical energy by the rotor shaft. The gearbox located in the hub increases and transmits the rotational motion of the rotor shaft to the generator. The electrical energy produced by the generator can be stored or directly supplied to consumers (Manwell et al., 2009).

### 2.2.1. History of Wind Turbines

Humanity has used the power of the wind for operations such as windmills, irrigation and grain crushing for many years in the past. Scottish Academician Professor James Blyth built the first wind-powered windmill in 1887 and patented it in England in 1891.

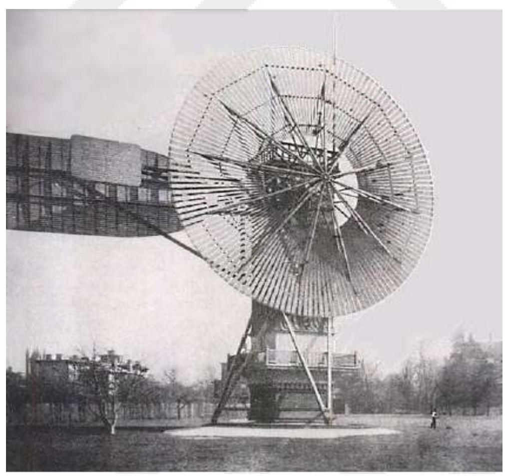

**Figure 2.4.** Mill for electricity generation produced by Charles Brush (Kalmikov, 2017).

Scottish Academician Professor James Blyth built the first wind-powered windmill in July 1887. Scottish Academician Professor James Blyth received a patent in England in 1891. In the USA, in 1887-1888, Charles Francis Brush succeeded in producing electricity from the mill of James Blyth, which had been built before which was much larger and more scientific. As a result, with the windmill in figure 2.5, he met the electricity needs of his laboratory and house until 1900.

During the 1890s, Poul la Cour, a Danish inventor and scientist, constructed wind turbines to produce electricity, which was subsequently employed for hydrogen generation.

**Figure 2.5.** The wind turbine was designed by Poul La Cour (Tong, 2010).

The contemporary wind power industry originated in 1979 when Danish firms Kuriant, Vestas, Nordtank, and Bonus commenced the large-scale manufacturing of wind turbines. The turbines produced during that period were smaller than the current standards, with a power output of 20-30 kW. Eventually, the turbines' capacity grew to 7 MW and their deployment expanded to several countries. If we simply list the turning points of wind turbines. A significant event in wind turbine development occurred in 1939 when a 53-meter diameter wind turbine with a 1.25 MW capacity, called the Smith Putnam turbine, was installed in the United States. The next milestone was the Gedser wind turbine, which was established on the southeastern Danish Island of Gedser in 1956-1957. This turbine had a 24-meter diameter and generated 200 kW of power.

**Figure 2.6**. 1.250 MW capacitated Smith-Putnam wind turbine (Ragheb, 2010).

During the early 1960s, Prof. Ulrich Hütter designed the Hütter Allgaier wind turbine, featuring a 34-meter diameter, 2-blade unstable propeller and 100-kW capacity. Currently, the power output of a single wind turbine has progressed to be measured in megawatts and is continuously growing. Presently, there are powerful wind turbines operating with a capacity ranging from 7-10 MW. Thanks to the improvements made in the structure and mechanical parts of wind turbines, it is aimed to increase these values even more soon. The Aerogenerator X turbine, which draws attention with its design as well as its high power, can be given as an example of a new generation high power turbine (Tummala et al., 2016).

### 2.2.2. Classification of Wind Turbines

The classification of wind turbines may depend on several factors. Wind turbines are classified in several different ways, such as number of revolutions, number of blades, axis of rotation, and installation location (Figure 2.7). The most used classification method among these classification methods is the classification made according to the axes of rotation.

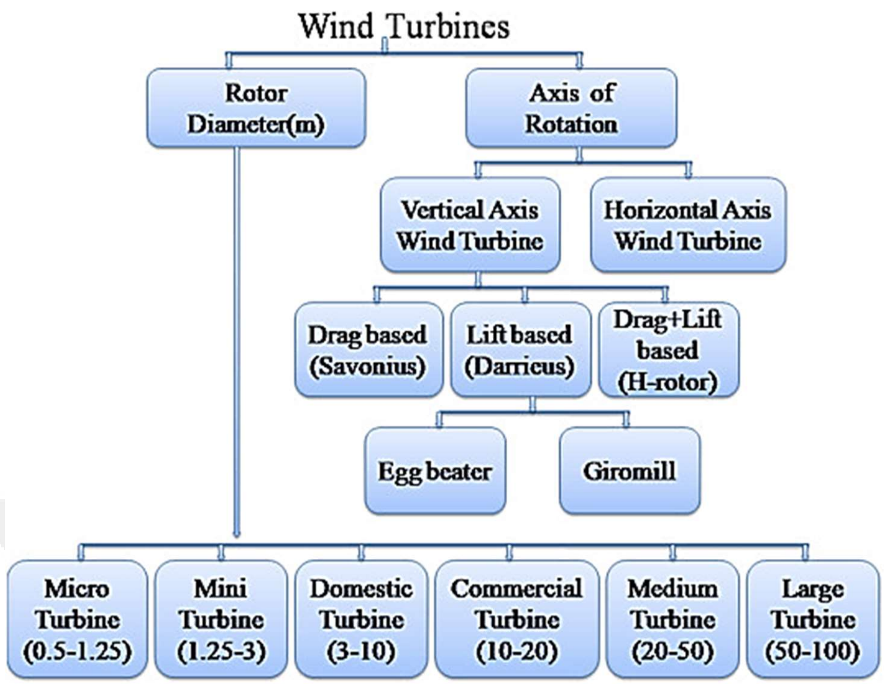


**Figure 2.7.** Classification of wind turbines (Tasneem et al., 2020).

#### 2.2.2.1. Horizontal Axis Wind Turbines

These types of turbines have their rotation axis aligned parallel to the direction of wind, while their blades are perpendicular to it. When there are fewer rotor blades, the rotor will rotate at a higher speed. These turbines are approximately 45% efficient. The ratio between wind speed and rotor blade tip speed is referred to as the blade tip velocity ratio (λ). If

- If the λ value is between 1 and 5, it represents the rotor with a large number of blades.
- If the λ value is between 6 and 8, it represents the rotor with 3 blades.
- If the λ value is between 9 and 15, it represents the rotor with 2 blades.
- If the λ value exceeds 15, it represents the rotor with 1 blade number (Arrival, 2021).

**Figure 2.8.** Horizontal axis wind turbines (Arrival, 2021).

Horizontal Axis Wind Turbines can also come in different configurations with varying numbers of rotor blades and can be designed to face the wind either from the front or the rear (Sen, 2003).

The advantages of horizontal axis wind turbines are as follows (Saad and Asmuin, 2014):

- "Due to its tall towers, it can reach strong winds. In some areas, the wind speed can increase by 20% for every ten meters high. Due to the high height of the tower, it can better use the increasing wind speeds at high altitudes.
- It has higher efficiency than horizontal axis turbines because the blades move perpendicular to the wind direction. Thanks to this movement, while the rotating wing completes one full revolution, there is not much change in blade tip speed as in horizontal axis turbines".

The disadvantages of horizontal axis wind turbine are as follows (Xie et al., 2017):

- Large tower construction is required to carry the gearbox, generator, turbine blades.
- Due to their high height, it may cause image pollution.
- Since they have a large structure, they can cause sound pollution. - In addition to vertical axis wind turbines, yaw control systems are needed to start the blade movement at low wind speeds. - At high wind speeds, the turbine blades bend and hit the body and the turbine is damaged. A braking system is required to avoid damage.

#### 2.2.2.2. Vertical Axis Wind Turbines

In such turbines, the turbine shaft is vertical axis and perpendicular to the wind direction. Savonius-type and Darrieus-type are the main species. Vertical axis wind turbines are omnidirectional and rotate in varying wind directions. Thus, they accept the wind from all directions. The vertical axis of rotation allows the driver to be placed even at ground level. Due to their power factor of less than 0.15, this particular kind of wind turbine is not commonly utilized for electricity generation (Sen, 2003).

The vertical axis Savonius wind turbine was first invented by Finnish engineer Sigurd Savonius in 1924 and patented in 1929. Its simple structure and easy construction made it attract all the attention. Savonius turbines have high starting torques. This is due to its ability to take the wind blowing from any direction due to its aerodynamic structure. Their efficiency is quite low compared to horizontal axis wind turbines. The maintenance and operation of Savonius wind turbines is quite simple (Dursun et al., 2005). When wind flows at a certain velocity, there is a moment that causes a force in the inner part of the impeller cylinder and an opposite force in the outer part. The positive force in the inner part is stronger than the negative force in the outer part, resulting in a rotational movement in the direction of the positive force (Bhutta et al., 2012).

The Darrieus wind turbine was invented by the French scientist George JM Darrieus in 1931. The biggest reason for the high performance of this wind turbine is that its blades have a smooth aerodynamic structure. The tensile stress on the turbine blades has a slight slope and therefore the tensile stresses on the blades are minimized. These turbines can continue to operate at high speeds. The turbine has 2 or 3 blades. For these turbines to start the first movement, a propulsion engine is required (Castelli, Englaro and Benini, 2011).

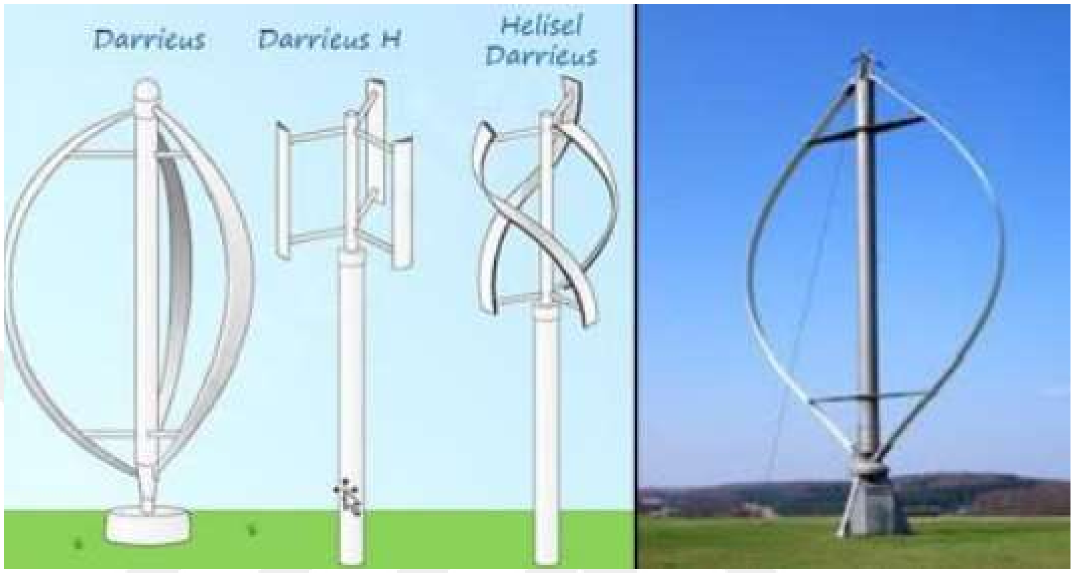


**Figure 2.9.** Darrieus- type wind turbines (Castelli, Englaro and Benini, 2011).

The Savonius wind turbine, which was created by Finnish engineer Sigurd J Savonius in 1925, generates a positive moment in the inner part of the cylinder and a negative moment in the outer part, regardless of the wind flow. Since the positive moment is higher than the negative moment, the rotation starts, and this rotational movement occurs in the direction of the positive moment. The reason for the interest of these turbines is their simple geometry and easy installation, as well as their high starting torque. This is due to their ability to use the wind blowing in any direction due to their aerodynamic structure. Since Savonius wind turbines are low compared to other turbines and have a small structure, maintenance and operation are very cheap and easy (Akwa et al., 2012).

When the research was reviewed, the initial study by Aldoss and Najjar aimed to enhance the performance of the Savonius wind turbine. To achieve this, they developed the turbine to rotate both against and with the wind by adjusting the impeller blades to swing backwards at an optimal angle. Alongside their work, Reupke and Probert modified the turbine blades by replacing the curved sections with a row of hinged blades. These new blades were positioned to move in the direction of the wind, and they would automatically open under wind pressure, resulting in reduced flow resistance and improved efficiency of the Savonius wind turbine. The researchers discovered that the corrected segment bladed impellers achieved greater torque than traditional Savonius turbines at very low tip speed ratios. They also observed that the blades of the corrected segment impellers closed automatically upon reaching the initial position.

**Figure 2.11.** Savonius-type wind turbines (Elibüyük ve Üçgül, 2014).

When determining the performance of wind turbines, the speed coefficient and power coefficient are considered and analyzed to produce performance curves. In this context, Savonius also examined the aspect ratio of the turbine in Mahmoud's experimental studies on the performance curve of wind turbines, and in this study, he concluded that there is an increase in the power coefficient with an increase in the aspect ratio. Based on this result, an increase in performance was observed (Keleş et al., 2019).

