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Artificial Neural Network for Standalone Induction Generator Control Wind DC Microgrid

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we ask allah to make this work purely for His face and to benefit us and others.

Dedicate

Appreciatively, I dedicated this thesis to ***ME****, another part of myself that always eager for challenges in life. And especially for:*

My beloved parents. Thank you so much for everything! Words can hardly describe my thanks and appreciation to you. You have been my source of inspiration, support, and guidance. You have taught me to be unique, determined, to believe in myself, and to always persevere. I am truly thankful and honored to have you as my parents.

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All those who have helped the researcher to complete the thesis which may not be mentioned one by one.

Bekhelifa Fatna Nourhane

Dedicate

With heartfelt gratitude and profound appreciation,
I would like to dedicate this thesis
To 54,880 martyrs since October 7, 2023
To those who live in tents and are arrested for no sin other than their love for their land
To every oppressed and free person in this wounded world.
To Gaza of pride.
To the great lessons Gaza has given us in courage and pride..
To those heroes who struggle with certainty and resist for the nation.
To myself
That girl who stood firm, fought bravely, shone through all the storms who were not broken from fatigue and did not give up in the face of adversity...
I dedicate this success to you — you were the true heroine at every step of this journey.
To my beloved parents
My source of strength and support throughout my days
Thank you for your prayers that were beating in my heart
And for your love that lit up my darkest moments.
I dedicate to you the fruit of this effort, you are the foundation and my legacy.
To my sisters and brothers
Companions of the first path, and the warm light of home.
Thank you for your hearts that contained me
And for your joyful words when I stumbled.
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Partners in staying up late, laughing, and participating in difficulties
You were the other beautiful half on this journey.
I dedicate this moment to you — Our long-awaited dream has come true.
Unforgettable Class of 2020
May our journey always remain a bright memory.
To my university
Who embraced me and directed me
In its corridors, dreams blossomed and shaped the future.

Chouikh Widad

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List of abbreviations

ρ_0 : Reference air density (kg/m^3).

ρ : Air density (kg/m^3).

A : Rotor Swept Area.

ANN : Artificial neural network.

ANNs : Artificial neural networks.

ARIMA : AutoRegressive Integrated Moving Average.

B : Friction coefficient.

batt_V : Battery voltage (V).

batt_Ah: Battery capacity (Ah).

BP : Backpropagation.

Cdc : DC-link capacitance (F).

CHP : Combined Heat and Power.

CNN : Convolutional Neural Network.

Cp : Fraction of energy captured by the turbine.

CP : Power efficiency coefficient.

C_t : Torque coefficient of the wind turbine.

D : Diameter of the rotor (m).

DC-link : Direct Current link “ Volt (V) or Joule (J), depending on context ”.

DFIG : Double-Fed Induction Generator.

DNN : Deep Neural Network.

E : Kinetic energy (J).

error_signal : Error signal used for control or ANN training.

EV : Electric vehicle.

FLC : Fuzzy Logic Control.

FNN : Fuzzy Neural Network.

FNN : Feedforward Neural Network.

G : Gear ratio.

GPC : Generalized Predictive Control.

HAWT : horizontal-axis wind turbines.

HCS : Hill Climb Search.

Hm : Site elevation (m).

Id : Stator current at d frame (A).

Idq : Dq-frame stator current (A).

IncCond : Incremental Conductance.

Iq : Stator current at q frame (A).

J : Moment of inertia (kg·m^2).

Lm : Mutual inductance (H).

LMI: Linear Matrix Inequality.

LQR : Linear Quadratic Regulator.

Lr : Rotor inductance (H).

Ls : Stator inductance (H).

$\dot{m}$: Mass flow rate per second.

m : Mass.

MPPT_output : Optimal operating point determined by MPPT.

Net : Trained neural network used for rotor speed estimation.

net_updated : Updated neural network after training or online tuning.

P : Air pressure (Pa).

P : Mechanical power of the wind turbine (W).

P : Number of poles.

P_gen : Generated electrical power (W).

P_prev : Previous error covariance matrix (Kalman Filter).

Pr : Rated power (W).

prev_wr : Rotor speed estimated at the previous time step.

Psi_r : Rotor magnetic flux.

Pv : Non-linear relationship between power and wind speed.

Pwind : Output power generated by the air (W).

Q-prev : Process and measurement noise covariance matrices for Kalman filter.

R : Radius of the turbine (m).

R : Stator resistance (Ω).

R : Gaz constant.

RAPS : Remote Area Power Supply.

RBF : Radial Basis Function.

Rdc : DC-link resistance (Ω).

Rr : Rotor resistance (Ω).

T : Torque of the wind turbine (N·m).

T : Temperature on the obsolute scale (°F).

t_final : Final simulation time ‘a single numeric value representing final time.

Ts : Sampling time (s).

V : Velocity (m/s).

V_{ci} : Cut-in wind speed (m/s).

V_{co} : Cut-out wind speed (m/s).

Vdc : DC link voltage (V).

Vdq : Dq-frame voltage components (V).

V_r : Rated wind speed (m/s).

V_{ref} : Reference velocity (m/s).

Wr : Actual rotor speed from the physical system (m/s).

wr_est : Estimated rotor speed from the ANN (m/s).

Z : Grossness length of the direction of the wind (m).

Z : Height above ground grade for the coverted speed V (m).

Z ref : Reference height, i.e. height at which wind speed is Vref (m).

β : Pitch angle (°).

λ : Tip speed ratio.

ω : Turbine’s angular velocity (rad/s).

General introduction

Renewable energy is a promising and sustainable alternative to traditional energy sources, contributing to the reduction of carbon emissions, promoting energy independence, and supporting economic growth through the creation of new jobs. In contrast, fossil energy sources represent a serious environmental and health threat, endangering global energy security as a result of market fluctuations and geopolitical tensions [1]. In this context, wind energy is emerging as a strategic option thanks to its great availability and high efficiency, making it a fundamental pillar in the transition towards a sustainable and safe energy system [2]. In this perspective, we will analyze in this thesis a wind system based on intelligent estimation and control techniques, using a Kalman filter and neural networks, in order to improve the accuracy of rotor speed estimation and energy extraction efficiency.

In the first chapter we will discuss the general concepts related to wind energy, starting with its definition and classification of wind turbines, passing through its basic components, the working principle of wind energy systems, and reaching its most prominent applications. It will also evaluate the factors that influence the power production of turbines, and present the modeling of wind turbines and system components that were adopted in this study.

The second chapter will focus on estimation methods in wind energy systems, where the role of Kalman filter and artificial neural networks in improving estimation efficiency and control within renewable energy systems will be addressed, reviewing their types and functions in wind energy applications. The chapter also discusses Maximum Power Point Tracking (MPPT) techniques and their different types.

In the third and last chapter, the system developed and studied within this work will be presented, the results obtained will be presented and analyzed, and the effectiveness of the proposed methodology in improving the performance of the wind energy system will be thoroughly explained.

CHAPTER I

GENERALITIES ABOUT WIND ENERGY

I.1 Introduction

The growing global demand for energy, coupled with the depletion of fossil fuel reserves and the rising levels of environmental pollution, has spurred the search for alternative, clean, and sustainable sources of energy. One of the most promising solutions to this challenge is wind energy, which harnesses the power of the wind to generate electricity. Wind power is a renewable, abundant, and environmentally friendly energy source, offering a significant advantage in reducing greenhouse gas emissions compared to traditional fossil fuels. The increased use of energy and the depletion of the fossil fuel reserves combined with the increase of the environmental pollution have encouraged the search for clean and pollution-free sources of energy. One of these is wind energy. The wind power industry has seen an unprecedented growth in the last few years, driven by advances in technology, decreasing costs, and increasing awareness of the need for sustainable energy solutions [4].

This chapter provides an overview of wind energy and its role in electricity generation. It introduces the fundamental concepts of wind turbines, wind energy conversion systems, and the key components involved in transforming kinetic wind energy into electrical power. Additionally, the chapter explores various factors that affect wind energy production, including wind speed, air density, terrain, and turbine design.

I.2 Definition

Wind energy is the process of converting the kinetic energy of moving air into mechanical or electrical energy using wind turbines. Wind is caused by the movement of air, which occurs due to the uneven heating of the Earth’s surface by the sun. This heating creates differences in air pressure, which in turn causes air to flow from areas of high pressure to areas of low pressure, generating wind. The speed and consistency of the wind are influenced by various factors, such as the sun’s heat, geographical features, and humidity levels [5].

Wind turbines capture the energy from this moving air through blades that rotate when the wind blows. This rotational movement drives a generator, which converts the kinetic energy into electricity. Wind turbines, which harness this energy, are primarily classified into horizontal-axis turbines and vertical-axis turbines. Both types of turbines play a crucial role in converting wind energy into electricity, contributing to the expansion of renewable energy sources worldwide [5]. As wind energy is naturally replenished through atmospheric processes, it is considered a renewable resource, and its operation generates no greenhouse gas emissions [4].

As such, it plays a key role in the transition to cleaner, sustainable energy sources and is an important tool in addressing climate change [5].

The efficiency of wind energy generation depends on several factors, including wind speed, the design of the wind turbine, and the location of the wind farm [4]. Areas with higher wind speeds are typically better suited for large-scale wind energy production, as they provide a more consistent and reliable source of energy [5].

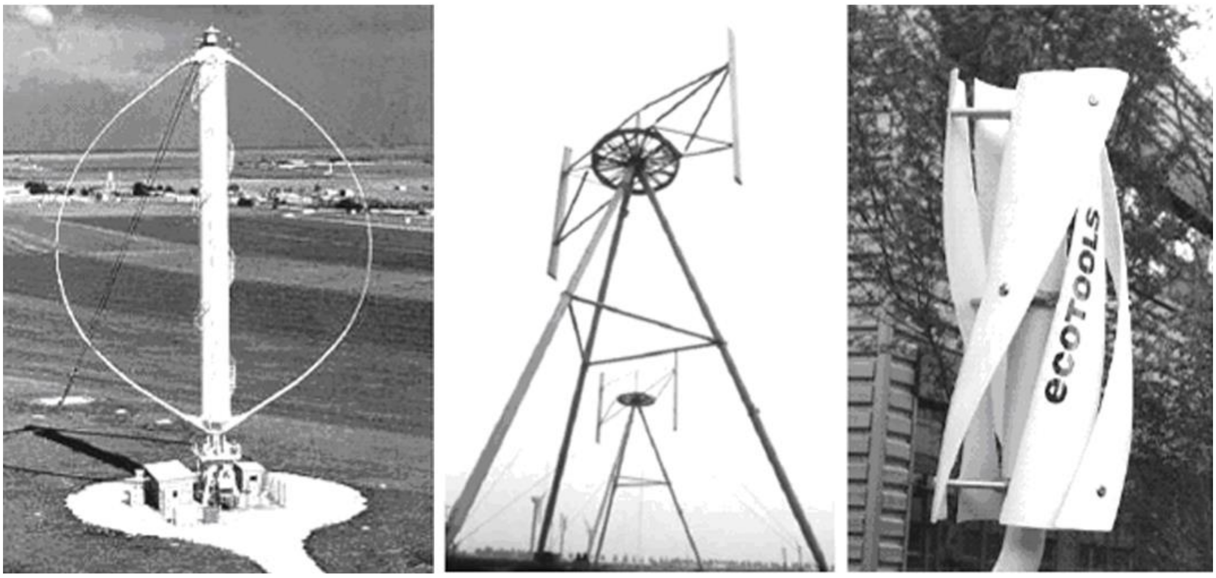
I.3 The main types of wind turbines

There are many different technical solutions for harvesting wind energy. There are two types : vertical-axis wind turbines (VAWT) and horizontal-axis wind turbines (HAWT).

I.3.1 Vertical-axis (VAWT)

Vertical-axis wind turbines (VAWTs) were among the first structures developed for electricity generation. Unlike horizontal-axis wind turbines (HAWTs), VAWTs have blades that rotate around a vertical axis, allowing them to capture wind from any direction without the need for adjustment. This feature makes them particularly versatile. They offer advantages such as ground-level machinery, making maintenance easier and eliminating the need for tall towers. Additionally, VAWTs can operate in a wider range of wind conditions without needing to orient toward the wind direction. They also have high starting torque, enabling them to function even at low wind speeds, with Savonius-type turbines being especially simple and low-noise. However, one disadvantage is the need for mechanical guides, especially the low bearing, which must support the turbine's weight, introducing wear and complexity to the system.

The main types of VAWTs include the classic Darrieus, H-type, and Savonius-type turbines, each typically featuring two or more blades, These turbines are suited for various applications depending on wind conditions and site-specific requirements [6].



(a) **(b)**

Figure I.1 : Examples of Vertical Axis Wind Turbine (VAWT) Designs :
(a) General VAWT constructions , **(b)** Darrieus and Savonius types [6].