Savonius wind turbines advantages are as follows (Casini, 2016):

- "The geometries of Savonius wind turbines are simple and inexpensive to manufacture.
- They do not have as many elements as in vertical axis turbines and they do not need a tower.
- Good starting characteristics in low wind speed conditions.
- There is no need for an additional force during the start of movement, they can work on their own.

- Savonius wind turbines can operate independently of the direction of the wind. When the wind direction changes, there is no need to change the direction of the wheel.
- It is a cheap and simple windmill to meet the small amount of energy needed in places far from city centers.
- The parts in this wind turbine are easy to maintain and repair.
- Since the energy produced is at the ground level, it is easy to transport the power.
- Due to their aesthetic structure, they can be used even in city centers and do not cause visual pollution.
- They do not make disturbing noises during operation, so they do not cause sound pollution".

The disadvantages of Savonius wind turbines are as follows (Zemamou, Aggour, & Toumi, 2017):

- Their aerodynamic performance is lower than horizontal axis turbines. Therefore, they have limited usage areas such as ventilation and water pumping.
- They are not often used for commercial use.
- Today, studies are carried out for the development of aerodynamic structures.
- They have rotors positioned close to the ground, which cannot benefit from higher wind speeds in higher regions.

- **2.2.3. Comparison of Wind Turbines**

Wind turbines with single or double blades are not commonly used due to their unappealing appearance, high levels of noise, and expensive cost. The most favored type of wind turbine in use today is the three-bladed wind turbine, which is cost-effective, visually pleasing, produces minimal noise, and operates at high sp

**Table 3.1.** Comparison of Wind Turbines (Elibüyük and Üçgül, 2014).

| | **Horizontal Axis Wind Turbines** | | | | **Vertical Axis Wind Turbines** | |
|---|---|---|---|---|---|---|
| | Single Wing | Double Wing | Tri Wing | Multi Wing | Savonius | Darrieus |
| Cost | High | High | Low | Low | Low | Low |
| Aesthetic look | Bad | Bad | Good | Good | Good | Good |
| Working Speed | High | High | Low | Little | Little | Little |
| Tower Need | yes | yes | yes | yes | no | no |
| Purpose of usage | Electric | Electric | Electric | Little electricity and water pumping | Little electricity and water pumping | Little electricity and water pumping |
| Today's Usage | no | no | yes | yes | Little | Little |
| Wind To Rotate The Rotor | Removes | Removes | Removes | Lifts and drags | Lifts and drags | Lifts and drags |

Multi-bladed wind turbines, Savonius and Darrieus wind turbines, on the other hand, are used today for personal uses (electricity generation on farms or water pumping) due to their low operating speed. Savanius wind turbines are not only suitable for individual use due to their aesthetic appearance, but also can be used for purposes such as lighting in city centers and even on the busiest streets (Varış, 2021).

### 2.2.4. Wind Turbine Elements and Functions

Most modern large wind turbines are typically three-bladed horizontal axis turbines. These turbines generally consist of the tower, blades and many electrical-electronic components, as well as the rotor, gearbox and the core that contains the generator.

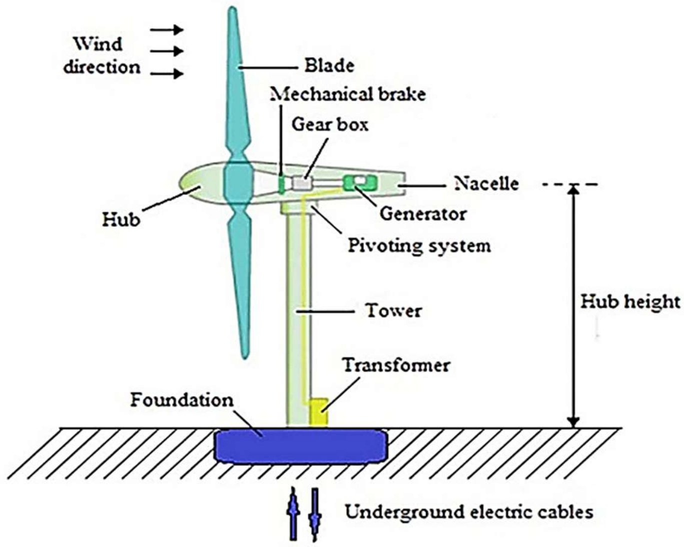


**Figure 2.12.** Wind turbine components (Nastase, 2017).

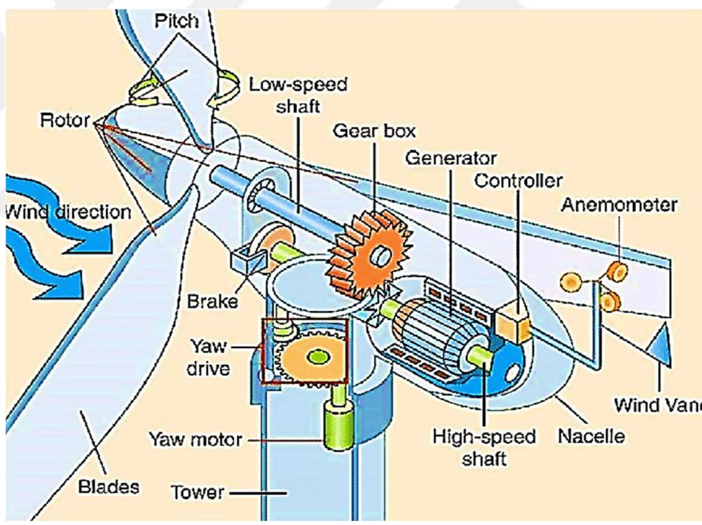


**Figure 2.13.** Nacelle interior view (Dehghanimadvar et al., 2019).

As shown in the hub structure in Figure 2.14, a wind turbine consists of the engine compartment, which houses many turbine components and is placed at the top of a tower. The rotor hub has 3 blades attached to it (not depicted in the image), which are linked to the gearbox via the main shaft. This mechanism amplifies the slow rotational velocity of the rotor hub to the required high rotational speed of the generator rotor.

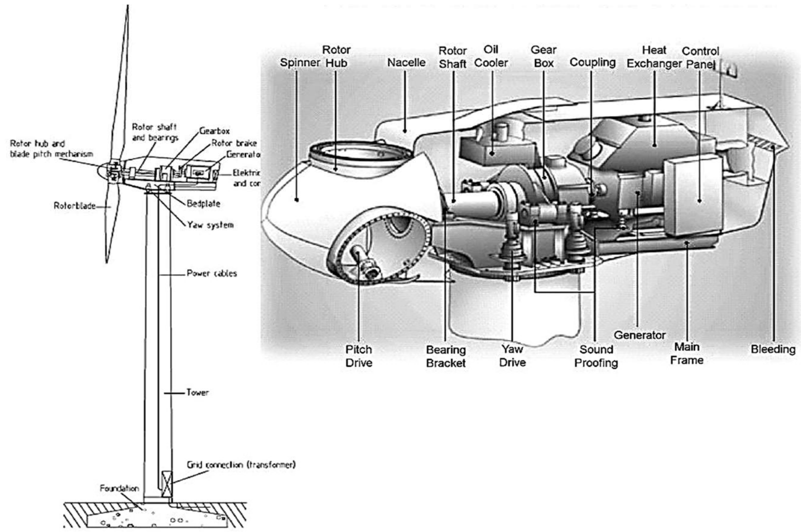


**Figure 2.14.** A horizontal axis wind turbine configuration (Tong, 2010).

The pitch control system adjusts the angle of attack of each blade independently to achieve better energy conversion under normal conditions and to protect turbine components in emergency situations. The yaw control system, using feedback from wind direction and speed sensors, ensures that the turbine constantly faces upwind, thereby providing optimal performance (Tong, 2010).

### 2.2.4.1. Tower

Towers, whose material is usually steel or concrete, are cylindrical-conical supports that carry the nacelle and turbine hub to take advantage of high wind speeds. Each section of the towers, which are produced section by section by the conical bending method, is attached to each other by means of internally welded flanges. This component, which is used for support and transportation, must pass all kinds of aerodynamic, dynamic and structural tests due to both its function and cost. The tower height is determined by the optimal solution between the increase in energy obtained with increasing height and the cost of the tower, which varies with increasing tower height. Typically, the height of the tower should be equal to or greater than the diameter of the rotor. It is recommended that the tower height should not be less than 24 meters as the wind near the ground becomes more turbulent (Manwell, McGowan, & Rogers, 2009).

#### 2.2.4.2. Turbine Blades and Rotor

The most important component of wind turbines, which are in constant contact with the wind and provide energy production, are the turbine blades. Wind turbine blades are vital components that transform the wind's kinetic energy into mechanical energy by rotating, resulting in a substantial power output. Composite materials like glass fiber reinforced epoxy or polyester are commonly used to manufacture these blades. Currently, modern turbine blades are made from glass fiber reinforced plastic. While the blades are fixed to the rotor hub in old-style wind turbines, today's modern wind turbines can rotate the blades around their longitudinal axis. The rotor blades are designed as twisted in order not to reduce the carrying force of the blades because of the wind coming at right angles towards the blade body and the rotor center (Manwell, McGowan and Rogers, 2009). There are many things to consider in turbine blade design, but these are mainly considered in two categories: (1) aerodynamic performance and (2) structural strength. All this to minimize the cost of the energy cycle. This means that not only turbine costs, but also operating and maintenance costs should be low. Other important design considerations are listed below (Özdemir, 2021).

- Aerodynamic performance
- Structural strength
- Blade material
- Recyclability
- Wing manufacturing and methods
- Noise reduction
- Condition monitoring
- Blade root and rotor hub connection
- Passive control options
- Costs

#### 2.2.4.3. Gear Box

The mechanical energy obtained by the rotor blades from the wind must be transferred to the generator in order to convert it into electrical energy. The gearbox located between the rotor shaft and the generator is the transmission system that increases the speed of the low-speed torque due to the slow rotation of the propellers during this transmission and makes it suitable for the generator. The rotation speed of a rotor ranges from 20 to 30 rpm, and since the rated speed of a generator shaft is between 1500 and 3000 rpm or more, a gearbox is needed to accelerate the low-speed shaft. This makes the gearbox one of the protagonists in the conversion from the kinetic energy of the wind to electrical energy. (Burton et al., 2001).

#### 2.2.4.4. Generator

The mechanical energy obtained from the wind is converted into electrical energy by wind turbine blades. First, the kinetic energy of the wind is converted into mechanical energy, which is then transmitted to the rotor shaft, gearbox, and generator. Generators are designed similar to electric motors, and they convert low torque mechanical energy into high torque energy, through the gearbox, and then convert the mechanical energy into electrical energy. The generator is connected to a high-speed shaft, and it needs to rotate at a speed corresponding to the frequency of the electrical grid, typically 50 or 60 Hz. However, turbine rotors cannot rotate at such high speeds, therefore a gearbox is used to increase the rotational speed of the turbine rotor (main shaft) to a speed that can be used by the generator. Modern high-capacity wind turbines typically use alternating current generators because the maintenance needs of direct current generators are frequent and they are expensive (Durak and Özer, 2008).

## 2.3. Wind Turbine Efficiency

Wind energy constitutes an important potential in the search for solutions to meet the rapidly increasing energy demand in our country as in the world. In wind turbines used to take advantage of this potential, good analysis of many factors, both during the installation phase and during the operation phase, is known as a factor that increases the system efficiency. The first theory about wind turbines was developed in 1926 at the Göttingen Institute by Dr. Introduced by Albert BETZ. In this theorem, it is assumed that the wind rotor is ideal. In other words, the rotor consists of an infinite number of blades that do not show drag against the air. In this way, it is assumed that the wind rotor is a perfect energy converter (Keleş, 2012).

As it is known, wind turbines consist of mechanical, electrical, and electronic components. The thought that we are often wrong about these components is that the malfunctions are concentrated on the mechanical components. However, in a study conducted in Federal Germany, considering the percentage distribution of damage and failures in approximately 1500 wind turbines, it was determined that most of the failures in wind turbines were on the electrical and electronic components of the system. Considering the technical durability and efficiency of the system, it is inevitable to make urgent optimizations in all electrical and electronic elements of wind turbines. In the maintenance and repair activities of the mechanical system elements of wind turbines, highly effective strategies can be developed thanks to smart integrations with electrical and electronic (sensory) elements. In this article, prepared under this basic idea, it will be explained how to develop efficiency-based maintenance strategies in wind turbines, considering the examples in the world. Thus, it will be emphasized that it is possible to get higher efficiency from the wind turbines, which are newly formed and installed in many regions of our country, most of which are imported from outside, based on maintenance strategies. The estimation of the efficiency and operating costs of wind turbines with minimum error is possible only a few years after the commissioning of the plant. For example, targeted maintenance planning and repair activities for wind turbines that are located in the open seas and are difficult to access, even only possible under limited conditions, are of great importance in terms of profitable operation of these facilities and reducing operating costs. The operational life of wind turbines installed in the Federal Republic of Germany is estimated as 20 years on average by the expert engineers who developed the facility. Unfortunately, the fact that the operating experience and data required to be obtained over a long period at these facilities are not yet scientifically sufficient, making it difficult to make real predictions about the operational lifetime of wind turbines. As can be understood from the literature, an inverse proportion is observed between the frequency of damage occurrence and the operating time. Although this situation is valid for all wind turbines belonging to three different power classes, it is determined that the frequency of damage and repair activities are higher in the plants that produce power over 1000 kW compared to other power classes. Again, according to the literature, since the second year of operation, the frequency of failures in wind turbines belonging to the power class below 1000 kW, which almost does not change throughout their operating life, is observed once or twice a year. On the other hand, the frequency of malfunctions and damage in large facilities in the Megawatt class draws attention and an average of three malfunctions are recorded in the first five years. It is observed that these rates decrease rapidly depending on the advancing operating times. Necessary investments constitute a large part of the costs incurred in energy production with wind turbines. In other words, 1/3 of all costs incurred in these facilities, which are expected to operate for an average of 20 years, belong to the operating costs. In line with expectations, the operating costs of wind turbines belonging to the power class above 1,000 kW are much lower than the facilities belonging to the lower power group.

As a result, maintenance strategies in wind turbine facilities must be created by considering efficiency. For this, the working conditions of these facilities and the elements that make up the facility should be considered in integrity (Özüarı and Eker, 2010).

# CHAPTER 3
# FUZZY INFERENCE SYSTEM

**In this section, information about the Fuzzy Inference System will be given.**

## 3.1. Fuzzy Logic

Lukasiewicz, a Polish logician philosopher, aimed to create a third truth value in 1920. His objective was to incorporate a third value for the term "possible," and thereby model the modalities "necessary" and "possible." Although his original purpose of using this concept in modal logic was not fully realized, Lukasiewicz systems and numerous theoretical studies based on these systems were developed as a result of his research. Parallel to Lukasiewicz's approach, the basic idea of additional degrees of truth was put forward by Emil L Post in 1921. To put it briefly, $a \geq 2$ for the value of $P_a$ has a set of degrees of truth $W_a$. Lukasiewicz took the uncertainty (possible) to the third value of the proposition (Gottwald, 2005). After this revolution defined as post logic, Lukasiewicz and Alfred Tarski together carried out a notation (spelling style) defined as Lukasiewicz – Tarski. In this notation, operations can be written without parenthesis. can be expressed with an internationally accepted symbol. In 1932 Gödel tried to understand intuitive logic in terms of many degrees of truth. He discovered that heuristic logic does not just have a characteristic logical matrix with multiple degrees of truth. In 1936, Jaskowski constructed an infinite-valued characteristic matrix for intuitive logic. Gödel and Jaskowski's work has proven that there is no single propositional multivalued system that coincides with the set of logically valid formulas and logically valid formulas of intuitive logic, which explains the interrelationships of heuristic and multivalued logic (Gottwald, 2005). While Lukasiewicz took uncertainty as the third value of the proposition, Bocvar determined the third value as "meaningless". Kleen, on the other hand, determined this value as "undefined". According to Lukasiewicz's four-valued and five-valued logic studies, it is possible to derive infinitesimal logic. Following these processes, which started in the 1900s with the evolution of the two-valued Aristotelian logic into a three-valued logic, at the end of the 1900s, the concept of logic was brought to a hazy dimension by Lütfi Rahim Son Askerzade, with the thought of the inadequacy of human expression by using numerical values. (Bai and Wang, 2001).

Lotfi A. Zadeh, a computer science professor at the University of California, Berkeley, is credited with creating fuzzy logic in 1965. Fuzzy logic was developed by Zadeh for solving problems where imprecise data should be used, or rules formulated in a general way using scattered categories. Fuzzy logic offers a means of modeling imprecise data, which makes it particularly useful for decision support and expert systems that require robust reasoning skills. Unlike traditional binary or multi-valued logic, fuzzy techniques rely on approximate reasoning and accept the presence of ambiguity in the human thought process. This is because much of our thinking is based on ambiguous facts, connections, and rules of inference. In essence, fuzzy logic is a type of logic that embraces this ambiguity (Bai & Wang, 2001).

Zadeh stated that most of people's thoughts are blurred (Zadeh, 2008). Discourse, which is expressed as fuzzy, is related to the inability to fully comprehend the event with human knowledge (Sen, 2004). Classical logic systems are based on two-valued logic (Boolean). Any proposition can be true or false. However, it is disadvantageous to analyze imprecise expressions such as weak, long, short. For this reason, the human thought system cannot be adequately explained with two-valued Boolean logic. It is possible to explain this situation with the Epimenides paradox. He is a Cretan philosopher. This paradox, known as the liar paradox or the Cretan paradox, is "All Cretans are liars". If this proposition is true, Epimenides, himself a Cretan, must be a liar. If Epimenides is a liar, the proposition is true. It is not possible for a proposition to be both true and false. A third truth value is needed. There are other methods that can be used in situations of unavoidable uncertainty and certainty (Baykal and Beyan, 2004). The environment of uncertainty generally arises when the probabilities of the situations to occur are not known precisely. If the decision maker cannot foresee the events and the actual results of the events and is not known, the probability value of the possible outcomes will not be assigned.

Uncertainty can arise in many ways. Errors related to the size of suitable alternative sets due to the imprecise boundaries of fuzzy sets, disagreements expressing conflicts between various alternatives are inherent in uncertainty. Uncertainty is divided into two as randomness and fuzziness. Randomness refers to the uncertainty in the occurrence of the event. To any degree it is blurry. There are two types of information in decision-making processes, qualitative and quantitative. While quantitative information can be solved by mathematical methods, it is impossible to solve qualitative information with mathematical problems (Mendel, 2001). Thanks to fuzzy logic, in cases of uncertainty, incomplete data can be processed. It brings simple solutions to the control of uncertain, variable, complex, undefined systems suitable for the flow of daily life. It is possible to include expert opinions and expert experiences in the model. Non-numerical, intellectual data can also be processed (Yılmaz & Arslan, 2005).

### 3.1.1. Fuzzy Set Theory

Fuzzy logic is a theory that is built upon fuzzy set theory and extends the classical set theory. In classical set theory, an element is either a member of a set or not. Membership is represented as a binary function where an item belongs to a set completely or not at all. However, in fuzzy set theory, there is partial membership, and the degree of membership can range from 0 to 1. Fuzzy logic is therefore a generalization of classical logic. Fuzzy set theory includes classical set theory and allows for partial membership, while classical set theory is a subset of fuzzy set theory where membership is either 0 or 1 (Dernoncourt, 2013).

### 3.1.2. Membership Functions

Membership function consists of three parts: essence, basis and support. Parameters with a membership degree of “1” express the essence of the set (Starczewski, 2012). Parameters with a membership degree greater than zero express the support of the set. The parameters defined for the highest membership degree define the height of the membership function (Çelikyılmaz & Türksen, 2009).

#### 3.1.2.1. Triangular Membership Function

Triangular membership function values are defined as $a_1$, $a_2$, $a_3$ as follows. While the "$a1$" and "$a3$" values seen in the function express the support limits of the cluster, the "$a_2$" value expresses the essence of the cluster. The triangular membership function is shown as the equation below (Sen, 2004).

$$\mu_{a(x:a_1,a_2,a_3)} = \begin{Bmatrix} a_1 < x < a_2, & \frac{(x-a_1)}{(a_2-a_1)} \\ a_2 < x < a_3, & \frac{(x_3-x)}{(a_3-a_2)} \\ x > a_3 \; veya \; x < a_1, & 0 \end{Bmatrix} \tag{3.1}$$

### 3.1.2.2. Trapezoidal Membership Function

The trapezoidal membership function values are $a_1$, $a_2$, $a_3$, $a_4$, and The definition of the triangular membership function is as follows. While the $[a_1,4]$ values seen in the function express the support of the cluster, the $[a_2,a_3]$ value expresses the essence of the cluster (Ahat, 2021).

### 3.1.2.3. Gaussian Membership Function

The Gaussian membership function is expressed in terms of "$m$, $\sigma$" values. In the Gaussian membership function, the value "$m$" denotes the center of the function, and the value "$\sigma$" denotes the width. The Gaussian membership function is expressed as the following equation (Bojadzviev and Bojadziev, 2007).

$$\mu_{a(x;m;\sigma)} = \text{ex} \left(\frac{x-m)^2}{\sigma^2}\right) \tag{3.2}$$

### 3.1.2.4. Sigmoid Membership Function

Sigmoid membership function is expressed with $a1ve\ a2$ values. The point where the membership degree is 0.5 is expressed as the break point. The sigmoid membership function is expressed as the following equation (Ahat, 2021).

$$\mu_{a(x;a_1,a_2)} = \left\{\frac{1}{1+e^{-a_1(x-a_2)}}\right\} \tag{3.3}$$

### 3.1.2.5. Bell Curve Membership Function

In the bell curve membership function, three parameters are defined as $a_1$, $a_2$, $a_3$. The bell curve membership function is expressed as the following equation (Bojadzviev and Bojadziev, 2007).

$$\mu_{a(x;a_1,a_2,a_3)}=\left\{\frac{1}{1+\left|\frac{x-a_3}{a_1}\right|^2}\right\} \tag{3.4}$$

### 3.1.3. Advantages and Disadvantages of Fuzzy Logic

The main advantages, weak points and criticisms of fuzzy controllers used based on fuzzy logic are explained below.

Fuzzy logic offers a straightforward solution for managing complex, dynamic, and ill-defined systems - much like those encountered in everyday life. While traditional testing methods may suffice for systems that can be easily described using mathematical models, applying conventional logic to intricate systems can prove challenging and costly. In contrast, fuzzy logic control provides a more effective means of analyzing such systems and is also more cost-effective. In fuzzy logic, the use of preprocessed signals and a small number of membership functions allows for more rapid and efficient fuzzy control. This is because the values that cover a broad range can be reduced to a smaller set of membership functions, resulting in fewer rules to be applied to a smaller set of values, which ultimately leads to faster results. The same principle applies to the traditional computing environment. Fuzzy control can be implemented using specially developed hardware, which can result in even faster processing times. The engineers at Sanyo-Fisher chose to use fuzzy control in a video recorder due to the limitations of the microcomputer they were considering. Fuzzy control allows for smaller software sizes, which eliminates the need for external memory. Additionally, fuzzy logic control enables direct user inputs and user experience. This can be seen in automatic gear changes in vehicles, where the engine speed triggers the change. Conversely, in a car with a manual transmission, the driver manually shifts gears in response to various factors such as the road conditions, load, and their own driving style. Subaru has developed a system for changing the powertrain in their Justy model vehicle using fuzzy logic. This system involves adjusting the position of a belt, allowing for continuous adjustments to the car's acceleration and performance. Subaru refined the membership functions for the fuzzy logic system by conducting tests with drivers and analyzing their preferences for the optimal transmission ratio based on factors such as acceleration and performance. Similar studies have also been conducted by Honda and Nissan (Ok, 2010).

The rules utilized in fuzzy control are largely based on empirical evidence, and there is no established method for selecting membership functions. Identifying the optimal features typically involves a process of trial and error, which can be time-consuming. (Sagdatullin, 2019).

### 3.1.4. Fuzzy Number

According to Dubois D and Prade H, fuzzy number is any fuzzy subset, $M=\{(x,\mu M(x))\}$ , $x \in R$ and $\mu M(x) \in [0,1]$ . The membership function defines the degree of accuracy with which M takes a given number $x'$. Two fuzzy numbers are equal only if they have the same membership function. Converting any number, to a fuzzy number is performed using membership functions. It is represented as the algebraic expression ($x_1$, $x_1$, $x_3$) of the transformation of a number from a membership function to a fuzzy number. To qualify a fuzzy set as a fuzzy number, this set must satisfy some conditions. These conditions are given below (Sen, 2004: 102):

- Fuzzy numbers are convex normalized fuzzy sets.
- Segments α are closed sets of real numbers.
- The basis of the fuzzy number is limited.
- Fuzzy numbers are convex fuzzy sets.

When we say "about x" subjectively (as opposed to subjective), we are describing a fuzzy number (concept) whose center is the value x. The membership degree is assigned to the extent that the number of x is in the center of the membership function, and it takes the membership degree of 1 in x, and its closeness to the numbers on both sides of x. The degree of membership on both sides of the center x value will decrease from 1 to 0. These numbers are called fuzzy numbers. Various fuzzy numbers can be utilized based on the topic being discussed (Baykal and Beyan, 2004).

With $a \leq b \leq c$, a and c values represent the lower and upper basis of the triangular fuzzy number, respectively. If $a = b = c$, the number can be expressed as an ordinary number, not fuzzy. The number $A\ (a, b, c)$ is shown as the triangular fuzzy number. It is possible to add, subtract, multiply and divide fuzzy numbers.

### 3.1.5. Fuzzy Inference System

Fuzzy inference system, together with fuzzy set theory, is a structure that equates a rule-based input field with fuzzy logic-related concepts and operations to the output, creates specific inputs and outputs based on stored information (Khanmohammadi & Jassbi, 2012).