I.3.2 Horizontal axis (Hawt)

Horizontal-axis wind turbines (HAWT) are the most widely used type of wind turbine, especially for large-scale power generation. These turbines have blades that rotate around a horizontal axis, similar to the blades of an airplane propeller. HAWTs are typically mounted on tall towers, and they use a yaw mechanism to orient the blades towards the wind direction for optimal performance. The turbine can be located at the front or rear of the nacelle : upwind or downwind (**Figure I.2**).

This type of wind turbine is particularly effective in areas with consistent, high wind speeds, which is why they are commonly found in both onshore and offshore wind farms. Due to their larger size and higher energy output, HAWTs are typically employed in industrial-scale wind farms and are highly efficient at capturing kinetic energy from the wind. Their performance increases as wind speed rises, which is why many modern HAWT designs can generate several megawatts of power [6].

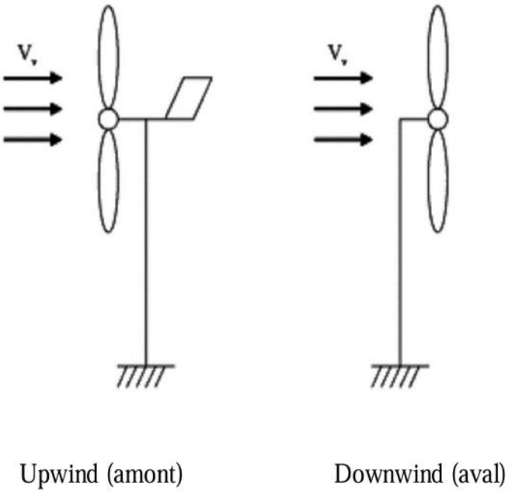


Figure I.2 : Type of wing assembly [6].

Figure I.3 : Horizontal-axis wind turbines on a wind farm [7].

I.4 Principle of wind energy conversion

The kinetic energy in the wind is partially converted into mechanical energy on the turbine shaft, and then into electrical energy by the generator. This energy is then distributed to the power grid via a transformer [8]. The general process is illustrated in the **figure I.4**.

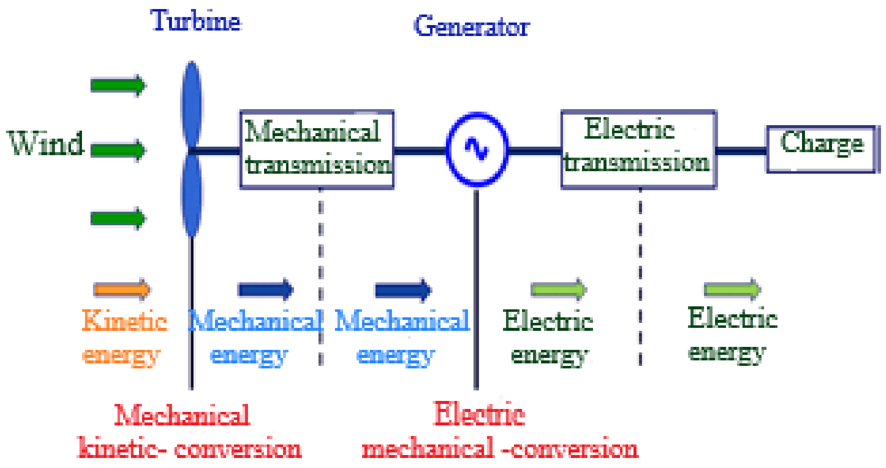


Figure I.4 : Principle of the energy transformation of a wind turbine [9].

I.4.1 The main components of wind turbine

When air flows over a surface, it generates two types of aerodynamic forces: one acting in the direction of the airflow, known as drag force, and another acting perpendicular to the airflow, known as lift force. These forces can be utilized to produce the driving torque required to rotate the blades. Modern wind turbines operate based on aerodynamic lift forces. A typical wind turbine consists of blades, a rotor, a tower, a gearbox, and a generator [10]. **Figure I.6** illustrates all the components of a wind turbine which are described below.

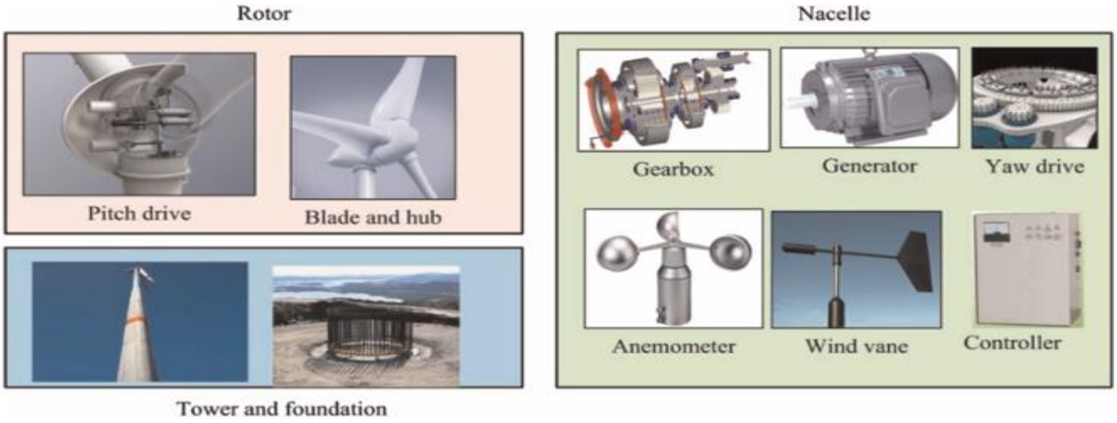


Figure I.5 : Illustration of the main components of wind turbine [10].

- **Rotor :** The rotor consists of large blades that resemble an airplane wing. While three-bladed turbines are the standard, two-bladed designs are also functional. Rotor blades are typically very large. Additionally, a component known as the "pitch drive" is used to minimize the impact of lift forces during high wind speeds. This ensures that the alternator operates within a stable power range of 1000–3600 RPM (revolutions per minute) [10].

The hub located at the front center of the wind turbine, is the part where the blades are attached.

- **Nacelle :** Positioned at the top of the turbine tower, the nacelle houses essential technical components, including the rotor shaft, gearbox, and generator .It is connected to the tower via bearings, allowing it to rotate based on wind direction to maximize wind energy capture [10].
- **Gearbox :** The turbine rotor generally rotates at speeds below 100 RPM, while most generators require speeds between 1000 and 3600 RPM to produce electricity. The gearbox serves to increase the rotor’s low speed to the required levels, enabling the generator to function effectively [10].
- **Generator :** The generator is responsible for converting the rotor’s mechanical energy into electrical energy [10].

Between the dc and ac generators, the dc generators are not popular in the wind energy conversion system due their higher expenditure and maintenance with lower rating. The ac generators mostly dominate the market [11].

A brief review on the synchronous and asynchronous generators is discussed below.

1. Synchronous Generator

In wind energy conversion systems, salient pole machines are used due to their high number of poles, which helps in generating power at low wind speeds. Currently, the Permanent Magnet Synchronous Generator (PMSG) with a full power electronic conversion system is considered an attractive option for power generation without the need for a gearbox. This type of generator offers high efficiency and low maintenance because it does not use slip rings. Moreover, the PMSG is more stable and lighter in weight compared to the asynchronous generator, thanks to its capability to control reactive power [11].

2. Asynchronous Generator (Induction Generator)

Thanks to their durability and brushless construction (in the case of the squirrel cage), as well as their low cost, induction generators are widely used in wind energy conversion systems. Constant-speed wind systems using induction generators can be connected directly to the electrical grid. Since an induction generator always draws negative power from the grid, a capacitor bank is used to compensate for this power. A current limiter or soft starter is also used to reduce the inrush current when the induction generator is started. A variable-speed induction generator with a full power converter reduces stress on the shaft and gears compared to fixed-speed generation systems. Currently, the dual-feed induction generator (DFIG) accounts for approximately 50% of the wind power market, due to its use of low-capacity power converters and improved efficiency. The power converter used in this type often accounts for about 25-30% of the system's nominal capacity [11].

- **Tower and Foundation**

Wind speed, quality (reduced turbulence), and quantity improve with height. The tower elevates the rotor to higher altitudes, allowing it to harness greater wind energy [10].

In addition, several other components play crucial roles in the operation of a wind turbine. The controller, which is a computer-based system, that controls the turbine's operation. The heat exchanger is responsible for cooling the generator. The anemometer measures the wind speed, while the wind vane detects the direction of the wind [10].

- **Necessity of energy storage system in WECS**

Energy storage devices have the ability to store excess generated energy and supply it to consumers during periods of power shortage. Since wind power generation is typically inconsistent and varies over time due to fluctuations in wind flow, this results in unstable energy output. Observations from typical wind farms show that the generated wind power is not steady because of the intermittent nature of wind, which highlights the importance of using an energy storage system (ESS) to ensure the reliability of wind energy conversion systems (WECS).

Available energy storage technologies include battery energy storage, superconductive magnetic energy storage, capacitor energy storage, pumped hydro storage, flywheel energy storage, hydrogen storage systems, and others. There are also combined energy storage systems that integrate multiple technologies. Some solutions, such as capacitors, high-speed flywheels, and sodium-sulfur batteries, offer higher round-trip efficiency.

A supervisory control system, integrated with external energy sources and properly sized storage devices, can significantly enhance the performance of wind energy systems. Coordinated operational schemes have been proposed for wind farms combined with battery storage, along with innovative approaches for integrating ESS into microgrids. Additionally, control algorithms and appropriate sizing strategies have been developed to address energy imbalances in wind power systems.

Regarding the placement of ESS, it has been suggested to install storage systems close to wind farms, so that both the generated and stored energy can share the same transmission lines when connected to the main grid. It has been observed that integrating energy storage into wind energy systems significantly improves power quality, stability, and overall system reliability [11].

I.4.2 Wind Energy Systems and Applications

A wind energy system is designed to capture and convert wind energy into a useful form. Wind turbines can be installed individually or grouped together in wind farms. These farms can be connected to a utility power grid or integrated with other renewable energy sources [10].

- **Wind Parks**

A wind park, also known as a wind farm, is a designated area where multiple wind turbines are installed for large-scale electricity generation. The nameplate capacity of modern wind parks has increased significantly, reaching thousands of megawatts (MW). Based on their location, wind parks can be classified as either onshore or offshore.

(a) (b)

Figure I.6 : Wind Park Types : **(a)** Offshore [12], **(b)** Onshore [7].

There are three primary types of wind turbine systems :

1. **Constant-speed wind turbine system** – Uses a standard squirrel cage induction generator (SCIG).

2. **Variable-speed wind turbine system** – Utilizes a double-fed induction generator (DFIG).
3. **Variable-speed wind turbine system with full power conversion** – Employs a synchronous generator with a full-rated power electronics conversion system [10].

- **Types of Wind Energy Systems**

1. **Grid-Connected Systems** – These systems are typically large in size and have a high nameplate capacity. Due to the variable nature of wind power, integrating it with the power grid presents several technical challenges. Issues such as voltage fluctuations, frequency stability, power quality, harmonics, and flicker must be carefully managed. Before connecting to the grid, wind power systems must meet stability requirements governed by parameters such as voltage and frequency to ensure reliable operation, even during system faults. Today, wind parks play a crucial role in modern power grids. In addition to large wind turbines, many manufacturers also produce small wind turbines, which can be installed on rooftops or in backyards to provide electricity for individual households [10].
2. **Standalone Systems** – Small-scale wind turbines can be used for various applications where grid connection is not feasible [10].

- **Applications of Wind Energy**

Street Lighting – Wind-powered street lights are successfully used in many parts of the world. These systems typically consist of a small wind turbine and an LED panel. A recent innovation, Firewinder, is a hanging wind-powered LED light that operates even with minimal air movement. Hybrid street lights powered by both wind and solar energy are also widely adopted.

Wind-Solar Powered EV Charging Stations– A new concept in renewable energy, wind and solar-powered fast plug-in electric vehicle (PEV) charging stations are gaining popularity due to the growing adoption of electric vehicles. These eco-friendly charging stations can be conveniently installed along roads or in parking lots, providing accessible charging options for EV users.

Water Pumping– Wind pumps have been used for centuries to extract groundwater. Deploying wind-powered water pumps on a large scale can significantly benefit the economies of agricultural countries like India. Since agricultural regions are often located far from power grids, wind pumps provide a cost-effective solution by eliminating the need for expensive transmission infrastructure while also reducing electricity consumption. In India, for example, farmers make up 50% of the total population, yet only 20% of them have access to electric water pumps. Replacing electric pumps with wind-driven alternatives in regions with high wind energy potential could result in significant energy savings and reduced installation costs.

Other Applications– Wind energy is also used in small-scale applications, including wind-powered cell phones and gadget chargers. One notable example is the Ecotricity Greenbird, a wind-powered land yacht that set a record-breaking speed of 126.1 mph. According to its designer, the Greenbird operates like a high-performance sailboat but uses solid wings instead of traditional sails for propulsion [10].

- **Off-Grid or Standalone Systems**

Standalone wind power systems, also known as remote area power supply (RAPS) schemes, are ideal for locations where conventional electricity transmission and distribution networks are inefficient or unavailable. These systems are particularly beneficial for electrifying remote and rural areas, especially in developing countries.

Standalone wind power solutions provide a reliable, cost-effective, and continuous power supply for homes, schools, and offices. Additionally, wind turbines can be integrated into hybrid systems, such as wind–photovoltaic (PV)–hydrogen and wind–diesel configurations, to maximize efficiency. **Figure I.7** illustrates a model of a hybrid off-grid wind energy system.

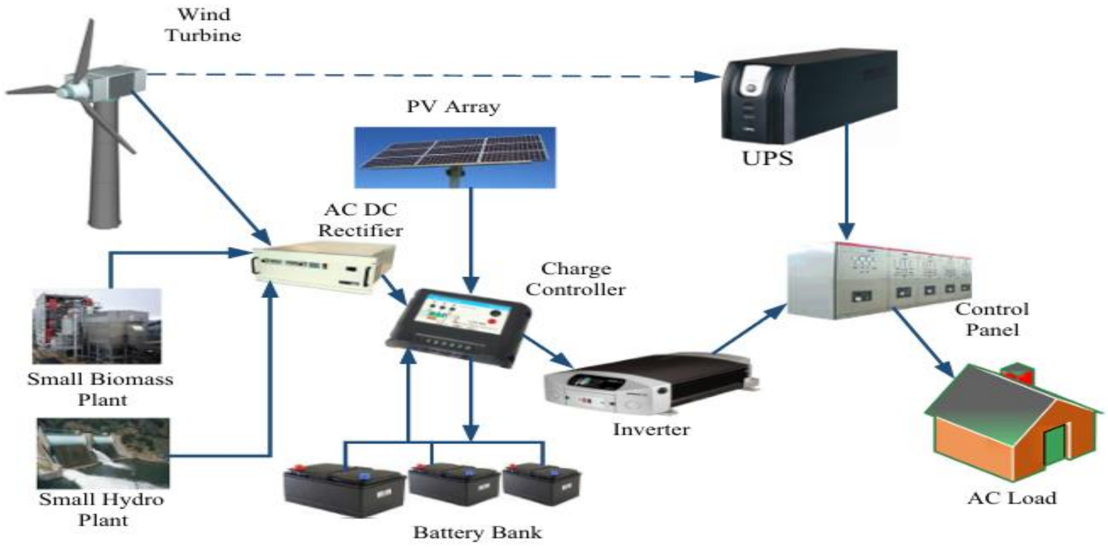


Figure I.7 : Example of a hybrid stand-alone wind power system [10].

I.5 Assessment of the aerodynamic factors influencing wind turbine power output

Currently, wind energy conversion systems are receiving increasing global attention for electricity generation, as they are among the fastest-growing sectors in the energy industry, with an average annual growth rate exceeding 25% over the past decade. Although wind energy conversion sites exist worldwide, selecting an appropriate location is crucial to reducing the overall cost of a wind energy conversion system (WECS). Maximizing the efficiency of a WECS requires designing wind turbines specifically for the site where they will be installed.

Wind characteristics, such as velocity and orientation, are influenced by various factors, including geographic location and site properties. The power generated by a wind turbine depends on multiple site-specific factors and the aerodynamic performance of its blades. The most critical factors include the average annual wind speed, blade pretwist, pitch, angle of attack, and rotor swept area. Additionally, air density significantly impacts turbine performance, as it varies with altitude and temperature.

Several climatic factors must be considered when designing a wind turbine, such as wind speed, rotor swept area, air density, site temperature, and tower height. The selection of a wind turbine should be based on the specific climatic conditions of the site, as power output is directly proportional to these factors [13].

I.5.1 Wind turbine modeling

A. Speed and Power relation

The kinetic energy E of a mass m moving through the air at a velocity v can be expressed as :

$$E = \frac{1}{2} m v^2 \tag{I.1}$$

The relationship between the output power generated and wind velocity can be represented as:

$$Pwind = \frac{dE}{dt} = \frac{1}{2} \dot{m} v^2 \tag{I.2}$$

Where $\dot{m}$ represents the mass flow rate per second. When air flows through the area A, the power generated by the air can be calculated using :

$$Pwind = \frac{1}{2} (\rho A v) v^2 = \frac{1}{2} \rho A v^3 \tag{I.3}$$

Here ρ resents the air density.

B. Mechanical Power Extracted from the Wind

Extracting all the kinetic energy from the wind is impossible because the air does not remain still behind the wind turbine. The airflow continues moving, meaning a completely stable condition cannot be achieved. The wind turbine slows down the wind, extracting only part of its energy.

The power efficiency coefficient Cp represents the fraction of energy captured by the turbine. Therefore, the mechanical power of the wind turbine, according to the definition of Cp , is determined by the total energy in the wind Pwind, which can be calculated using [13] :

$$p = Cp\ Pwind \tag{I.4}$$

That means :

$$p = \frac{1}{2} Cp\ A\ v^3 \tag{I.5}$$

The theoretical maximum efficiency for wind turbines is 16/27, meaning that about 59% of the wind's kinetic energy can be extracted. This is known as Betz's limit.

$$Cp = fcp(\lambda, \beta) \tag{I.6}$$

Where : λ is the tip-speed ratio and β is the pitch angle.

The tip-speed ratio is defined as :

$$\lambda = \frac{\omega R}{v} \tag{I.7}$$

where ω represents the turbine's angular velocity, and R is the radius of the turbine.

The torque of the wind turbine can then be expressed as :

$$T = \frac{1}{2} Ct\ \rho\ A\ R\ v^2 \tag{I.8}$$

This $Ct(\lambda, \beta) = \frac{Cp(\lambda,\beta)}{\lambda}$ represents the torque coefficient of the wind turbine.

The power coefficient of the turbine $Cp(\lambda, \beta)$ can be calculated using the following equation structure :

$$Cp(\lambda,\beta) = C1\left(\frac{C2}{\lambda i} - C3\beta - C4\beta^{C5} - C6\right)\exp(-\frac{C7}{\lambda i}) \quad (I.9)$$

Where :

$$\lambda i = \left[\left(\frac{1}{\lambda + C8\beta}\right) - \left(\frac{C9}{\beta^3 + 1}\right)\right]^{-1} \quad (I.10)$$

However the constants $C1$ to $C9$ can be found in Appendix **Table I.1** [13].

Table I.1 : Power coeficient constants.

C1	C2	C3	C4	C5	C6	C7	C8	C9
0.5	116	0.4	0	---------	5	21	0.08	0.035

I.5.2 Aerodynamic factors affecting wind turbine output power

There are aerodynamic factors influence wind turbine power generation, including wind speed, air density, temperature, air pressure, swept area, and height, among others. The impact of these factors will be discussed as the following :

A. Wind Speed

Figure I.8 shows the curves of wind power Pwind and mechanical power P extracted by the wind turbine in relation to wind speed. The value of P is always lower than Pwind due to aerodynamic power losses.

Typical wind speed ranges are:

- Cut-in speed : 3–5 m/s (minimum speed for turbine operation).
- Rated speed : 10–15 m/s (speed at which the turbine generates maximum power).
- Cut-out speed : 25–30 m/s (maximum speed before shutdown for safety).

For wind speeds below the cut-in value, the turbine produces very little power and is usually kept in parking mode. Similarly, for safety reasons, the turbine is shut down and kept in parking mode when wind speeds exceed the cut-out value or in emergency situations.

Between the cut-in and rated wind speeds, the power P follows a cubic relationship with wind speed. However, between the rated and cut-out speeds, the turbine regulates its output power to stay at its maximum rated value using aerodynamic control [13].

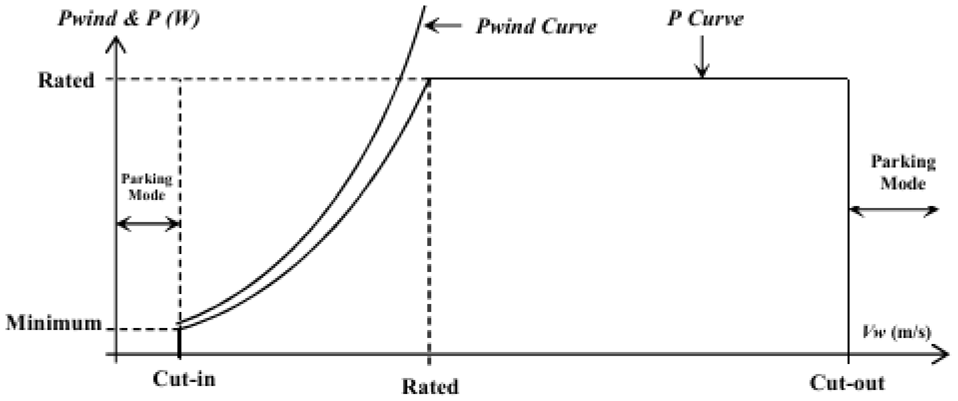


Figure I.8 : Wind Turbine characteristics curves with respect to wind speed [13].

The relationship between wind velocity and energy is described as follows [13] :

$$P = \begin{cases} 0 & v < vci \quad or \;\; v > vco \\ Pv & vci \le v < vr \\ \mathrm{Pr} & vr \le v \le vco \end{cases} \tag{I.11}$$

Where P is the electrical power (W), vci is the cut-in wind speed (m/s), vco is the cut-out wind speed (m/s), vr is the rated wind speed (m/s), Pr is the rated power (W), and Pv represents the non-linear relationship between power and wind speed.

Figure I.9 illustrates this relationship between the power extracted from the wind turbine and wind speed, based on the simulated wind turbine model (SIEMENS SWT-3.2-113). The model parameters are provided in Appendix **Table I.2** [13].

Table I.2 : Wind Turbine SWT-3.2-113 Data Sheet.

Type	Diameter	Nominal power	Frequency
3-bladed,horizontal axis	113 m	3200KW	50 Hz or 60 Hz
Swept area	Speed range	Hub height	Cut-in wind speed
10.000 m^2	4-16.5 rpm	83.5 -115 m	3-5 m/s
Blade length	voltage	Nominal power at	Cut-out wind speed
55 m	690 V	12-13 m/s	32 m/s

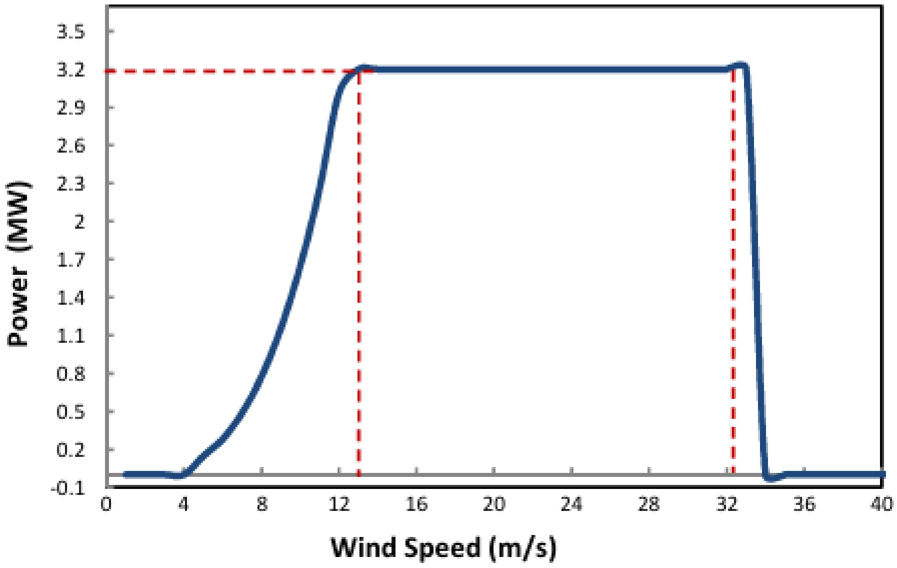


Figure I.9 : Relationship between Wind Turbine Output Power and Wind Speed [13].

From the simulated curve above, it is observed that the turbine reaches its rated power of 3.2 MW at a wind speed of 13 m/s. The cut-in wind speed is 4 m/s, and the cut-out wind speed is 32 m/s, which matches the manufacturer's data sheet.

According to equation (I.5), wind power is proportional to v^3. This means that the energy produced by the rotor blades does not increase linearly with wind speed, as shown in **Figure I.9**. The figure also indicates that the power generated in the upper third of wind speeds is almost double the power produced in the lower two-thirds of the wind speed range.

Therefore, it is more beneficial to install a wind energy system in locations with consistently high wind speeds rather than in areas with low wind speeds.

B. Air Density

Wind turbine performance is typically linked to air density. The energy generated by the wind is directly proportional to air density. This relationship is illustrated in **Figure I.10** [13].