The literature on fuzzy systems identifies three main types that are frequently used: pure fuzzy systems, fuzzy systems with fuzzifiers and defuzzifiers, and Takagi-Sugeno-Kang (TSK) fuzzy systems. Wang classified these systems as pure fuzzy systems, TSK fuzzy systems, and fuzzy systems with defuzzifiers. In the pure system shown below, the fuzzy rules represent IF THEN rules. The linguistic use of input and output values in clean fuzzy systems is considered a disadvantage, because in real systems these values are not fuzzy but precise (Ahat, 2021).

#### 3.1.5.1. Blur

Blurring refers to the blurring of linguistic variants that are not fuzzy. With the determination of the membership degrees, the membership of the variables to the clusters is determined. The preparation of blurred linguistic variables as input is expressed as blurring (Kıyak & Kahvecioğlu, 2003). The representation of linguistic variables in the rule base is made compatible with the fuzzy set representation thanks to the process of fuzzification (Cirstea et al., 2002).

#### 3.1.5.2. Inference

Inference appears as a decision-making unit in the literature. At the same time, expressions such as fuzzy inference engine, fuzzy associative memory, fuzzy system, fuzzy rule-based system are used to explain the fuzzy inference system. Inference is the stage where the fuzzy data coming from the blurring stage is processed by the rule base and the database and a fuzzy output is obtained because of the process. Database and rule base are generally referred to as knowledge bases. The knowledge base of a facility is comprised of its database, which contains essential definitions for fuzzy operations. These definitions may include enrollment capacities, representation of input-output factors using fuzzy sets, and the mapping capacities between physical and fuzzy space. Abraham Kandel, in his book "Fuzzy Expert Systems" in 1991, explained the knowledge base as "the data structure containing information about the problem, as well as the frameworks, semantic networks and production rules about the problem". As such, it is obvious that it is not only a database but a complex system consisting of a rule base (Cirstea et al., 2002).

The task of the database is to act as the fuzzification rule base and to ensure the correct operation of the defuzzification processes. The rule base contains fuzzy control rules that perform control operations. Fuzzy rules are created by methods such as expert experience, fuzzy model of the process, learning, and modeling of the operator's control movements (Tay & Lim, 2006). The rule base is the control strategy of the system. It can be defined as a set of IF-THEN rules, usually derived from expert knowledge and heuristics. The rules are based on the concept of fuzzy inference; antecedents and conclusions are related to linguistic variables (Cirstea et al., 2002).

#### 3.1.5.3. Defuzzification

Defuzzification is defined as converting fuzzy output values to classical (exact) values. There are no specific steps when determining the rinse method. It is necessary to determine and choose a method suitable for the characteristics of the process (Baykal and Beyan, 2004). When choosing the appropriate method, the data obtained (result/results) must be specific and reasonable. The method chosen should be easy to calculate. What is meant by the reasonableness of the result is expressed as the definition of a certain area approximately in the middle. If the result is specific, it expresses a single value (Sharma et al., 2005). In short, fuzzy inputs and outputs are expressed as inferences to make them understandable and useful variables by using fuzzy logic rules (Şen, 2004).

Looking at the literature, there are more than fifty clarification methods. In 2020, there are three newest methods: ERD, WAERD, WAERD2. In the work of Hellendoorn and Thomas named "Defuzzification of Controllers" in 1993, six defuzzification methods were determined as the central method of sums, the largest membership principle, the central method of the largest area, the first maximum method, the middle of the largest membership method, and the central method of the sums. Ross TJ, in his book titled “Fuzzy Logic With Engineering Application” published in 1995, referred to four methods as the largest membership method, the centroid method, the weighted average method, and the middle of the largest membership, benefiting from the work of Hellendoorn and Thomas (Erdun, 2007). 2020).

Defuzzification is a process that converts a fuzzy set or fuzzy output into a crisp set or crisp output. Fuzzy rule-based systems use fuzzification, inference, and composition techniques to evaluate language-based if-then rules, which provide fuzzy results that must be transformed into clear outputs. Defuzzification is used to transform fuzzy results into crisp ones. The defuzzification process converts a fuzzified output into a single crisp value with respect to a fuzzy set. In Fuzzy Logic Controller (FLC), the defuzzified value represents the action to be taken to control the process. There are various defuzzification techniques available, some of which are commonly used (Jean, 2004):

- **Center of Sums Method:** This method is the most commonly utilized defuzzification technique, which counts the overlapped area twice. The formula for determining the defuzzified value, denoted by $X^*$ is given below. Here, N denotes the total number of fuzzy variables, $\mu_{A_k}\ (x_i)$ represents the membership function for the kth fuzzy set, and n indicates the total number of fuzzy sets.

$$X^* = \frac{\sum_{i=1}^{N} x_i \cdot \sum_{i=1}^{n} \mu_{A_k}(x_i)}{\sum_{i=1}^{n} \cdot \sum_{i=1}^{n} \mu_{A_k}(x_i)} \tag{3.5}$$

- **Center of Gravity:** This approach provides a unique benefit by utilizing the fuzzy set centroids as a starting point. The membership function distributions used to represent combined control actions are divided into several subdomains within the overall domain. The technique involves determining the area and centroid of each patch to obtain the non-fuzzy value of a discrete fuzzy set. The sum of all those patches is then used in the process. The defuzzified value $X^*$of

- the discrete membership function is defined as $\mu(x_i)$ is the membership function of the kth fuzzy set and n is the total number of fuzzy sets. where $x_i$ is the sample element, $\mu(x_i)$ is the membership function, and n is the total number of elements in the sample.

$$X^* = \frac{\sum_{i=1}^{N} x_i}{\sum_{i=1}^{n} \mu(x_i)} \tag{3.6}$$

- **Center of Area / Bisector of Area Method**: This technique can be used to identify locations on curves with equal areas on both sides. This triggers the action of dividing the zone into two regions sharing the same region.

$$\int_a^{x^*} \mu_A(x)dx = \int_{x^*}^{\beta} \mu_A\ (x)dx\ , where\ a = min\{x|x \in X\}\ and\ \beta = max\{x|x \in X\} \tag{3.7}$$

- **Weighted Average Method**: This approach yields outcomes that are pretty similar to those of the COA technique and is valid for fuzzy sets with symmetrical output membership functions. This approach requires less computing. The maximum membership value of each membership function determines its weight. The definition of the defuzzified value is below. Here, x is the element with the highest membership function, and $\sum$ stands for the algebraic summation.

$$x^* = \frac{\sum \mu(x).x}{\sum \mu(x)} \tag{3.8}$$

- **Maxima Methods**: This approach takes into account values with the highest membership. For multiple maxima, there are many maxima procedures with various conflict-resolution techniques.
  - First of Maxima Method (FOM): This step finds the minimum value of the domain with the maximum membership value.
  - Last of Maxima Method (LOM) : Find the domain's highest value with the highest membership value.

- Mean of Maxima Method (MOM): This approach determines the defuzzified value by selecting the element with the highest membership value. If multiple elements have maximum membership values, the average of the maximum values is used.

# CHAPTER 4
# ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

**In this section, information about the Adaptive Neuro Fuzzy Inference System will be given.**

## 4.1. Neural Network

Today, the term "neural network" refers to an artificial network of synthetic nodes or neurons. In contrast, a neural network can also refer to a circuit or network of biological neurons. Therefore, neural networks can exist as either biological networks consisting of biological neurons or artificial networks developed for solving problems in artificial intelligence (AI). Artificial neural networks emulate biological neuronal connections using weights between nodes, where positive weights signify excitatory connections and negative weights denote inhibitory connections. Before being added, each input is assigned a weight, and this process is called a linear combination. An activation function is utilized to regulate the output amplitude. Artificial neural networks have an output range of 0 to 1 and can be trained using data sets for applications like adaptive control and predictive modeling. These networks can learn and make decisions from complex and seemingly insignificant data sets. Biological neural networks are made up of functionally or chemically connected neurons, which can number in the millions and have multiple connections. Signal transduction in these networks is through the diffusion of neurotransmitters, as well as electrical signals. The way biological nervous systems process information is the basis for artificial intelligence, cognitive modeling, and neural networks. Artificial neural networks are commonly used in adaptive control for applications such as speech recognition, image analysis, and artificial intelligence. Unlike digital computers, neural networks don't separate processing from memory, and they're based on the theory of modeling biological information processing. The development of neural networks has aided our understanding of how neurons work in the brain and has helped progress artificial intelligence research. Alexander Bain and William James independently proposed the fundamental hypothesis for modern brain networks in 1873 and 1890, respectively. They suggested that interactions between neurons in the brain were responsible for both thoughts and bodily movements. Bain believed that each activity activated a particular subset of neurons, and that the connections between those neurons grew stronger as activities were repeated, leading to the formation of memory. James proposed that the brain's electrical currents were the source of memories and actions, and that memories and actions did not require distinct neural connections. However, his theory was later contradicted by experiments that showed a decrease in electrical current strength over time, leading to the discovery of habituation. Threshold logic was a mathematical and algorithmic model for neural networks developed by McCulloch and Pitts in 1943. This model led to two distinct approaches to neural network research: one that focused on the application of neural networks to artificial intelligence, and the other that focused on biological processes in the brain. In the late 1940s, Donald Hebb proposed a theory of learning based on brain plasticity, which is now called Hebbian learning. Hebbian learning served as an early model for long-term potentiation and is considered a typical unsupervised learning rule. These concepts were applied to computational models in 1948 with Turing's B-type machines. Farley and Clark were the first to simulate a Hebbian network using computational machines at MIT in 1954. In 1956, Rochester, Holland, Habit, and Duda developed additional computational machines based on neural networks. In 1958, Rosenblatt developed the perceptron, an algorithm for pattern recognition based on a two-layer learning computer network that used simple addition and subtraction. Rosenblatt also used mathematical notation to describe non-basic perceptron circuits, such as the exclusive-or circuit, which could not be processed mathematically until Werbos developed the backpropagation algorithm in 1975. After Marvin Minsky and Seymour Papert's research on machine learning was published in 1969, neural network research stagnated because they found two significant issues with neural network processing computational machines. Initially, two main issues hindered the development of neural networks. First, single-layer neural networks were incapable of processing the exclusive-or circuit. Second, computers lacked the required power to handle the extended run time necessary for large neural networks. Consequently, research into neural networks slowed down until computers became more advanced, and the backpropagation algorithm emerged, which helped solve the exclusive-or problem (Werbos, 1975). In the late 1970s and early 1980s, researchers showed brief interest in examining the Ising model in relation to Cayley tree topologies and large neural networks. The Ising model was eventually accurately solved for the general case of closed Cayley trees (with loops) with an arbitrary branching ratio in 1981, revealing unusual phase transition behavior in its local-apex and long-range site-site correlations. In the mid-1980s, parallel distributed processing became popular, known as connectionism. Rumelhart and McClelland's 1986 book thoroughly explained how connectionism was utilized in computers to simulate neural processes. Although it is unclear to what degree artificial neural networks mimic brain function, neural networks utilized in artificial intelligence have traditionally been viewed as simplified models of neural processing in the brain, though the connection between this model and the biological structure of the brain is a matter of debate.

### 4.2. Artificial Neural Network Models

Artificial neural networks (ANNs), more commonly abbreviated as NNs or neural nets, are computer systems modeled after the neural networks found in animal brains.

Artificial neural networks (ANNs) are comprised of interconnected nodes or units, which mimic the structure of biological neurons. These units can transmit signals to other nodes like synapses in a living brain. Upon receiving and processing signals, an artificial neuron can communicate with other connected neurons. A neuron's output is determined by a non-linear function of the sum of its inputs, and the signals transmitted between nodes are represented by real numbers. These connections between nodes are called edges, and the weight of both the neurons and edges often changes as learning progresses. The strength of the signal at a connection is influenced by the weight, and neurons may have a threshold beyond which they fire a signal. Neurons are arranged in layers, with different layers performing various transformations on their respective inputs. Signals propagate from the input layer to the output layer after passing through multiple layers, and neural networks learn to form weighted associations between inputs and outputs by processing examples with known input and output values. The network's output is compared to the target output to calculate an error value, which is then used to adjust the weighted associations according to a learning rule. The adjustments continue until the network's output becomes more similar to the target output, and the training process stops after a certain number of adjustments based on specific criteria. Through this process, neural networks can learn to perform tasks without explicit instructions. For example, in image recognition, they can recognize cats by analyzing examples labeled as "cat" or "no cat," even without knowing that cats have fur, tails, whiskers, and facial features, and generating identifying features automatically based on the analyzed examples. Artificial neural networks greatly simplify human neural systems. Artificial neural networks (ANNs) are composed of computational units that resemble the neurons in biological nervous systems. ANNs generally have three layers: input, output, and hidden. Each neuron in the nth layer is connected to the neurons in the (n+1)th layer via a signal, and each connection is assigned a weight. By multiplying each input by its weight, the result is calculated, and the final output is obtained by passing the output through an activation function. ANNs have various applications, including differential equations, image compression, function approximation, stock market forecasting, medical diagnosis, and signal processing. (He, J. (2019).