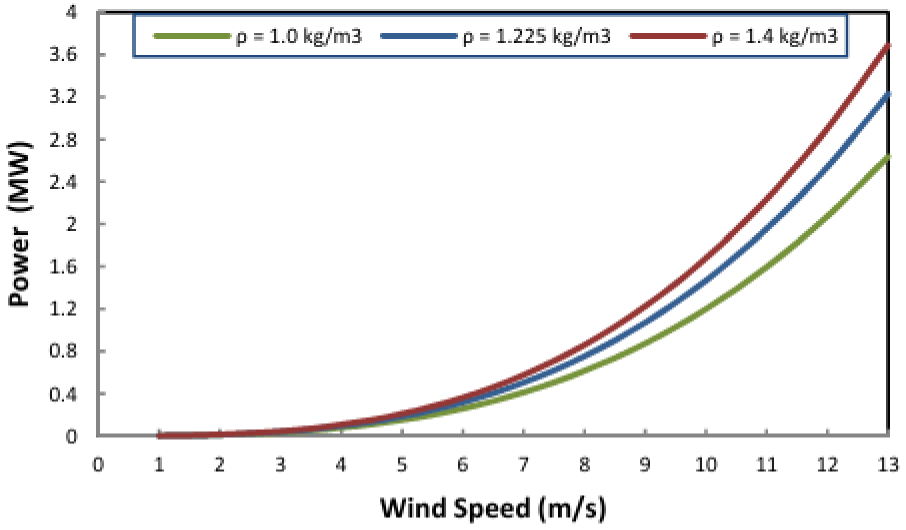


Figure I.10 : Air density effect on Wind Turbine output Power [13].

Air density varies with changes in pressure and temperature according to the gas law.

$$\frac{P}{TR} = \rho \tag{I.12}$$

Where :

P : Air pressure.

T : Temperature on the obsolute scale.

R : Gaz constant.

The air density at sea level at 1 atm (14.7 psi) and 60°F is 1.225 kg/ m^3.

The equation above confirms that air pressure and temperature affect air density. Air density is directly proportional to pressure and inversely proportional to temperature.

Figure I.11 and **I.12** illustrate how changes in air pressure and temperature impact the output power.

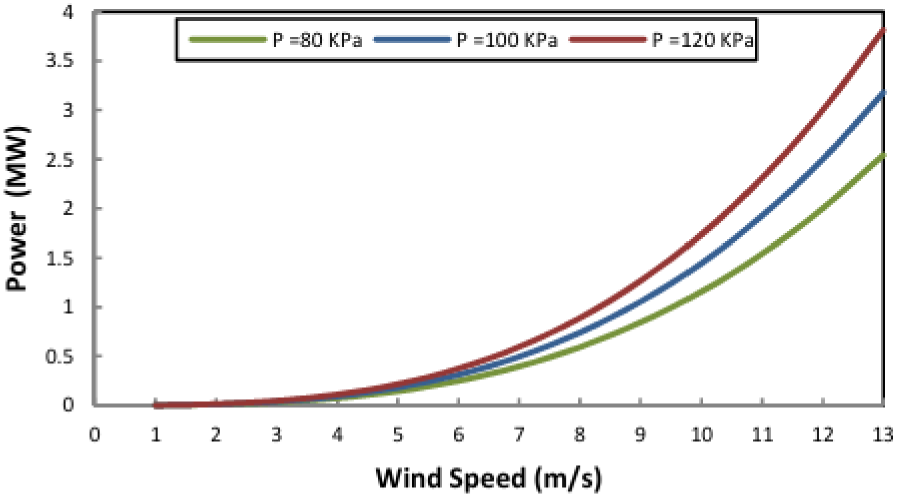


Figure I.11 : Air Pressure effect on Wind Turbine output Power [13].

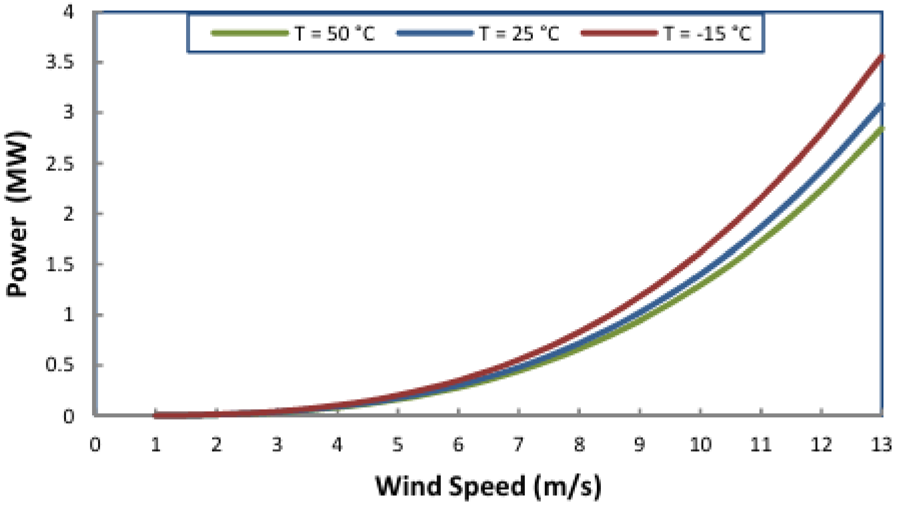


Figure I.12 : Temperature effect on Wind Turbine output Power [13].

Additionally, as elevation increases, both pressure and temperature decrease. This variation in elevation affects the amount of energy produced due to changes in air density. The impact of temperature and pressure on air density is more evident in the following equation, which is valid for site elevations up to 6,000 meters (20,000 feet) above sea level [13].

$$\rho = \rho_0 - (1.194 \times 10^{-4} Hm) \quad (I.13)$$

Where Hm represents the site elevation in meters, and ρ_0 is the reference air density value (1.225 kg/m³) at sea level.

C. Rotor Swept Area

From equation (I.5), it can be concluded that the generated power is directly proportional to the rotor-swept area (A). The rotor-swept area is given by :

$$A = \frac{\pi}{4} D^2 \tag{I.14}$$

D : represent the diameter of the rotor.

According to the equation above, since the swept area is proportional to the square of the rotor diameter, even a small increase in blade length significantly boosts theenergy available to the turbine, as shown in **Figure I.13 :**

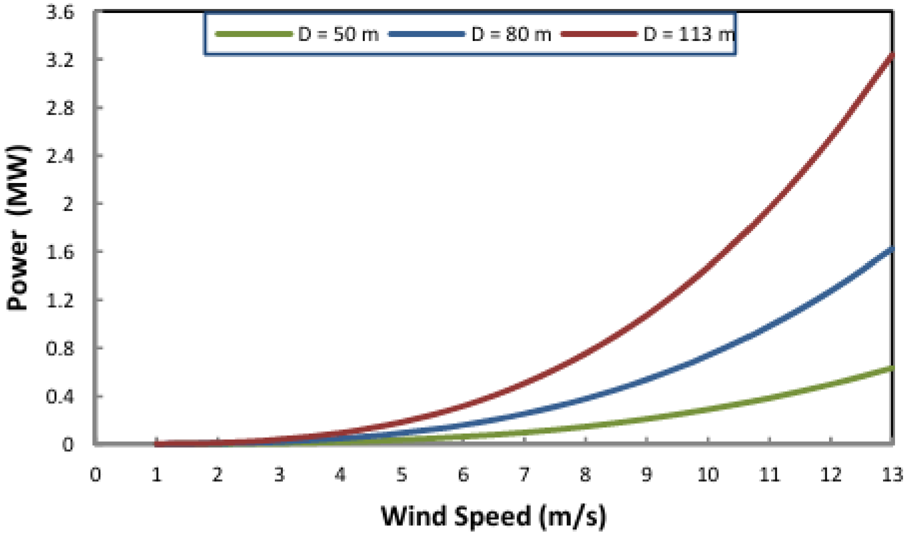


Figure I.13 : Swept-Area effect on Wind Turbine output Power [13].

When the rotor's swept area and diameter increase, more energy can be harvested from the wind.

D. Effect of Tower Height

It is well known that the power available in the wind is proportional to the cube of wind velocity. Therefore, even a small increase in wind speed can have a significant economic impact. One effective way to access stronger winds is by installing turbines on taller towers.

Near the ground, wind speed is significantly affected by friction as air moves across the Earth's surface. Smooth surfaces, such as a calm sea, create minimal resistance, resulting in only slight variations in wind speed with height. In contrast, rough surfaces, like forests and buildings, cause greater wind resistance, slowing it down considerably [13].

The following equation is commonly used to describe the effect of Earth's surface roughness on wind speed :

$$v = vref * \left(\frac{\ln\left(\frac{z}{z_0}\right)}{\ln\left(\frac{zref}{z_0}\right)}\right) \tag{I.15}$$

Where :

v : wind velocity at height Z over sea level.

$vref$: reference velocity, i.e. a wind velocity at height Zref .

Z : height above ground grade for the coverted speed v .

Zref : reference height, i.e. height at which wind speed is $vref$.

Z_0 : grossness length of the direction of the wind .

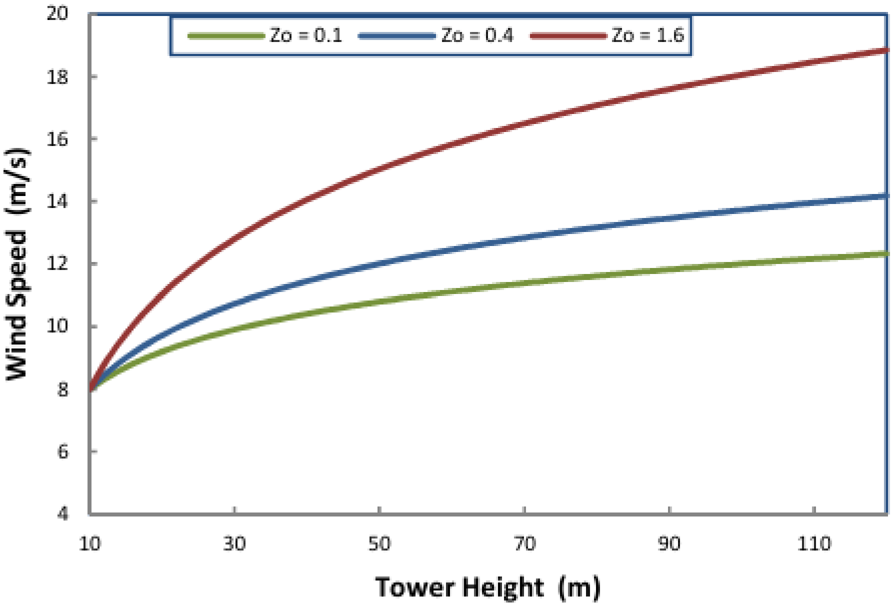


Figure I.14 : Tower Height effect on Wind Speed [13].

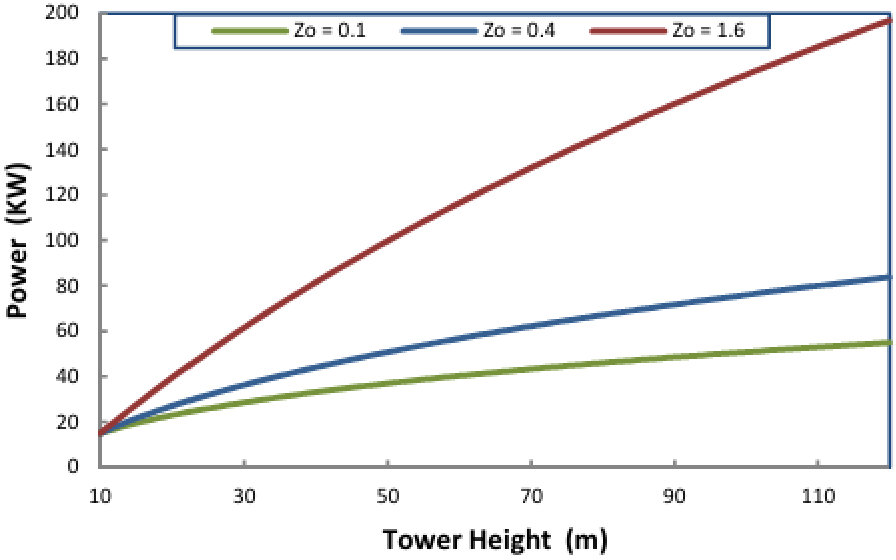


Figure I.15 : Tower Height effect on Wind Turbine output Power [13].

The roughness characteristics are listed in **Table I.3** in the Appendix [13].

Table I.3 : Roughness Classifications.

Roughness Class	description	Roughness Length (Z0)
0	Water Surface	0.0002
1	Open areas in a few windbreaks	0.03
2	Farm land with some windbreaks more than 1 km apart	0.1
3	Urban districts and farm land with many windbreaks	0.4
4	Dense urban or forest	1.6

Figure I.14 and **I.15** illustrate how tower height affects wind speed and power output for different roughness lengths (0.1, 0.4, and 1.6). More details on roughness characteristics can be found in Table I.3.

A height of 10 meters is taken as a reference, with a wind speed of 8 m/s.

As shown in **Figure I.14 :**

In open farmland with few windbreaks more than 1 km apart Z_0 =0.1, a turbine at 100 meters produces 50% more power than at 10 meters.

In dense urban areas or forests Z_0= 1.6, a turbine at 100 meters experiences wind speeds more than twice as high as at 10 meters.

Figure I.15 further highlights the impact of tower height on energy generation.

E. Obstacles to Wind Flow

Obstacles such as buildings, trees, and other natural barriers can negatively impact wind speed and create turbulence in their surroundings. When wind passes over an obstacle, the turbulence zone can extend up to three times the height of the obstacle, with more noticeable turbulence behind it than in front.

To ensure optimal turbine performance, it is important to avoid placing wind turbines near major obstacles, especially when they are located upwind in the prevailing wind direction (i.e., directly in front of the turbine). To minimize the impact of obstacles on wind flow, the following recommendations should be considered [13] :

a) Increase the turbine hub height above obstacles.

- The higher the turbine is positioned above the obstacle, the less wind disturbance it will experience.

b) Maintain sufficient distance between the obstacle and the turbine.

- If the turbine is placed closer than five times the height of the obstacle, wind conditions become less predictable due to variations in the obstacle's shape and structure.

I.6 Conclusion

Renewable energy sources have emerged as a crucial solution to meet the energy market's demand over the past few decades. Currently, there is increasing global attention on wind energy conversion systems for electricity generation, as they are among the fastest-growing sectors in the energy industry.

This chapter offers a concise overview of the wind energy sector and the main factors that impact the energy production of a wind system.

In the next chapter, we'll look at the most important strategies that control the wind power system.

CHAPTER II

Estimation strategies and ANNs in wind energy systems

II.1 Introduction

Accurate estimation techniques play a critical role in enhancing the performance, reliability, and efficiency of wind energy systems. These strategies are essential for forecasting wind speed and power, monitoring system health, and optimizing energy production. In recent years, artificial neural networks (ANNs) have emerged as powerful tools in renewable energy applications due to their ability to model complex, nonlinear relationships and learn from historical data. Within the context of wind energy, ANNs are widely used for tasks such as wind speed prediction, power output estimation, fault detection, and control system optimization.

This chapter explores various estimation methods in wind energy systems and highlights the growing role of neural network-based approaches in advancing renewable energy technologies.

II.2 Estimation Strategies in Wind Energy Systems

II.2.1 Hard Control

- **PID Control**

PID control strategies have been proposed to enhance the efficiency of wind energy conversion systems by controlling power electronic circuits. In one approach, a thyristor rectifier—controlled through a firing angle—is placed between the wind generator and a resistive load. The controller functions as an integrator, computing the integral of the error between the reference maximum power (derived from changes in the wind rotor's angular speed) and the actual output power, which is measured from the load's voltage and current. However, the integrator gain in this method is not rigorously determined.

In another approach, an AC-DC-AC conversion link is used between the wind energy system and the utility grid. This link includes a rectifier and an inverter, each regulated by its own firing angle. These angles are controlled by two separate PI controllers, whose gains are optimally calculated based on the nonlinear dynamic model of the system, considering different sampling rates for each controller. The goal is to compare the performance of multi-rate sampling versus single-rate sampling, with the multi-rate controller yielding better results.

Additionally, another method uses a PI controller to adjust the inverter’s firing angle. This controller operates based on the power-speed characteristic curve to determine the control actions, ensuring that maximum power is consistently achieved [16].

- **Optimal Control**

To maximize energy extraction from wind energy conversion systems (WECS), one method applies MPPT without relying on wind speed sensors, using electrical signals such as voltage and current in systems equipped with permanent magnet synchronous generators (PMSG). Another technique utilizes wind turbulence as a probing signal and detects phase shifts through Fast Fourier Transform (FFT) to identify optimal operating points, adjusting generator speed via a PI controller.

Under partial load conditions in variable-speed systems, linear control using PI controllers and nonlinear methods like sliding mode control and fuzzy logic are used, with mechanical load variations taken into account during optimization.

In large-scale systems, frequency separation is applied to address multiple objectives such as system stability, mechanical stress reduction, and power quality. Pitch control is optimized using a Linear Quadratic Regulator (LQR) based on a linear state-space model, achieving better performance in real wind farm applications.

Additionally, PI controller performance is enhanced by tuning parameters through Particle Swarm Optimization (PSO), improving accuracy, reducing overshoot, and enhancing steady-state response [16].

- **Adaptive Control**

Adaptive control is increasingly used in wind energy conversion systems (WECSs) to address the complexity and nonlinear behavior of these systems. One method involves a direct adaptive control approach based on Lyapunov analysis, combining a supervisory controller with an adaptive controller that uses Gaussian neural nodes. The controllers switch depending on the system's state to ensure rapid error convergence.

A variation of this method replaces the neural adaptive controller with a PID controller while still utilizing Lyapunov theory for stability. Another technique employs a self-tuning PID controller that adapts in real time using a wavelet-based neural network to model system dynamics and adjust the PID parameters accordingly.

Moving beyond Lyapunov-based methods, another adaptive approach uses a modified Hill Climb Search (HCS) algorithm along with a memory module to store and recall optimal operating values in real time. While effective, initial versions of this method sometimes led to inaccurate optimization.

To address this, improvements were made by introducing multiple search modes and dynamic step sizing within the HCS algorithm, significantly enhancing both convergence speed and accuracy in tracking the maximum power points [16].

II.2.2 Soft Control

- **Fuzzy control**

Fuzzy logic control in Wind Energy Conversion Systems (WECSs) operates by handling nonlinearities and uncertainties without requiring detailed mathematical models. The control decisions are based on rule-based logic using input/output signals such as error and error variation, rather than full state-space models.

In one approach, a Takagi-Sugeno (TS) fuzzy controller uses output feedback and Linear Matrix Inequality (LMI) methods to achieve robust tracking of reference signals. To eliminate the need for precise modeling, simplified fuzzy controllers use error signals to adjust generator voltage for maximum power extraction or blade pitch angle for power stabilization, improving tracking and minimizing power fluctuations.

Another method uses error variation as input to regulate turbine speed, while fuzzy controllers applied to power converters adjust generator output and maintain power balance with the grid. For MPPT, fuzzy logic is combined with Hill Climb Search (HCS) to regulate DC voltage, avoiding the need to measure wind or rotor speed.

A master-slave fuzzy structure can be used, where the master detects wind variations and the slave ensures optimal rotor speed tracking. Generator speed reference is also generated using fuzzy logic, with a PI controller handling the actual speed regulation. To minimize steady-state reactive power, an additional fuzzy-PI controller is applied.

In systems using Doubly-Fed Induction Generators (DFIGs), TS fuzzy controllers regulate both rotor and grid-side converters to reduce speed fluctuations and mechanical stress during voltage faults. During grid disturbances, fuzzy logic is used to control both Superconducting Magnetic Energy Storage (SMES) systems and pitch mechanisms, with the SMES controller delivering superior performance. Additionally, a Quasi-TS fuzzy model accounts for uncertainties and is stabilized using parallel distributed compensation for enhanced reliability [16].

- **Neural Networks Control**

Artificial neural networks (ANNs) are used to estimate wind speed in WECSs, eliminating the need for mechanical sensors. A typical setup involves a three-layer ANN that takes turbine power and generator speed as inputs to estimate wind velocity based on the turbine's power curve. The estimated wind speed is then used to calculate the optimal rotor speed reference, and the error between actual and reference speeds is fed into a PI controller for regulation.

Another method uses phase voltages and currents as ANN inputs to directly estimate wind speed.

A more advanced approach employs a Jordan recurrent ANN with inputs such as wind velocity, rotor speed, output power, and desired maximum power. The network outputs the reference rotor speed and uses feedback with a time delay to improve prediction accuracy, with training done via backpropagation [16].

II.2.3 Hybrid Control

- **Fuzzy and PID**

Hybrid control in WECSs combines fuzzy logic with traditional controllers to improve performance and adaptability. One method uses a PD controller based on a Takagi-Sugeno fuzzy model of the pitch system, dividing the system into linear subsystems and tuning PD gains using pole placement or LQR to minimize rotor speed and pitch angle fluctuations.

Another approach employs a Mamdani fuzzy controller that receives the error and its derivative between actual and reference generator speed to regulate generator torque and enhance energy capture.

A fuzzy-PID controller integrates fuzzy-PD and fuzzy-PI schemes, using closed-loop fuzzy reasoning to auto-tune PID parameters in real time, improving system robustness.

In other designs, a conventional PID controller is initially created, then augmented with fuzzy logic to adjust its parameters dynamically, as applied in both pitch and yaw control. For yaw control, an immune PID controller is introduced, inspired by biological immune systems, where fuzzy logic is used to approximate nonlinear behaviors, resulting in a fuzzy-immune PID system suitable for hardware implementation.

Additionally, a fuzzy-PI controller is used to stabilize AC voltage and frequency at the output of a DC-AC converter, especially effective when accurate system modeling is not feasible [16].

- **Neural networks and PID**

Neural networks are combined with PID control in wind turbine systems to automatically tune the PID parameters (Kp, Ki, Kd) for improved power regulation. Backpropagation (BP) neural networks are used to adjust the PID gains in real time based on system behavior.

In pitch angle control, a Radial Basis Function (RBF) neural network is employed to fine-tune PID parameters, enhancing response to wind variations.

For rotational speed control, a wavelet neural network adjusts the PID gains by capturing dynamic system features at multiple time scales, improving accuracy and adaptability [16].

- **Fuzzy and Neural Networks**

To smooth the output power of wind farms, Generalized Predictive Control (GPC) is used to adjust the pitch angle based on a power output command. Due to wind speed fluctuations that can cause large power errors and potential instability, a Fuzzy Neural Network (FNN) is integrated to enhance the adaptability of the control system.

The FNN dynamically tunes GPC parameters in real time, allowing the controller to respond effectively to changing wind conditions. Additionally, FNN is used to adjust parameters of controllers managing frequency and power output, ensuring stable and accurate system performance [16].

II.3 Kalman Filter

The Kalman filter is an algorithm that provides an efficient (recursive) computational method for estimating the state of a given process, in a way that minimizes the mean squared error. This algorithm is highly powerful in many aspects, as it allows for the estimation of past, present, and even future states, and it can do so even when the exact nature of the modeled system is uncertain.

The main objective is to simulate the evolution of an unknown process (state vector) over time, where its value at time t is denoted by x_{t} . The Kalman filter offers a recursive method for estimating the unknown state based on all measurements obtained up to time t.

Accordingly, the Kalman filter equations are divided into two groups: time update equations and measurement update equations. The first group is responsible for projecting the current state and covariance estimates forward in time to obtain the a priori (forecast) estimates for the next time step. The second group handles the feedback, i.e., incorporating the new measurement into the a priori estimate to obtain an improved a posteriori (analysis) estimate [17].

II.3.1 Kalman filtering for wind speed prediction

In recent years, Kalman filters have been widely used for meteorological applications, including data assimilation and improving weather forecasts. However, the linear nature of the algorithm and the sometimes discontinuous nature of wind speed time series can pose significant challenges for predicting wind parameters, potentially affecting the accuracy of the forecast. While traditional linear Kalman filters have generally been effective in enhancing local air temperature predictions, their application to wind speed forecasting often leads to less satisfactory results. The proposed method addresses this issue by correcting the 10-meter wind speed forecast bias using a "polynomial" Kalman filter, where the bias estimation is based on the direct output of the forecasting model over time [17].

II.4 Artificial Neural Networks

Modern artificial intelligence methods can be divided into various categories, with artificial neural networks (ANNs) and hybrid systems being the most notable. ANNs are recognized for their efficiency, owing to their fast processing, high accuracy, and relatively simple architecture. They are particularly effective in modeling complex systems involving multiple variables. Structurally, ANNs are inspired by the biological neural networks of the human brain and consist of interconnected processing units—commonly referred to as "neurons"—organized into layers. A conventional neural network architecture typically comprises three types of layers: the input layer, one or more hidden layers, and the output layer [18].

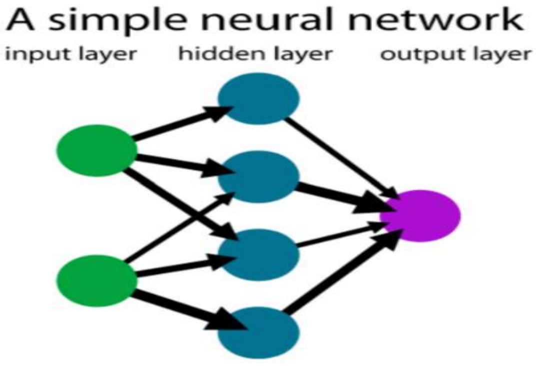


Figure II.1 : A simple neural network [19].

As shown in Figure II.1, a simple neural network operates through a layered flow of information. Each neuron in the network receives signals from previous layers, processes them using weighted connections, and applies an activation function to determine the output passed to the next layer. The input layer introduces external data to the network, the hidden layers apply nonlinear transformations to uncover relevant features, and the output layer delivers the final decision or prediction, such as classification results [18].