### 4.3. Neural Fuzzy Systems

In the realm of artificial intelligence, the merging of artificial neural networks and fuzzy logic is known as neuro-fuzzy. This combination brings together the human-like reasoning abilities of fuzzy systems with the learning and interconnectedness of neural networks, producing hybrid intelligent systems. Neuro-fuzzy hybridization is often referred to as either fuzzy neural network (FNN) or neuro-fuzzy system (NFS) in literature. The contemporary usage of the term "neuro-fuzzy system" encompasses fuzzy systems' human-like reasoning style, achieved through the utilization of fuzzy sets and "if-then" rules. These systems are comprised of language models. The key strength of neuro-fuzzy systems is that they are universal approximators capable of producing interpretable IF-THEN rules. In the realm of fuzzy modeling, neuro-fuzzy systems face a challenge in balancing two conflicting requirements: accuracy and interpretability. In practice, one of these factors tends to take priority over the other. The neuro-fuzzy component of fuzzy modeling can be divided into two main categories: the Mamdani model, which prioritizes interpretability-focused linguistic fuzzy modeling, and the Takagi-Sugeno-Kang (TSK) model, which prioritizes precise and accurate fuzzy modeling (Kosko, 1998).

While the typical interpretation of this phrase refers to the utilization of connectionist networks in implementing fuzzy systems, it may also refer to several other configurations, such as:

- Fuzzy logic-based tweaking of neural network training parameters.

- Deriving fuzzy rules from trained RBF networks.
- Fuzzy logic requirements for expanding a network.
- By utilizing clustering techniques for unsupervised learning in self-organizing maps (SOMs) and neural networks, a fuzzy membership function can be implemented.
- Using multi-layer feed-forward connectionist networks to represent fuzzification, fuzzy inference, and defuzzification.

It should be noted that Mamdani-type neuro-fuzzy systems may lose interpretability. Certain actions need to be taken to improve the interpretability of neuro-fuzzy systems, and essential aspects of this interpretability are also covered. The situation of data stream mining, where the neuro-fuzzy system is progressively updated with new incoming samples on-the-fly and on-demand, is the subject of current research. In order to better manage idea drift and ever-changing system behavior and keep the system/model always "up to date", system updates involve not only recursive tuning of model.

### 4.4. Adaptive Neuro Fuzzy Inference System

ANFIS (Adaptive Neuro-Fuzzy Inference System) is a hybrid model that combines the learning and adaptive capabilities of neural networks with the interpretability and linguistic representation of fuzzy logic. ANFIS is formulated as a set of fuzzy if-then rules and the parameters of these rules are adjusted through a hybrid learning algorithm.

The ANFIS model consists of five layers:

- Input layer: It receives the input variables and passes them to the next layer.
- Fuzzification layer: It maps the input variables to their corresponding membership degrees in the fuzzy sets.
- Rule layer: It computes the firing strengths of each rule by combining the membership degrees of the input variables using the logical operator "and".
- Normalization layer: It normalizes the firing strengths of the rules to ensure that they sum up to one.

- Output layer: It computes the final output by aggregating the outputs of each rule, weighted by their corresponding firing strengths.

The parameters of the fuzzy if-then rules are adjusted through a hybrid learning algorithm that combines the gradient descent method and the least squares method. The gradient descent method adjusts the parameters of the consequent part of the rules, while the least squares method adjusts the parameters of the antecedent part of the rules.

The ANFIS model has been widely used in various applications, such as system identification, control, and prediction. Its hybrid learning algorithm allows it to learn from data and improve its performance over time. Additionally, its fuzzy if-then rules provide a linguistic representation that can be easily interpreted and understood by humans.

An artificial neural network based on the Takagi-Sugeno fuzzy inference system is known as the Adaptive Neuro-Fuzzy Inference System "ANFIS". or adaptive network-based fuzzy inference system (ANFIS). This method was developed in his early 1990s. The advantages of neural networks and fuzzy logic he can combine in one framework, so both concepts can be combined. Its inference mechanism is similar to his collection of IF-THEN fuzzy rules with the ability to learn and approximate nonlinear functions. ANFIS is therefore considered a global estimator. You can use ANFIS more effectively and efficiently with the optimal parameters found by the genetic algorithm. It can be used in context-aware, intelligent energy management systems. A network structure can be divided into two distinct parts: the antecedent part and the consequent part. The architecture consists of five deeper levels. The first layer selects membership functions that correspond to the input values. Its colloquial name is the fuzzification layer. A set of underlying parameters, namely 'a', 'b', and 'c', are used to determine the degree of membership of each function. The rule shot strength is generated by the second layer. The second layer is called the "regulatory layer" because of its function. The function of the third layer is to normalize the calculated firepower by dividing each value by the total firepower. The normalized values and the resulting set of parameters p, q, r are the inputs to the fourth layer. The values returned by this level are defuzzified and the final level uses these values to return the entire output. The first layer of the ANFIS network describes how it differs from standard neural networks. To work, neural networks often preprocess data by transforming features to normalized values between 0 and 1. ANFIS neural networks do not require a sigmoid function but perform a preprocessing phase by converting numeric inputs to fuzzy values. A diagram is shown below.

Suppose a network receives as input the distance between two locations in 2D space. Distance is expressed in pixels and values range from 0 to 500 pixels. Numbers are converted to fuzzy numbers using a membership function consisting of semantic descriptors such as near, middle, and far. A single neuron provides all potential values of speech representation. If the distance falls into the proximity category, the neuron will generate proximity with values between 0 and 1. The central neuron fires when the distance falls into this category. The input value, the distance in pixels, is then divided into three neurons near, middle and far.

# CHAPTER 5
# CLUSTERING

## 5.1 Clustering

Clustering is commonly used in many fields such as biology and economics. Clustering results change as the number of cluster parameters changes. A primary challenge in cluster analysis is that the optimal number of clusters or model parameters is often unknown and must be established before clustering can occur. Despite this challenge, several clustering algorithms have been developed.

### 5.1.1. K-Means Clustering

The K-means clustering technique is a method for partitioning n observations into k clusters. It is based on vector quantization, a signal processing method. Each observation is assigned to the nearest mean or cluster centroid, which serves as a prototype for that cluster. The K-means algorithm is simple and fast compared to other clustering techniques. In this method, each observation is considered as an object with a position in space, and the goal is to group similar objects together in the same cluster while maximizing the distance between objects in different clusters. The distance measure used by the K-means algorithm can be tailored to suit the data type. K-means does not depend on the dissimilarity of each pair of observations and generates a single level of clusters rather than a hierarchical cluster tree, making it more suitable for handling large data volumes. Each cluster comprises member objects and a centroid that minimizes the sum of distances between the centroid and all cluster members. K-means has customizable options such as setting initial values for cluster centroids and the maximum number of iterations for the method. The K-means++ algorithm is used by default to create cluster centroids, and the squared Euclidean distance metric is employed to compute distances (Makwana, 2013). Follow these excellent practices while executing k-means clustering:

- To determine the optimal number of clusters for your data, experiment with various values of k for the k-means clustering algorithm.

- To assess clustering solutions, one can analyze silhouette plots and silhouette values.
- Cluster the data using multiple sets of randomly selected centroids and select the solution that has the minimum sum of distances across all the clustering.

K-means clustering is a method that aims to group a set of observations ($x_1$, $x_2$, ..., $x_n$) into k (n) sets, denoted as S = {$S_1$, $S_2$, ..., $S_k$}, such that the within-cluster sum of squares (WCSS) is minimized. Each observation in the set is represented by a d-dimensional real vector (i.e., variance). Specifically, the objective is to find the point in $S_i$ that minimizes the pairwise squared deviations of points within the same cluster, where $\mu_i$ is the mean of the points. This is equivalent to maximizing the sum of squared deviations across points in different clusters, since the overall variance is constant. The deterministic relationship described here is also related to the law of total variance in probability theory.

$$\text{argmins} \sum_{i=1}^{k} \frac{1}{|S_i|} \sum_{x,y \in S_i} \|x - y\|^2 \tag{5.1}$$

### 5.1.2. Fuzzy C-Means Clustering

Fuzzy clustering, also known as soft clustering or soft k-means, allows each data point to belong to multiple clusters, while non-fuzzy clustering, also called hard clustering, assigns each point to a single cluster. To perform clustering, a similarity metric is used, such as distance, connectivity, or strength, and you can choose multiple similarity measures depending on your data or application. The goal of clustering is to group items in the same cluster to be as similar as possible and different from items in other clusters. The fuzzy c-means method and k-means algorithm are similar. First, several clusters are selected, and each data point is assigned a random coefficient belonging to the cluster. Then, the algorithm iterates until it converges, with the centroid of each cluster calculated. The cluster membership coefficient for each data point is computed, with each point having a set of coefficients indicating how much it is part of the kth cluster. The cluster centroid using fuzzy c-means is the average of all points weighted by how much they belong to the cluster, with the fuzziness of the clusters determined by a hyperparameter.

$$c_k = \frac{\sum_x w_k(x)^m x}{\sum_x w_k(x)^m}$$

(5.2)

K-means aims to minimize a similar objective function as fuzzy clustering, but it restricts membership values to be either 0 or 1 and cannot have values between 0 and 1. On the other hand, fuzzy clustering allows for membership values between 0 and 1, where higher values of a parameter called "m" create more fuzzy clusters. As m approaches infinity, the membership values converge to either 0 or 1, similar to the K-means algorithm. Typically, m is set to 2 in the absence of prior knowledge or experimentation. The fuzzy C-means algorithm also minimizes within-cluster variation, but like K-means, it suffers from the problem of local minima, and the initial weight selection determines the final result (Xu, 2022).

# CHAPTER 6
# APPLICATION

The aim of this study is to evaluate turbine efficiency from an analytical point of view. Changing the location of two turbines in the same site was requested on the grounds that it would increase efficiency. With this study, we will learn whether it will be the right decision to take this action. Necessary data sets were created by interviewing the project managers of a renewable energy company that provides maintenance services to more than thirty wind turbine sites. Wind speed, blade length and proximity to other turbines, which are the three main factors affecting efficiency, were determined according to this information. Although there are sites with different turbine types, three main factors affecting efficiency gather them under the same roof. In this study, numerical ranges were determined for the factors affecting productivity. Fuzzy inference system and ANFIS were used to evaluate efficiency.

**Table 6.1** Data Set Range

| Wind Speed | Blade Length | Distance to Other Turbines |
|---|---|---|
| 1 - 24 m/s | 18m -107m | 0m – 1000m |

The wind effect plays a significant role in the efficiency of wind turbines. Wind turbines work by converting the kinetic energy of the wind into mechanical energy, which is then converted into electrical energy. The amount of energy that a wind turbine can generate depends on several factors, including the wind speed. Wind speed can take different values between 1 and 24. If the wind speed exceeds 24, the wind turbine is disabled. In order for the turbine to continue to produce energy at a wind speed of over 24m/s, various improvements were subsequently made to the turbines. However, in this study, we consider the turbine in its standard form. The distance between wind turbines can have a significant effect on their efficiency, as well as on the overall efficiency of a wind farm. When turbines are placed too close together, they can create turbulence in the wind, which can reduce the amount of energy that can be captured by the downstream turbines. This phenomenon is known as wake effect, and it can significantly reduce the efficiency of wind turbines. Distance to other turbines and efficiency are directly proportional. Therefore, the number of turbines built in the ocean is increasing day by day. The length of wind turbine blades is a critical factor in determining the efficiency of a wind turbine. Although efficiency seems to increase as the blade length increases, this is not always true. Using a long blade in a low wind site is not beneficial in terms of both efficiency and cost. The longer the blades, the more energy they can capture from the wind. Longer blades also allow the turbine to operate at lower wind speeds, which increases the overall efficiency of the turbine. However, there are limits to how long turbine blades can be. As the length of the blades increases, the weight of the blades also increases, which can make them more difficult and expensive to manufacture and install. Additionally, longer blades can also increase the structural stresses on the turbine, which can lead to fatigue and damage over time.

Using the Fuzzy C-Means Clustering method, optimum number of lingustic variables for each membership function for FIS and ANFIS were decided. Fuzzy C-Means (FCM) is a clustering method used in data analysis and pattern recognition. It is a fuzzy clustering algorithm that assigns data points to different clusters based on their degree of membership in each cluster. FCM is a variant of the traditional k-means clustering method, where each data point is assigned to a single cluster.

In FCM, each data point is assigned a membership value to each cluster, which represents the degree to which the data point belongs to each cluster. The sum of the membership values for each data point is 1, and the membership values are updated iteratively until the membership values converge to a stable solution.

The algorithm starts by randomly selecting the number of clusters (k) and initializing the membership values for each data point. Then, the algorithm calculates the centroid of each cluster based on the membership values of the data points. The membership values are then updated based on the distance between the data points and the centroids of each cluster. The process is repeated until the membership values converge to a stable solution.

An unsupervised machine learning technique called clustering may recognize clusters of related data points from the data itself. We frequently, however, do not know how many clusters exist in our data. In fact, determining the number of clusters may be the primary motivation for performing clustering in the first place. Undoubtedly, the number of clusters may be determined with the aid of domain knowledge of the data set. This, however, presumes that you are aware of the target classes (or, at the very least, the number of classes), which is not the case with unsupervised learning. We need a mechanism that informs us about the number of clusters without relying on a target variable. FCM was tried for different values but optimum value was obtained in autorun. As a result of FCM optimal cluster numbers have been decided as 4-4-3 where the order is wind speed, blade length and distance to other turbines. In addition to optimal cluster numbers, FCM also provides optimum ranges for the factors which effect the effiency of wind turbine.

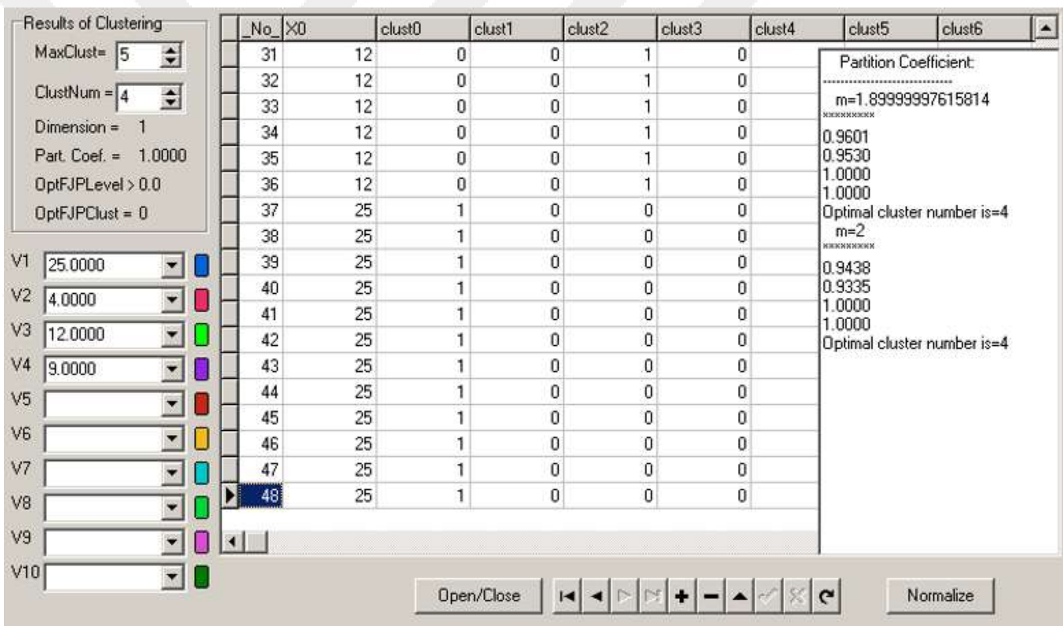


**Figure 6.1 Optimal Cluster Number for Wind Speed**

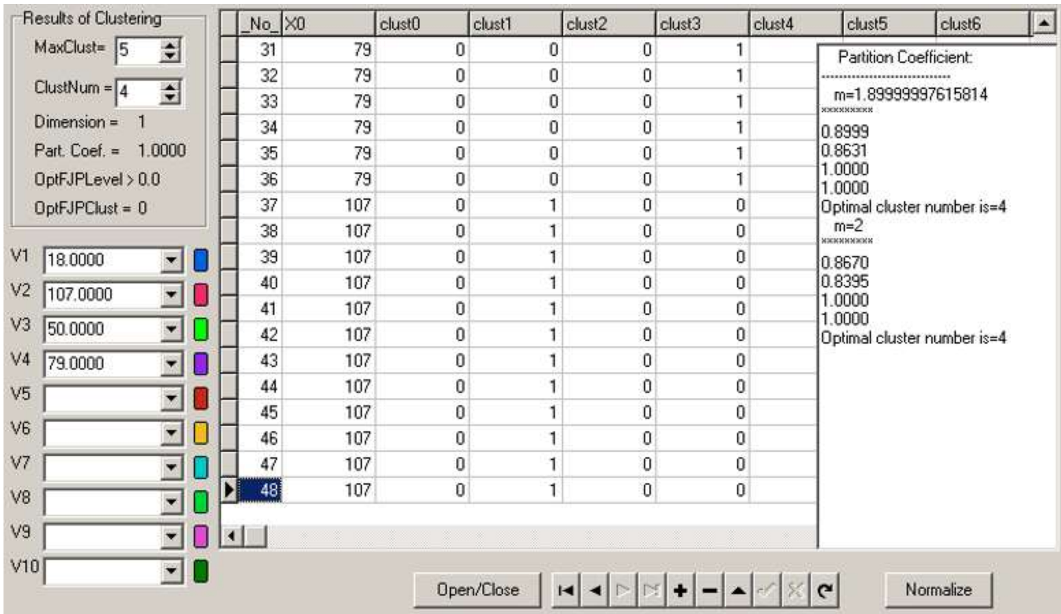


**Figure 6.2 Optimal Cluster Number for Blade Length**

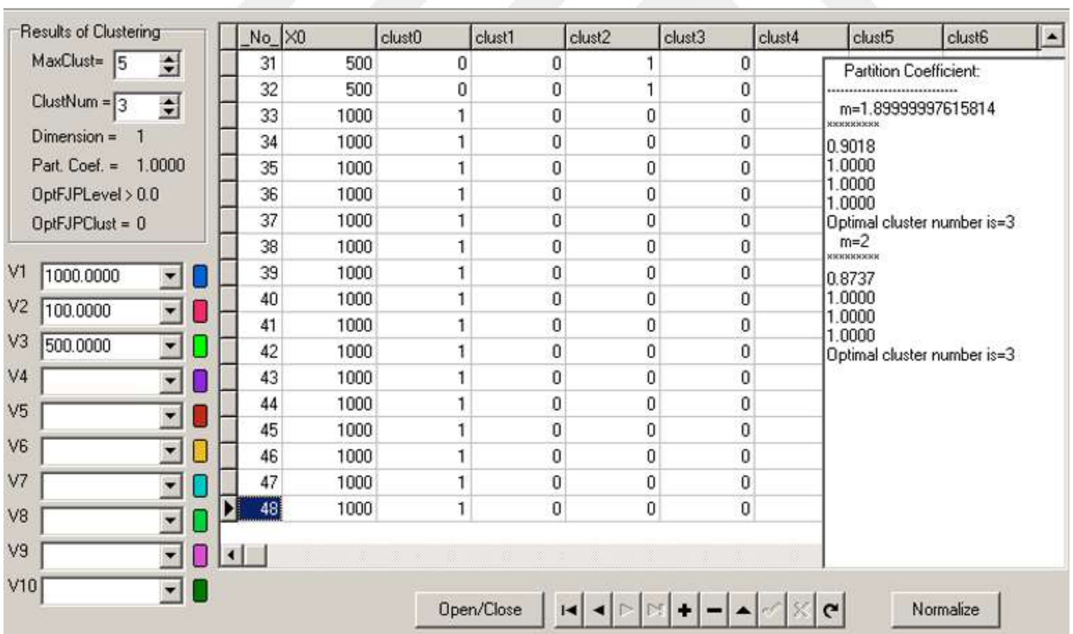


**Figure 6.3 Optimal Cluster Number for Distance to Other Turbines**

### 6.1. Adaptive Neuro Fuzzy Inference System

ANFIS consists of a set of fuzzy rules that are generated based on input-output training data. It uses a hybrid learning algorithm that alternates between a forward pass and a backward pass. During the forward pass, the input values are fuzzified and combined according to the fuzzy rules to produce an output. During the backward pass, the errors between the predicted output and the actual output are used to update the parameters of the fuzzy rules.

The train-test split is a common method used to evaluate the performance of machine learning models. The basic idea is to divide the available data into two parts: a training set and a testing set. The model is trained on the training set and evaluated on the testing set. The training set is used to fit the model and learn the underlying patterns in the data. The testing set is used to evaluate the performance of the model on unseen data. By evaluating the model on the testing set, we can estimate how well the model is likely to perform on new data. The train-test split is usually done by randomly partitioning the available data into two sets. The most common split is the 67/33 split, where 60% of the data is used for training and 33% for testing. According to the information received from wind turbine site employees, the three main factors affecting efficiency are wind speed, blade length and distance from other turbines. As a result of different combinations, a total of 288 different data were created.
67% of the data set was determined as the training set and 33% as the test set.
ANFIS was created by using all combinations of the three factors affecting productivity with different value ranges mentioned above.

In ANFIS, training data is used to generate the fuzzy rules that are used to make predictions or decisions. The training data consists of input-output pairs, where the input is a set of variables that describe the problem, and the output is the desired response or outcome. To define the training data in ANFIS, you need to specify the input and output variables and collect a set of training examples. The input variables should be chosen based on their relevance to the problem and should be quantifiable. The output variable should also be quantifiable and should represent the desired outcome.

**Table 6.2 A Portion of Training Data**

| **Training Set** | | | |
|---|---|---|---|
| Wind Speed (m/s) | Blade Length (m) | Distance (m) | Efficiency |
| 1 | 18 | 500 | 0,35% |
| 1 | 18 | 1000 | 0,70% |
| 2 | 50 | 1000 | 3,89% |
| 2 | 79 | 500 | 3,08% |
| 2 | 79 | 1000 | 6,15% |
| 2 | 107 | 500 | 4,17% |
| 2 | 107 | 1000 | 8,33% |
| 10 | 18 | 500 | 3,50% |
| 10 | 18 | 1000 | 7,01% |
| 10 | 50 | 500 | 9,74% |
| 10 | 50 | 1000 | 19,47% |
| 11 | 18 | 500 | 3,86% |
| 11 | 50 | 1000 | 21,42% |
| 12 | 79 | 1000 | 36,92% |
| 12 | 107 | 500 | 25,00% |
| 12 | 107 | 1000 | 50,00% |
| 13 | 18 | 500 | 4,56% |
| 13 | 18 | 1000 | 9,11% |
| 13 | 50 | 500 | 12,66% |
| 13 | 50 | 1000 | 25,31% |
| 22 | 18 | 500 | 7,71% |
| 22 | 18 | 1000 | 15,42% |
| 23 | 79 | 1000 | 70,76% |
| 23 | 107 | 500 | 47,92% |
| 23 | 107 | 1000 | 95,83% |
| 24 | 79 | 1000 | 73,83% |
| 24 | 107 | 500 | 50,00% |
| 24 | 107 | 1000 | 100% |

Above table is created based on below information.

Wind Speed (m/s): This column represents different wind speeds measured in meters per second (m/s). The values range from 1 to 24 m/s, indicating varying levels of wind intensity.

Blade Length (m): This column denotes the length of the blades used in the experiment or analysis, measured in meters (m). The values include 18, 50, 79, and 107 meters.

Distance (m): This column indicates the distance at which the experiment or analysis was conducted, measured in meters (m). The two available options are 500 and 1000 meters.

Efficiency: This column represents the efficiency of the system being analyzed, expressed as a percentage (%). The efficiency values range from 0.35% to 100%.

The table 6.2 and 6.3 provide data points that show the efficiency of the system based on different combinations of wind speed, blade length, and distance. Each row represents a unique combination, and the corresponding efficiency value is provided.

**Table 6.3 A Portion of Test Data**

| **Test Set** | | | |
|---|---|---|---|
| Wind Speed (m/s) | Blade Length (m) | Distance (m) | Efficiency |
| 1 | 18 | 100 | 0,07% |
| 2 | 79 | 100 | 0,62% |
| 3 | 50 | 100 | 0,58% |
| 4 | 18 | 100 | 0,28% |
| 10 | 18 | 100 | 0,70% |
| 11 | 79 | 100 | 3,38% |
| 12 | 50 | 100 | 2,34% |
| 13 | 18 | 100 | 0,91% |
| 14 | 79 | 100 | 4,31% |
| 15 | 50 | 100 | 2,92% |
| 23 | 79 | 100 | 7,08% |

Efficiency was measured for the same values using difference defuzzification and membership functions. There are two different defuzzification methods defined in ANFIS which are WTAVER and WTSUM. In addition to that eight membership function have been defined for each defuzzification method as trimf, tampmf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf and psigmf. For each defuzzification method, results are drawn using these eight membership functions. A summary table of the results is available below.

The coefficient of determination, that is, the value of R-squared (R2) is used for assesing the quality of results. R-squared ($R^2$) is a statistical measure that represents the proportion of variance in the dependent variable that is explained by the independent variable(s) in a regression model. It is also known as the coefficient of determination. The ratio of (1-total squared errors) to (all total squares) gives us R2.

$$R^2 \equiv 1 - \frac{SS_{err}}{SS_{tot}}$$

(6.1)

When deciding on efficiency, we used the efficiency information we gathered from the field technicians. This became our base data, and the sum of the efficiency values we have for all combinations forms $SS_{tot}$.

Afterwards, we get the $SS_{err}$ value by taking the difference between the efficiency results obtained as a result of ANFIS $SS_{tot}$.

With this information, $R^2$ was calculated and the most accurate defuzzification method and membership function were determined.