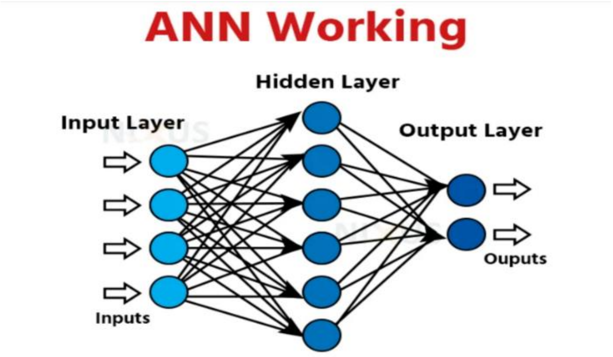


Figure II.2 : ANN Working [20].

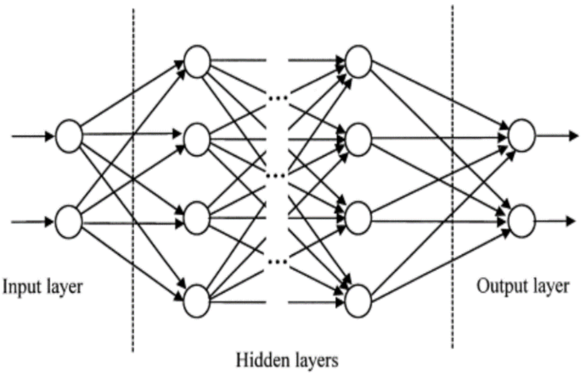


Figure II.3 : Feedforward Neural Network [21].

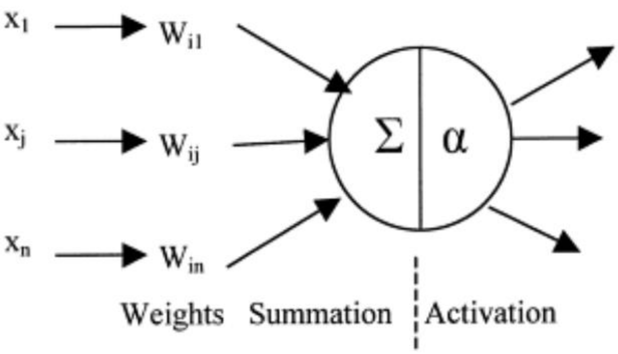


Figure II.4 : Information processing in a neural-network unit [21].

For the neuron i :

$$\alpha_i = f\left(\sum_{j=1}^{n} x_j w_{ij}\right) \tag{II.16}$$

This architecture allows neural networks to effectively model nonlinear and dynamic systems, which is essential in complex domains such as energy forecasting, image analysis, and natural language understanding. As foundational tools in machine learning, ANNs are widely employed in tasks including pattern recognition, classification, regression, and high-dimensional function approximation [18].

II.4.1 Artificial Neural Networks in Energy Systems

Artificial Neural Networks (ANNs) have become increasingly important in the field of renewable energy due to their ability to model complex and nonlinear relationships within dynamic systems. Unlike traditional modeling techniques, ANNs learn from data and can generalize patterns, making them particularly suitable for systems affected by environmental uncertainties, such as solar and wind energy systems. Their ability to adapt to dynamic data makes them well-suited for modern energy systems, particularly in modeling the variability of renewable energy sources, thereby improving efficiency and reliability [22].

ANNs are applied in various energy applications :

- **Forecasting and Prediction**

One of the most common applications of ANNs in renewable energy systems is the prediction of energy generation. For example:

In solar energy systems, ANNs are used to forecast solar irradiance and photovoltaic (PV) output based on historical data, temperature, and atmospheric conditions.

In wind energy systems, ANNs can predict wind speed, direction, and power output over short- and medium-term horizons, helping optimize energy dispatch and improve grid stability.

These predictions help reduce operational uncertainties and are crucial for integrating renewable energy sources into the power grid.

- **Control and Optimization**

ANNs are widely used for the control of energy systems. Their adaptive nature allows them to adjust to variations in system behavior and optimize performance in real time. Applications include :

Maximum Power Point Tracking (MPPT) in PV systems, where ANNs are used to continuously adjust voltage and current to extract the maximum possible power.

Control of hybrid energy systems, where ANNs manage multiple sources (solar, wind, diesel, batteries) to ensure efficient operation based on real-time load and generation [23].

- **Fault Detection and Diagnosis**

Reliability is a major concern in renewable energy systems due to the exposure of components to harsh environmental conditions. ANNs have been successfully applied to detect faults and abnormal operating conditions :

In wind turbines, ANNs can detect bearing faults, generator issues, and gearbox malfunctions.

In PV systems, they can identify shading, module degradation, and connection failures.

These diagnostic systems help reduce maintenance costs and prevent unexpected downtime.

- **Energy Management Systems (EMS)**

ANNs are also integrated into Energy Management Systems in microgrids and smart grids. In such systems, ANNs contribute by :

Predicting load demand, Managing battery charge/discharge cycles, Deciding the most

cost-effective or efficient energy source to use at any given time [22].

Table II.1 presents a categorized summary of the main Artificial Neural Network (ANN) types applied in renewable energy systems, with common use cases, advantages, and examples.

The synthesis is based on sources [24], [25], and [26].

Table II.1 : the main types of (ANNs) used in renewable energy systems.

ANN Type	Applications in Renewable energy	Advantages	Example
Convolutional Neural Network (CNN)	Spatial and image-based analysis (e.g. satellite data)	Excellent at recognizing spatial patterns	Mapping solar potential from satellite images .
Recurrent Neural Network (RNN)	Time-series forecasting (wind speed, solar irradiance, energy demand)	Captures time dependencies in data	Predicting hourly wind power generation .
Long Short-Term Memory (LSTM)	Long-range time-series forecasting in variable systems	Handles long-term dependencies, more accurate	Multi-day solar power forecast for grid operation.
Feedforward Neural Network (FNN)	Wind speed/power prediction, solar output, hydro flow	Simple, effective for basic predictions	Predicting daily solar PV output from weather data .
Radial Basis Function Network (RBFNN)	Localized, non-linear prediction in wind/solar/hydro	Fast training, good with noisy/nonlinear data	Predicting wind energy in complex terrains .
Hybrid ANN Models	Optimization tasks, combining ANN with other AI techniques	High accuracy, adaptable to complex systems	ANN + Genetic Algorithm for wind turbine power curve modeling .
Deep Neural Network (DNN)	Large-scale energy systems, smart grid integration	Models complex relationships with big data	Optimizing energy mix in national smart grid using multi-source input data .

II.4.2 Artificial Neural Networks in wind energy

Artificial Neural Networks (ANNs) have become increasingly prominent in wind energy applications due to their ability to process nonlinear, time-varying data—characteristics typical of wind behavior and turbine dynamics. Wind energy systems face unique challenges such as unpredictability of wind speed, changing atmospheric conditions, and mechanical wear in turbines. ANNs provide flexible and intelligent solutions to these challenges across various functional areas.

- **Wind Speed and Power Prediction**

One of the most prominent applications is wind speed and power forecasting. Models such as Feedforward Neural Networks (FNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks are used to predict wind behavior based on historical meteorological data. These predictions are essential for optimizing energy generation and improving grid stability. Neural networks have shown significant advantages in short-term wind forecasting due to their flexibility and ability to learn nonlinear temporal patterns [27].

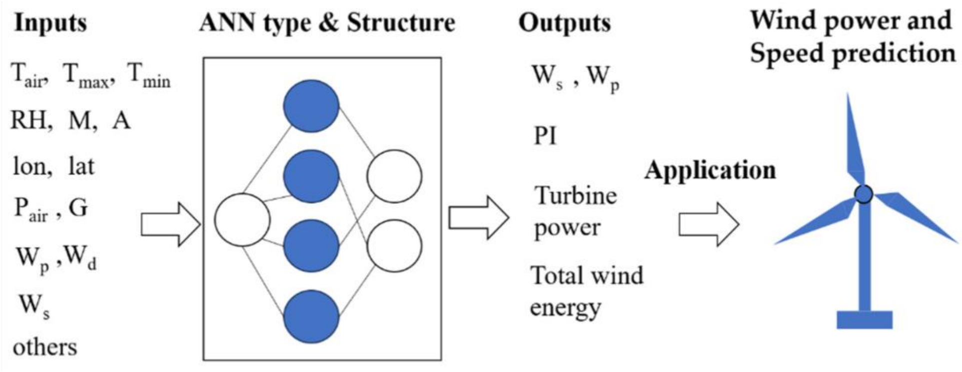


Figure II.5 : Inputs and outputs in ANNs applied to wind energy and wind speed prediction [28].

- **Fault Detection and Diagnosis of Wind Turbines**

Another important application is in the early detection of faults in wind turbine components such as gearboxes, blades, and generators. Deep Neural Networks (DNNs), Deep Belief Networks (DBNs), and Autoencoders are commonly used to identify anomalies based on sensor data, vibration signals, and operational conditions. These systems enhance the reliability of condition monitoring and significantly reduce maintenance costs and unplanned downtime [29].

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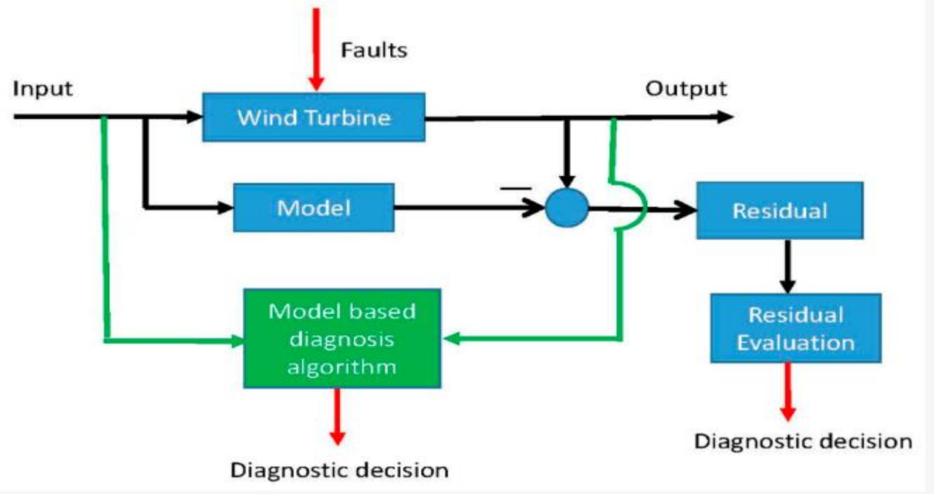

Figure II.6 : Schematic diagram example of model-based fault diagnosis [30].

- **Wind Farm Layout Optimization**

Neural networks also support wind farm layout optimization by analyzing topographical and environmental data to minimize wake effects and maximize energy output. In this domain, Artificial Neural Networks (ANNs) are often used in conjunction with Genetic Algorithms (GAs) to improve turbine placement strategies, leading to more efficient wind farm configurations [31].

- **Hybrid Forecasting Models**

Hybrid models that combine ANNs with statistical or signal processing methods have shown superior performance in prediction tasks. These include integrations with Autoregressive Integrated Moving Average (ARIMA) models, Wavelet Transforms, and Genetic Algorithms.

Such hybrid techniques improve accuracy and robustness by capturing both linear and nonlinear data characteristics [32].

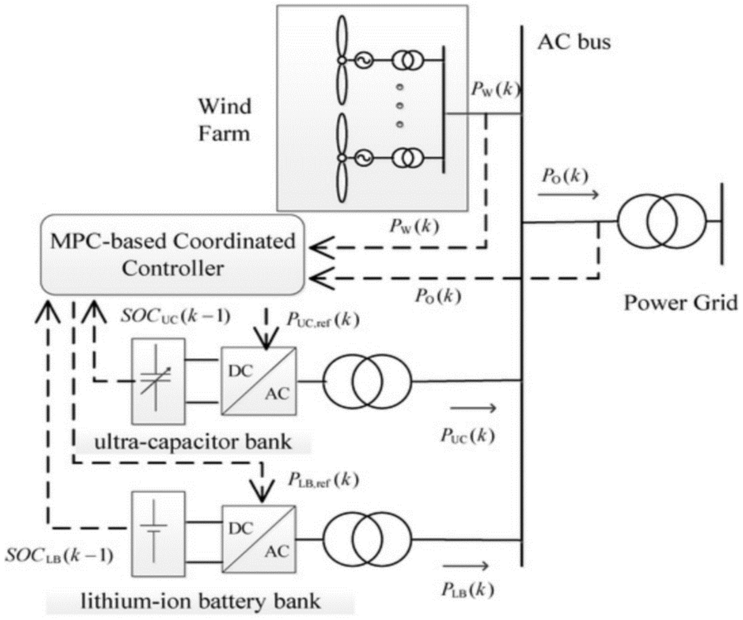

Figure II.7 : Diagram of a wind/HESS hybrid power generation system [33].

- **Rotor Speed Estimation**

A critical application in wind energy systems is rotor speed estimation, especially in systems using induction generators, where direct measurement may not be feasible. Estimation schemes use only electrical quantities (such as stator voltage and current) as inputs. Here Multilayer Perceptrons (MLPs) and Radial Basis Function (RBF) networks are among the most commonly used architectures. These networks effectively learn the relationship between input signals and rotor speed, offering a sensorless solution that enhances robustness against parametric variations and system uncertainties [34].