**Table 6.4 Efficiency Percentage for the Combination of Defuzzification and Membership Function**

| **Efficiency** | WTAVER | WTSUM |
|---|---|---|
| Trimf | 9% | 9% |
| Trapmf | 9% | 9% |
| Gbellmf | 94% | 94% |
| Gaussmf | 93% | 93% |
| Gauss2mf | 94% | 94% |
| Pimf | 9% | 9% |
| Dsigmf | 94% | 94% |
| Psigmf | 94% | 94% |

This table presents the efficiency percentages achieved by different combinations of defuzzification methods and membership functions. The data reflects the performance of the system under varying approaches for converting fuzzy sets into crisp values. Defuzzification methods and membership functions are fundamental components in fuzzy logic systems, enabling the handling of uncertain or imprecise information. The table showcases the outcomes obtained by employing diverse combinations of these techniques. Each row in the table corresponds to a specific combination, with the columns indicating the following:

Defuzzification Method: This column presents the selected approach for defuzzification, responsible for transforming fuzzy sets into crisp values. Examples of defuzzification methods include centroid, maximum membership, or mean of maximum.

Membership Function: This column represents the chosen membership function utilized in the fuzzy logic system. Membership functions define the extent of an element's membership or relevance to a fuzzy set. Common types of membership functions include triangular, trapezoidal, or Gaussian functions.

Efficiency Percentage: This column demonstrates the resulting efficiency percentage achieved by the combination of defuzzification method and membership function. The efficiency percentage offers an indication of the system's performance based on the chosen combination.

By analyzing the data presented in this table, valuable insights can be gained regarding the effectiveness of different defuzzification methods and membership functions in achieving desired efficiency levels. This information serves as a guide for decision-making and optimization of fuzzy logic systems across various applications.

### 6.2. Fuzzy Inference System

A Fuzzy Inference System (FIS) is a type of artificial intelligence system that uses fuzzy logic to process and interpret input data. Fuzzy logic is a mathematical approach to handling uncertainty and imprecision in data, which makes it particularly useful in situations where traditional binary logic may be insufficient.

Fuzzy Inference Systems consist of three main components: the fuzzy rule base, the fuzzy logic engine, and the fuzzification/defuzzification process. The fuzzy rule base contains a set of rules that define how the system should react to different inputs, while the fuzzy logic engine applies these rules to generate an output. The fuzzification/defuzzification process involves converting crisp input values into fuzzy values and then converting the fuzzy output into a crisp value.

As a result of interviews with field workers, the data sets we used in ANFIS were also used for FIS. This time, definitions were used instead of mathematical values. It was stated that there are 3 options for blade length: short blade, average blade and long blade. Definitions were made for wind speed as low wind, average wind and high wind. Finally, the range given for the distance to the other turbines was also divided into three parts and defined as short distance, average distance and long distance. Wind turbine site employees were interviewed in order to correctly divide each value range into 3 parts. The detailed table is available below.

**Table 6.5 Intervals for Factors Affecting Wind Turbine Efficiency**

| | Wind Speed(m/s) | Blade Length(m) | Distance(m) | Efficiency |
|---|---|---|---|---|
| **Low** | 1-8 | 18-51 | 1-101 | 0-30 |
| **Average** | 8-12 | 51-80 | 101-501 | 31-70 |
| **High** | 12-24 | 81-107 | 501-1000 | 71-100 |

Input of FIS are defined by using the three main efficiency factors which wind speed, blade length, distance from other turbines and output is defined as efficiency. To define a fuzzy system based on above detaiks below steps were followed.

- Define the input variables: Define the input variables and their membership functions using the fuzzy function.
- Define the output variables: Define the output variables and their membership functions using the fuzzy function.
- Define the fuzzy rules: Define the fuzzy rules that specify how the input variables are mapped to the output variables.

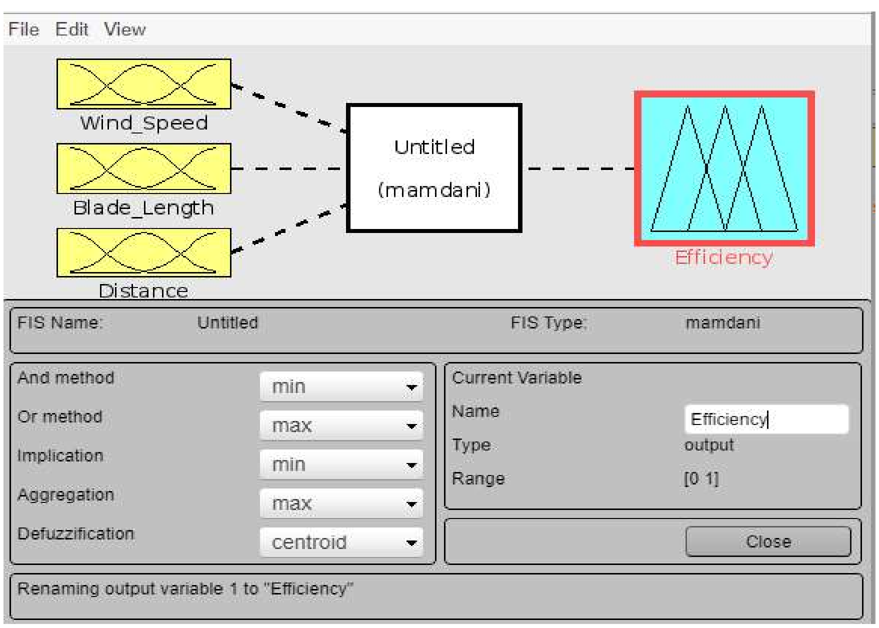


**Figure 6.4 Fuzzy Logic Designer**

The rules were defined according to the information in Table 6.6. Some of these rules are given below. As seen in the first row we have low efficiency for the result of low wind, short blade and short distance combination.

**Table 6.6 Rules for FIS**

| Wind Speed | Blade Length | Distance | Efficiency |
|---|---|---|---|
| Low Wind | Short Blade | Short Distance | Low Efficiency |
| Low Wind | Short Blade | Average Distance | Low Efficiency |
| Average Wind | Short Blade | Short Distance | Low Efficiency |
| Average Wind | Long Blade | Long Distance | Average Efficiency |
| High Wind | Short Blade | Short Distance | Low Efficiency |
| High Wind | Average Blade | Long Distance | Average Efficiency |
| High Wind | Long Blade | Long Distance | High Efficiency |

As a result of all this information, FIS was created using MATLAB. Below is an example created using "trimf" as membership function and the "centroid" as defuzzification method. Since there are 65 different combination which includes 5 different defuzzification method and 13 different membership function, only trimf and gaussmf are given as an example in below.