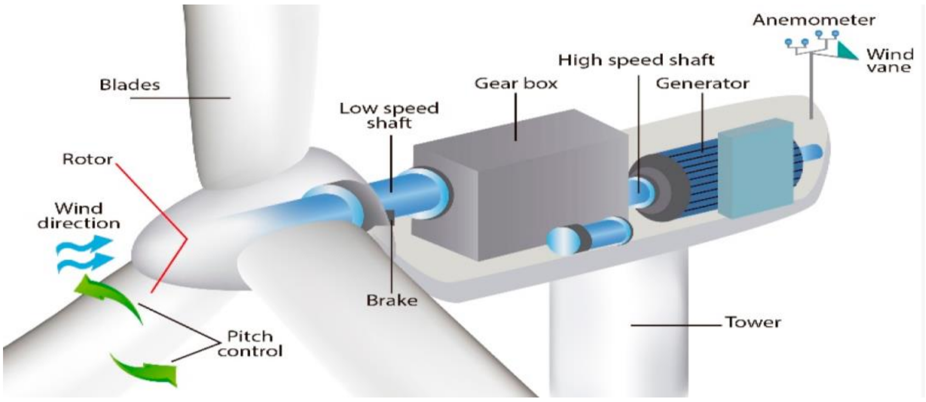

Figure II.8 : Parts of wind turbine including rotor [34].

- **Control of Wind Turbines**

Neural networks are also incorporated into control systems to manage blade pitch and generator torque in real time. ANN-based control strategies, such as Model Predictive Control (MPC) enhanced by neural networks, adapt to wind fluctuations and improve energy capture and mechanical stability. These intelligent controllers have demonstrated superior performance compared to conventional methods [35].

These diverse applications highlight the growing importance of neural networks in enhancing the efficiency, reliability, and predictability of wind energy systems, making them indispensable tools in the global transition toward sustainable energy.

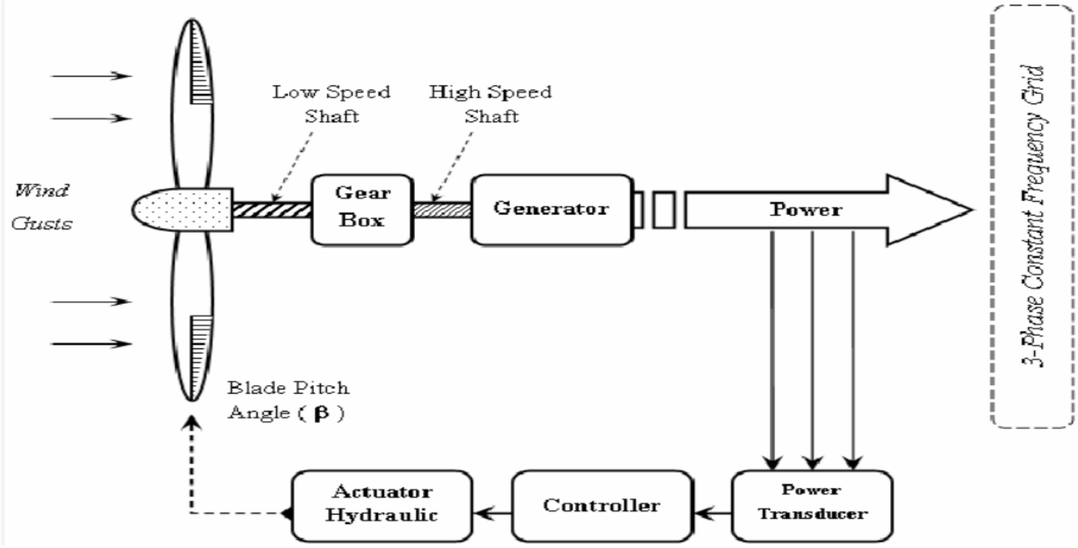

Figure II.9 : General wind turbine control loop [36].

II.5 Maximum Power Point Tracking (MPPT)

Maximum Power Point Tracking (MPPT) is a control strategy employed in wind energy systems to maximize the energy harvested from wind turbines. The power generated depends on wind speed, rotor speed, and turbine characteristics, with each turbine having a specific power curve (cut-in, rated, and cut-out speeds). MPPT algorithms such as Perturb and Observe (P&O) and Incremental Conductance (IncCond) continuously adjust the rotor speed or electrical load to ensure the turbine operates at the optimal point for maximum power extraction [37]. This approach significantly enhances system efficiency and ensures effective power extraction, particularly under fluctuating wind conditions. MPPT is especially critical in variable-speed, constant-frequency wind power generation systems [38], where maintaining maximum power output despite wind variability is essential for system performance and stability [37].

MPPT has many types, the most famous of which are [39] :

- **Perturb and Observe (P&O).**
- Incremental Conductance (IncCond).
- Tip Speed Ratio (TSR).
- Fuzzy Logic Control (FLC).
- Neural Network (ANN-based).
- Hill Climb Search.

II.5.1 Perturb and Observe (P&O)

Perturb and Observe (P&O) is a simple and effective MPPT algorithm used in wind energy systems. It adjusts the operating point slightly and observes the change in power. If power increases, the adjustment continues; if it decreases, the direction is reversed. This process repeats until maximum power is reached, though it may cause slight oscillations around the optimal point [39].

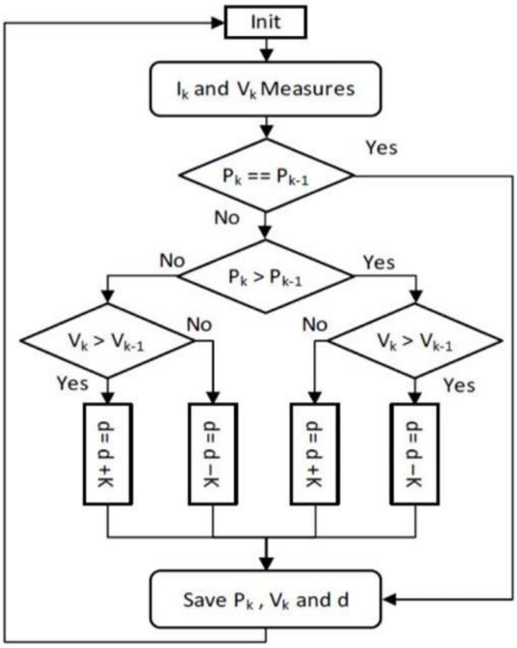

Figure II.10 : Flow Chart Of P&O MPPT [39].

II.6 Conclusion

In summary, this chapter has provided an overview of estimation strategies essential for improving the accuracy and efficiency of wind energy systems. It also highlighted the significant role of artificial neural networks (ANNs) in renewable energy applications, particularly in wind energy, where they are employed for forecasting, fault detection, and system optimization in addition to the use of MPPT. The ability of ANNs to model complex, nonlinear systems makes them valuable tools in addressing the dynamic nature of wind power. Building on these foundations, the next chapter will present the methodology and design of ANN models implemented in MATLAB/Simulink, including a detailed case study and a description of the wind energy system model used for simulation and analysis.

CHAPTER III

Simulation of Induction Generator Rotor Speed

III.1 Introduction

This chapter presents an integrated approach for rotor speed estimation in autonomous induction generator, implemented within the MATLAB environment. The proposed methodology combines a Maximum Power Point Tracking (MPPT) algorithm with a Kalman filter to develop a robust and accurate speed estimation strategy that eliminates the need for mechanical sensors while maintaining optimal performance across varying wind conditions.

The system architecture intelligently merges these two components through an artificial neural network (ANN) that incorporates both their outputs along with recurrent feedback from previous ANN estimations.

The MPPT algorithm dynamically adjusts to changing wind speeds, with its output serving as a critical input to enhance the neural network's estimation capability. Simultaneously, the Kalman filter compensates for measurement noise and system parameter uncertainties, significantly improving estimation reliability. The ANN processes these combined inputs while utilizing its adaptive learning mechanisms for continuous error correction and performance optimization.

This solution represents a significant advance in control technology for wind energy systems as this integrated approach ensures maximum energy extraction under all operating conditions while delivering reliable performance.

III.2 Description of the Simulation Model Used for Rotor Speed Estimation

In this application study, a simulation model in a MATLAB environment is developed to represent an autonomous wind energy conversion system based on a squirrel cage type three-phase induction generator (SCIG). The system aims to estimate rotor speed without the use of mechanical sensors, by intelligently processing available electrical signals, while maintaining high accuracy under non-ideal operating conditions such as wind and load changes and deviations in system parameters.

The estimation is based on a multi-layered artificial neural network with a single hidden layer. The network receives seven inputs: three-phase voltages and currents, and rotor speed estimated from the MPPT algorithm. Integrating MPPT outputs improves network performance under wind fluctuations. The network uses a feedback mechanism and its primary output is the rated rotor speed. Weights are gradually updated to adapt to operating changes, with 8 weights in the hidden layer and 7 in the output layer. Additionally, an adaptive Kalman filter is used to estimate the rotor magnetic flux (˚r) from dq-axis voltage and current measurements in the rotor reference frame, utilizing the ANN-estimated speed as an input. The filter's covariance matrices are adaptively updated to ensure numerical stability and precise computation of the electromagnetic torque. The system also contains a power management unit within an independent DC network, which regulates power distribution and battery charging by controlling the charging current and DC link voltage.

The system represents an integration of intelligent estimation, adaptive filtering and dynamic energy management technologies to ensure efficient and stable operation in autonomous wind systems. [3] [31].

The rotor speed is estimated by the artificial neural network (ANN) shown in **figure III.1**, it is a multi-layer network, where the hidden layer updates the weights : output layer (7), hidden layer (8). The ANN output is the rated rotor speed ‘ Wr_est ’. ANN has four inputs :

- Three external signals (rotor flow estimated from MPPT ‘ Wr ’ and rotor flow estimated from the KF : current and tension three-phases).
- A feedback from the ANN output with a delay [3].

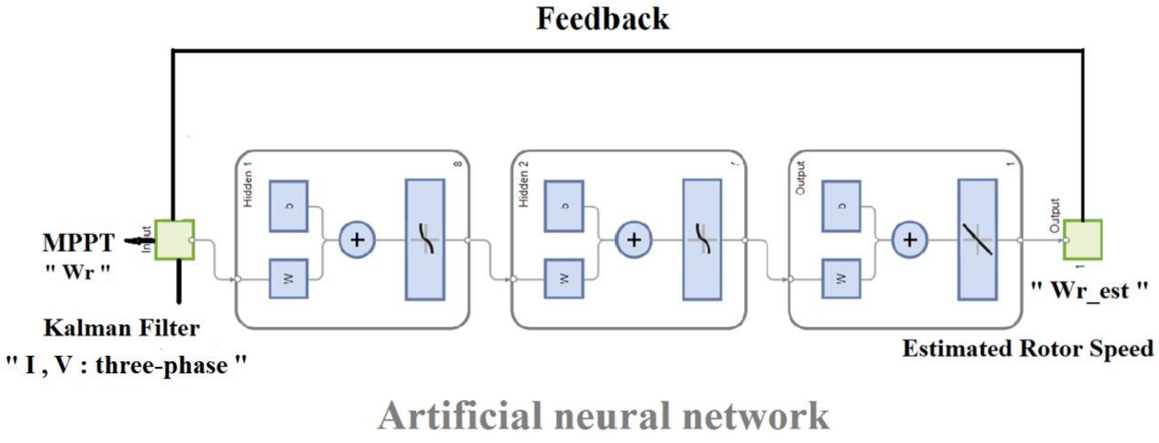

Figure III.1 : ANN-based speed estimation structure.

The following diagram **Figure III.2** shows a flowchart of the rotor speed estimation system :

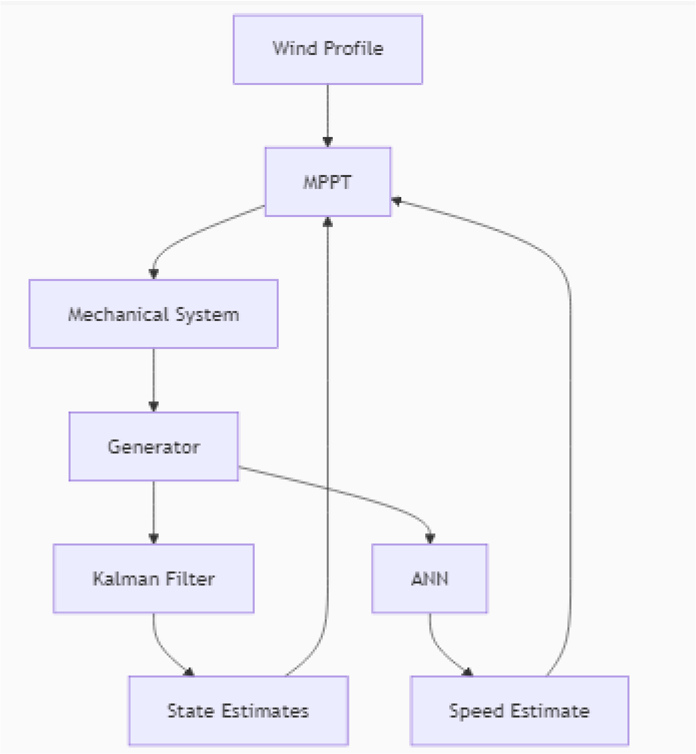

Figure III.2 : Speed Estimation System Flowchart.