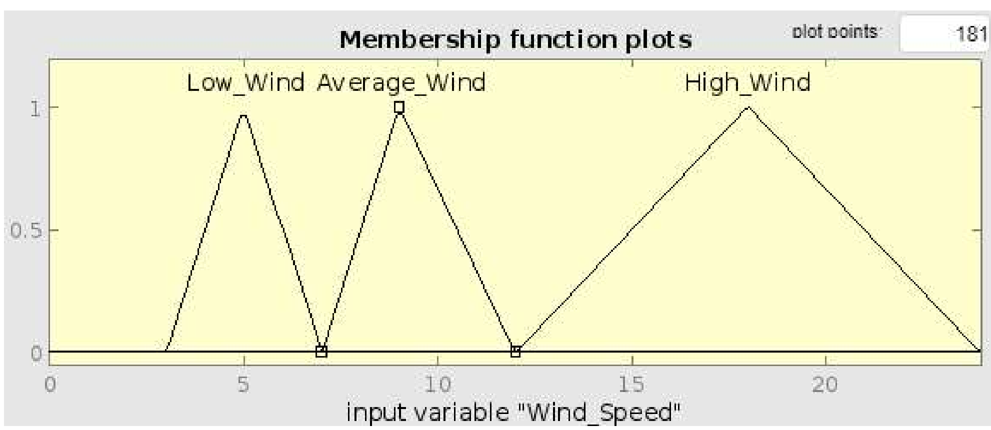


**Figure 6.5 Details for "Trimf" Membership Function for Wind Speed**

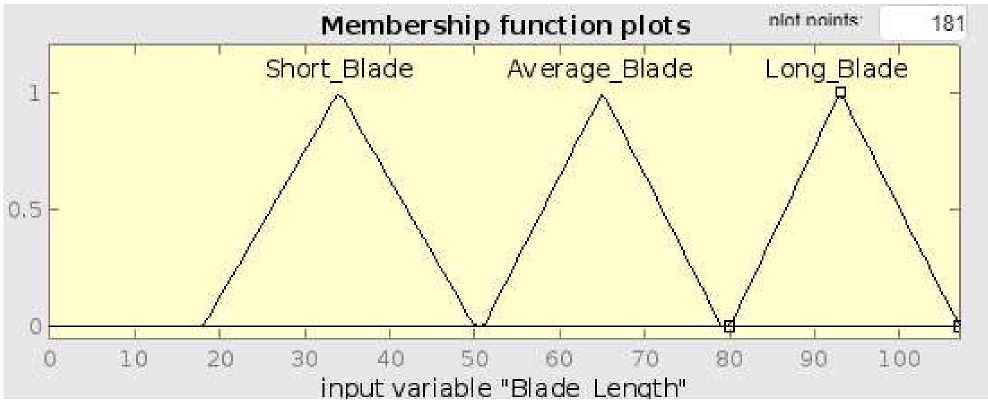


**Figure 6.6 Details for "Trimf" Membership Function for Blade Length**

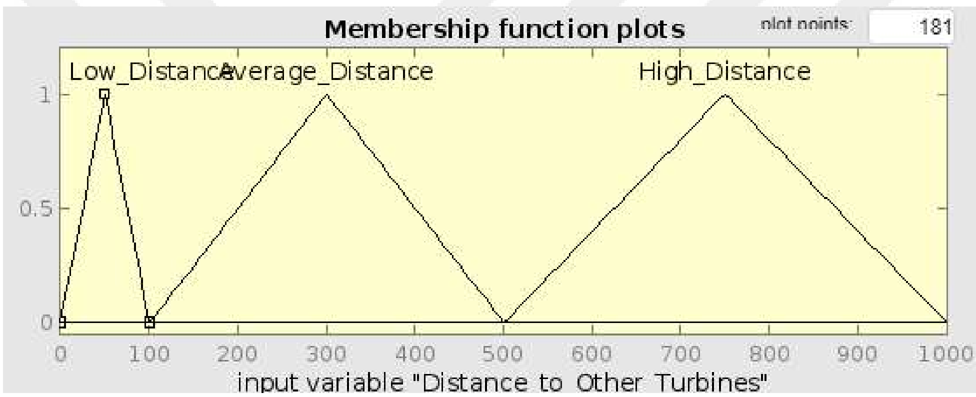


**Figure 6.7 Details for "Trimf" Membership Function for Distance to Other Turbines**

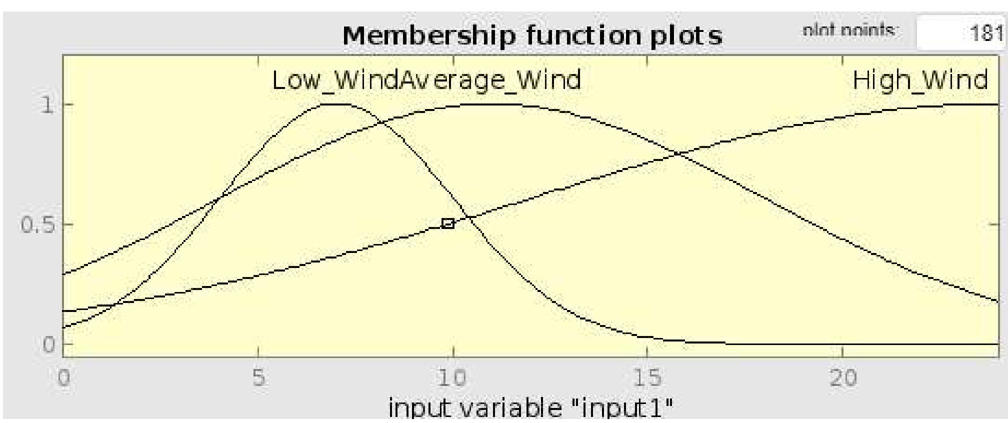


**Figure 6.8 Distribution for "Gaussmf" Membership Function for Wind Speed**

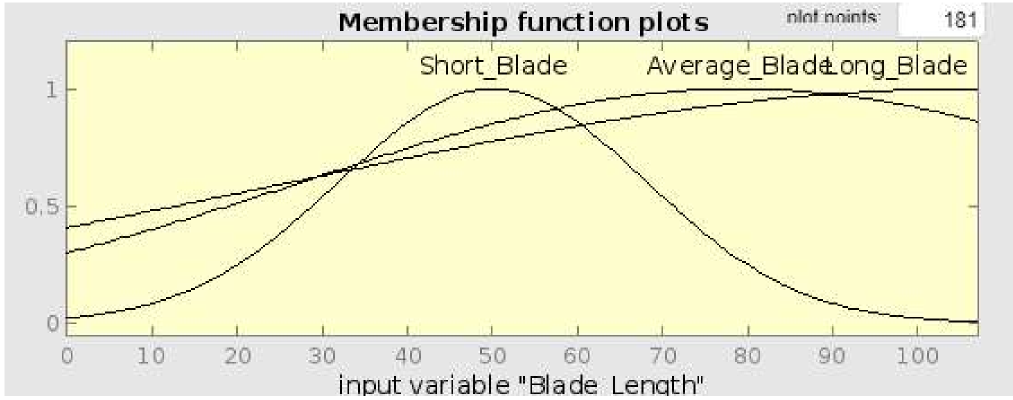


**Figure 6.9 Distribution for "Gaussmf" Membership Function for Blade Length**

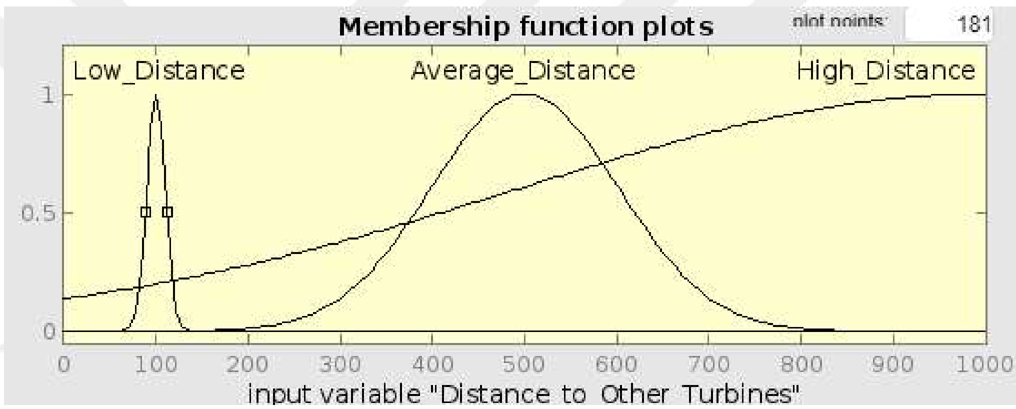


**Figure 6.10 Distribution for "Gaussmf" Membership Function for Distance to Other Turbines**

All data entered for Fuzzy is below. The following data is repeated for different membership functions

```
[System]
Name='fuzzy'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=0
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Wind_Speed'
Range=[0 24]
NumMFs=3
MF1='Low_Wind':'trimf',[3 5 7]
MF2='Average_Wind':'trimf',[7 9 11]
MF3='High_Wind':'trimf',[12 18 24]

[Input2]
Name='Blade_Length'
Range=[0 107]
NumMFs=3
MF1='Short_Blade':'trimf',[18 34 50]
MF2='Average_Blade':'trimf',[51 65 79]
MF3='Long_Blade':'trimf',[80 93 107]

[Input3]
Name='Blade_Distance_to_Other_Turbines'
Range=[0 1000]
NumMFs=3
MF1='Low_Distance':'trimf',[0 50 100]
MF2='Average_Distance':'trimf',[101 300 500]
MF3='High_Distance':'trimf',[501 750 1000]

[Output1]
Name='Efficiency'
Range=[0 100]
NumMFs=3
MF1='Low_Efficiency':'trimf',[0 15 30]
MF2='AverageEfficiency':'trimf',[31 50 70]
MF3='High_Efficiency':'trimf',[71 85 100]
```

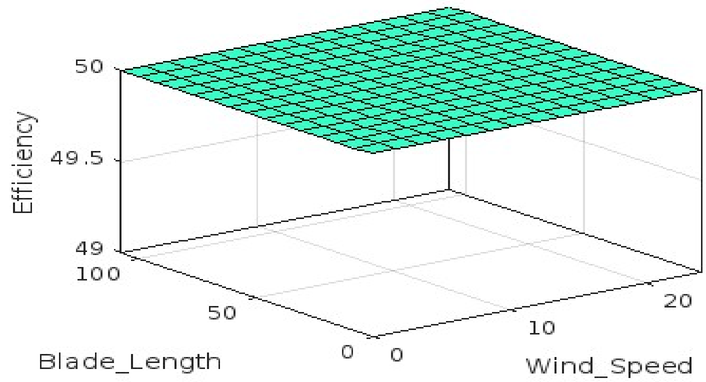


**Figure 6.11 Relationship between Blade Length and Wind Speed**

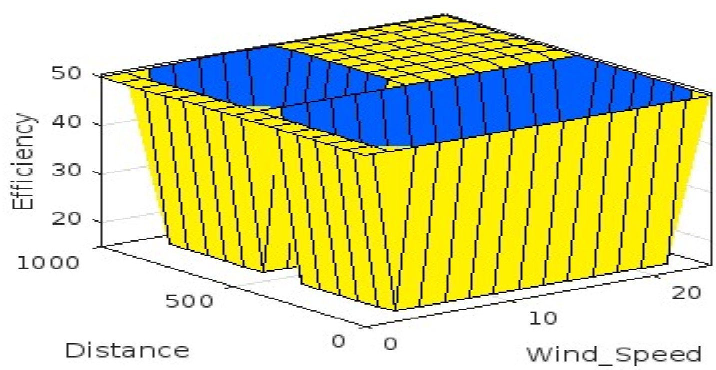


**Figure 6.12 Relationship between Distance and Wind Speed**

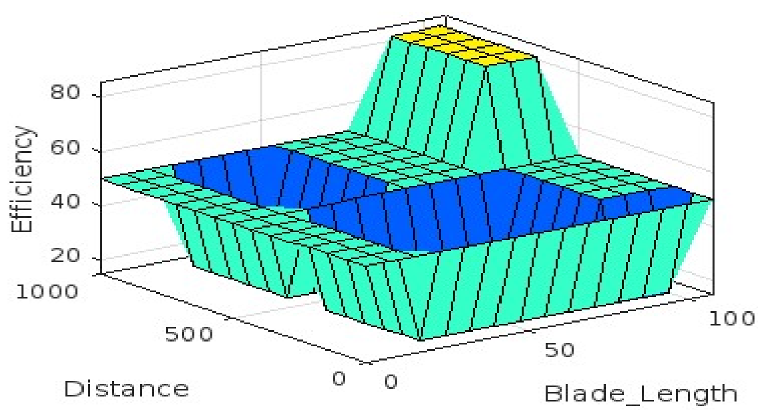


**Figure 6.13 Relationship between Distance and Blade Length**

In fuzzy logic, the output is determined by applying fuzzy inference rules to the input values. The output is a fuzzy set that represents the degree of membership of the output variable in each linguistic term or category.

The process of finding the output in fuzzy logic involves the following steps:

- Fuzzification: Convert the crisp input values into fuzzy sets by assigning membership values to each linguistic term or category.
- Fuzzy Inference: Apply fuzzy rules to the fuzzy sets obtained in step 1 to determine the degree of membership of the output variable in each linguistic term or category.
- Aggregation: Combine the results of the fuzzy inference step to obtain a single fuzzy set that represents the output variable.
- Defuzzification: Convert the fuzzy set obtained in step 3 into a crisp value by selecting a suitable defuzzification method, such as centroid, maximum, or mean of maximum. Efficiency was assessed using several defuzzification and membership functions for the same variables. Centroid, Bisector, Mom, Lom and Som are distinct defuzzification techniques that are defined in FIS. Additionally, twelve membership functions trimf, trampmf, gbellmf, gaussmf, gauss2mf, sigmf, dsigmf, psigmf, pimf, smf, zmf, linsmf and linzmf have been used together with each defuzzification approach. Results are generated for each defuzzification technique utilizing these eight membership functions.

**Table 6.7 Efficiency Percentage for the Combination of Defuzzification and Membership Function**

| Efficiency | Centroid | Bisector | Mom | Lom | Som |
|---|---|---|---|---|---|
| **Trimf** | %99,92 | %99,92 | %99,92 | %99,06 | %97,62 |
| **Trapmf** | %99,95 | %99,92 | %99,95 | %98,82 | %97,62 |
| **Gbellmf** | %99,89 | %99,92 | %99,92 | %99,06 | %97,62 |
| **Gaussmf** | %99,89 | %99,92 | %99,92 | %99,06 | %97,62 |
| **Gauss2mf** | %99,89 | %99,92 | %99,92 | %99,06 | %97,62 |
| **Sigmf** | %87,12 | %87,04 | %96,86 | %97,96 | %75,28 |
| **Dsigmf** | %99,99 | %99,99 | %99,99 | %99,06 | %98,82 |
| **Psigmf** | %99,99 | %99,99 | %99,99 | %99,06 | %98,82 |
| **Pimf** | %99,99 | %99,99 | %99,99 | %99,06 | %98,82 |
| **Smf** | %54 | %54 | %54,5 | %97,96 | 0,20% |
| **Zmf** | %81,63 | %81,63 | %81,63 | %81,63 | %81,63 |
| **Linsmf** | %88,01 | %92,16 | %90,15 | %97,96 | %0,05 |
| **Linzmf** | %81,63 | %81,63 | %81,63 | %81,63 | %81,63 |

# CHAPTER 7
# CONCLUSION

The objective of this master thesis was to examine the efficiency of wind turbines through the application of Fuzzy Inference System (FIS) and Adaptive Neuro Fuzzy Inference System (ANFIS). The research aimed to develop a comprehensive understanding of wind turbine performance, evaluate the effectiveness of FIS and ANFIS models in predicting efficiency, and identify the key factors that impact wind turbine performance. By conducting extensive data analysis and modeling, this study has made significant contributions to the field of renewable energy and wind turbine technology. The conclusions drawn from this research have the potential to contribute to the development of more efficient wind energy systems and facilitate the transition to sustainable energy sources.

The primary objective of this research was to analyze the efficiency of wind turbines using Fuzzy Inference System (FIS) and Adaptive Neuro Fuzzy Inference System (ANFIS). Throughout the study, we investigated wind turbine performance, assessed the applicability of FIS and ANFIS models for efficiency prediction, and identified the crucial factors influencing wind turbine performance. By achieving these objectives, we have expanded the knowledge base in the field of wind energy and taken significant steps towards improving the efficiency and effectiveness of wind turbine systems.

The analysis of wind turbine efficiency using FIS and ANFIS models has yielded promising results. Both modeling approaches have demonstrated their ability to capture complex relationships and nonlinearities within the data, resulting in accurate predictions of wind turbine efficiency. FIS models effectively utilize linguistic variables and fuzzy rules to represent the uncertainties and imprecisions associated with wind turbine performance. On the other hand, ANFIS models leverage the strengths of adaptive learning algorithms, allowing for the optimization of fuzzy rule parameters. Comparative analysis between FIS and ANFIS revealed that FIS models exhibited slightly superior accuracy and generalization capabilities.

Through the data analysis, we have identified several key factors that significantly influence wind turbine performance and efficiency. These factors include wind speed, blade length and distance to other turbines. Understanding the impact of these factors on overall performance enables wind turbine operators to make informed decisions regarding turbine operation and design. Moreover, this knowledge can guide policymakers and researchers in developing strategies to maximize energy production while minimizing environmental impact.

The findings of this research hold practical implications for the wind energy industry. The accurate modeling of wind turbine efficiency using FIS and ANFIS enables precise predictions of energy production and facilitates optimal operation and maintenance planning. Additionally, the identification of key factors influencing wind turbine performance allows for better design and selection of wind turbine systems, leading to improved overall efficiency and cost-effectiveness. Integrating these modeling techniques into industry practices can promote the adoption of renewable energy sources and contribute to a more sustainable future.

While this study has made significant progress in analyzing wind turbine efficiency, certain limitations should be acknowledged. The research focused on a specific dataset and turbine type, potentially limiting the generalizability of the findings. Future studies should consider multiple datasets and various wind turbine configurations to validate and extend the results. Furthermore, incorporating real-time data and advanced machine learning algorithms could enhance the accuracy and reliability of efficiency predictions. Additionally, exploring the influence of external factors such as grid integration and energy storage systems on wind turbine efficiency warrants further investigation.

In conclusion, this master thesis successfully analyzed wind turbine efficiency using Fuzzy Inference System (FIS) and Adaptive Neuro Fuzzy Inference System (ANFIS). The findings highlight the effectiveness of these modeling approaches in accurately predicting wind turbine.

If the necessary data could be obtained, the validity of the method could be checked over real data. Suppose two turbines are wanted to be relocated. This operation will incur a serious cost. Here we can test whether this operation will be profitable or not using our method. Write down the data for these two turbines, which have different blade lengths, wind speed and distances to other turbines. Let's measure turbine efficiencies with FIS and ANFIS. At the same time, let's take the last year's energy production amounts from the Scada system and examine the difference between them. We can get the amount to be earned by multiplying the difference between the amount of energy produced by the two turbines and the sales unit price. The decision can be made by comparing this profit with the operating cost. Here we can check whether we can get the same result by using FIS and ANFIS without dealing with energy data or unit price. In this case, we save a lot of time. This application is not shown in the thesis because real energy production data could not be obtained.

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