- The following table reviews the main parameters of the three-phase squirrel cage induction motor (SCIG) and the direct current link system (DC Link) used in the simulation model, explaining the technical characteristics that affect the efficiency and performance of the system [3] [32] :

Table III.1 : The main Parameters of the Induction Generator and DC-Link [1][32] .

Parameter (Unit)	**Value**
Number of poles	P = 4
Stator resistance (Ω)	R = 12.3
Rotor resistance (Ω)	Rr = 10.5
Stator inductance (H)	Ls = 68.6 × 10^{-3}
Rotor inductance (H)	Lr = 68.6 × 10^{-3}
Mutual inductance (H)	Lm = 440 × 10^{-3}
Moment of inertia (kg·m²)	J = 0.02
Friction coefficient (N·m·s)	B = 0.0001
Rated speed (rpm)	rated_rpm = 1670

Rated power (W)	rated_power = 175
Rated current (A)	rated_current = 1.2
Rated voltage (V)	rated_voltage = 208
Turbine radius (m)	R = 0.75
Air density (kg/m³)	rho = 1.225
Max power coefficient	Cp_max = 0.48
Optimal tip speed ratio	λ_opt= 7.2
Cut-in wind speed (m/s)	cut_in_speed = 4
Gear ratio	G = 1.5
DC-link voltage (V)	Vdc_nom = 220
DC-link capacitance (F)	Cdc = $8.8\times 10^{--6}$
DC-link resistance (Ω)	Rdc = 300
Battery voltage (V)	batt_V = 48
Battery capacity (Ah)	batt_Ah = 9

III.3 Program Code Explanation

1. Wind Mechanical Parameters

Mechanical parameters represent the physical properties that determine the amount of energy that can be extracted from the wind. Among them are the main ones :

Turbine radius (R) : Determines the wind capture area.

Air density (ρ) : Affects the amount of energy that can be generated.

Power factor (Cp) : Determines the efficiency of converting wind kinetic energy into mechanical energy.

Tip speed ratio (λ) : The speed of rotation relative to the wind speed.

2. MPPT (Maximum Power Point Tracking)

MPPT technology aims to ensure that the maximum possible capacity is extracted from the ever-changing wind energy. In wind energy systems, the wind speed varies permanently, affecting the mechanical power available for generation. MPPT tracks the optimal operating point of a wind turbine, where the Tip-Speed Ratio λ is at its optimal value. that achieves the highest power factor.

λ is calculated at each instant of time and compared to its optimal value.

The goal of MPPT is to keep λ close to the optimal value to achieve the maximum possible power.

3. Artificiel neural network

A neural network is used in this system to estimate the rotor rotation speed based on voltage and current data in the three phases.

Network inputs: Voltages and currents of the three phases, as well as the previous estimated rotor speed (feedback) and rotor speed from the mppt.

The network contains :

An input layer (3 voltages + 3 currents + previous estimated rotor speed (feedback) + rotor speed from the mppt), a hidden layer and output layer with (estimated rotor speed).

Simplified network weights are updated every 100 time steps to promote adaptation to changes this is to enable the network to gradually adapt to dynamic changes in operating conditions (such as changing wind speed or electrical load). This periodic update improves estimation accuracy over time without the need to retrain the entire network during operation.

4. Kalman Filter

The Kalman filter is used to accurately estimate the rotor flux, which is necessary for calculating the electromagnetic torque and controlling the generator. The adaptive filter deals with noise and uncertainty in mathematical models and current and voltage measurements, the filter is based on a mathematical model according to appendix A [31] of the situation involving:

- Variables : Stator currents and rotor flux.
- Inputs : estimated speed from ann, measured dq stator currents and voltages, generator characteristics.

The Kalman filter does the following :

Integrate measurements and the model to minimize the effect of noise and predict the future state and update it with new measurements by using the difference between actual and predicted measurements and finally give a smooth and stable estimate of the magnetic flux.

5. DC-Link Voltage

DC-link voltage is the voltage on the DC-link that connects the wind generator to the storage circuits (battery) and the load. maintaining a stable voltage on the DC line is vital for securing power quality and system stability the change in DC voltage is calculated according to the power differential equation.

The DC voltage is monitored via a graph to check that it stays close to the nominal value.

III.4 Interpreting graphs

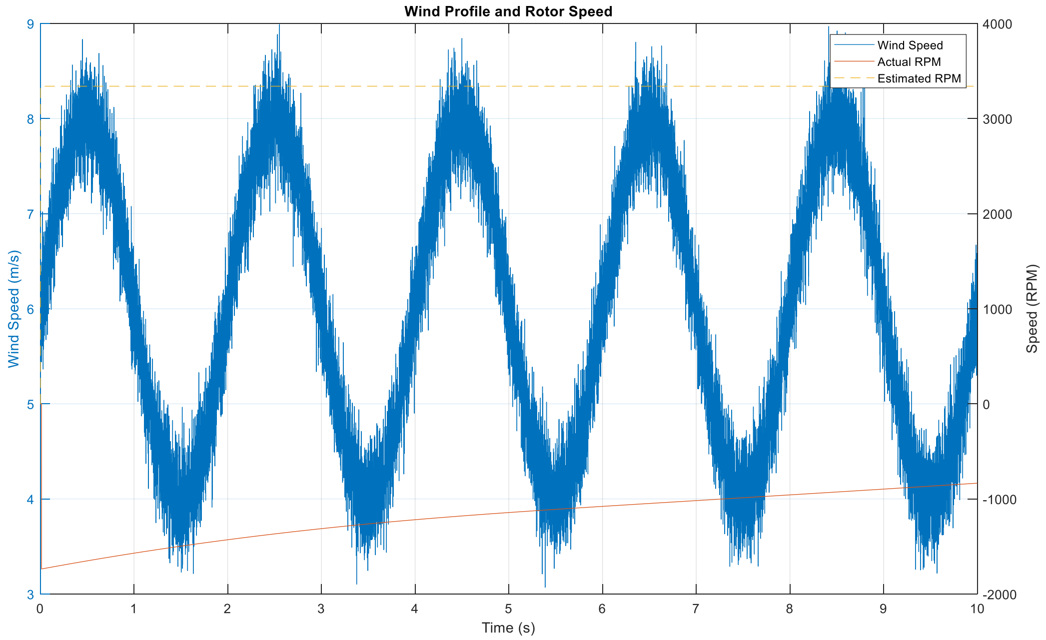

Figure III.3 : Wind Profile and Rotor Speed.

The top (blue) plot represents wind speed over time and is a sinusoidal signal with random noise and the dashed red line represents the speed estimated using ANN. The estimate from ANN is close to the maximal of the actual value around 8.4 m/s which shows the accuracy of the estimation model.

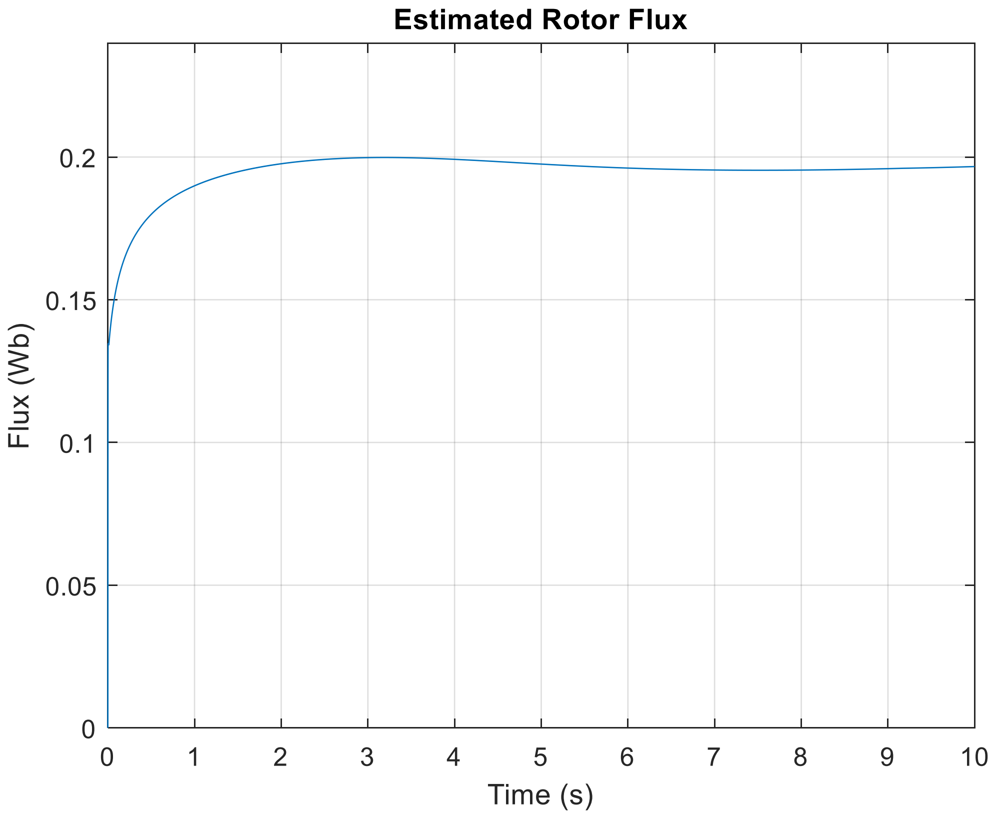

Figure III.4 : Estimated Rotor Flux.

The figure represents the magnitude of the magnetic flux in the rotor (in Weber Wb) with time. The flow starts from zero and increases until it reaches a steady state value around 0.18 Wb.

Flux oscillations reflect changes in rotor speed and stator currents. Flow stability is important for effective torque control.

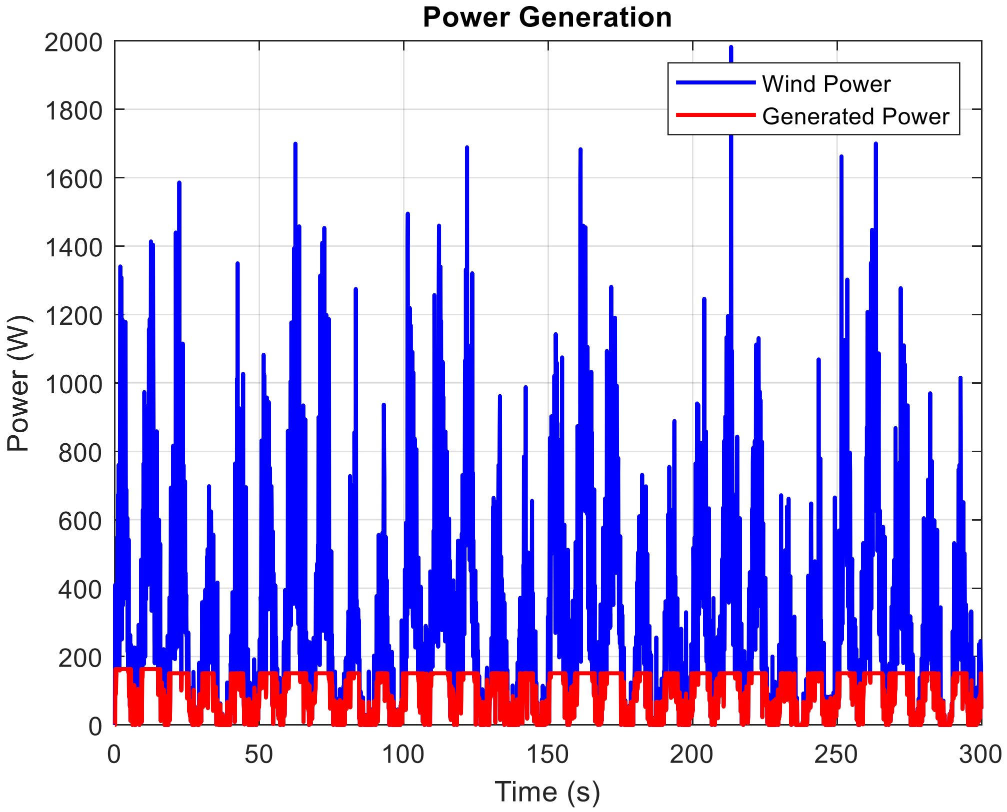

Figure III.5 : Power generation.

The Blue line represents wind power and the red line represents electrical power generated in watt.

High and oscillating wind power is an indication of rapidly changing wind speed it reaches 2000 W and the generated power (in red) appears relatively stable it starts from 0 and stable at the value of 163.5 W due to the presence of an MPPT control system that stabilizes the output.

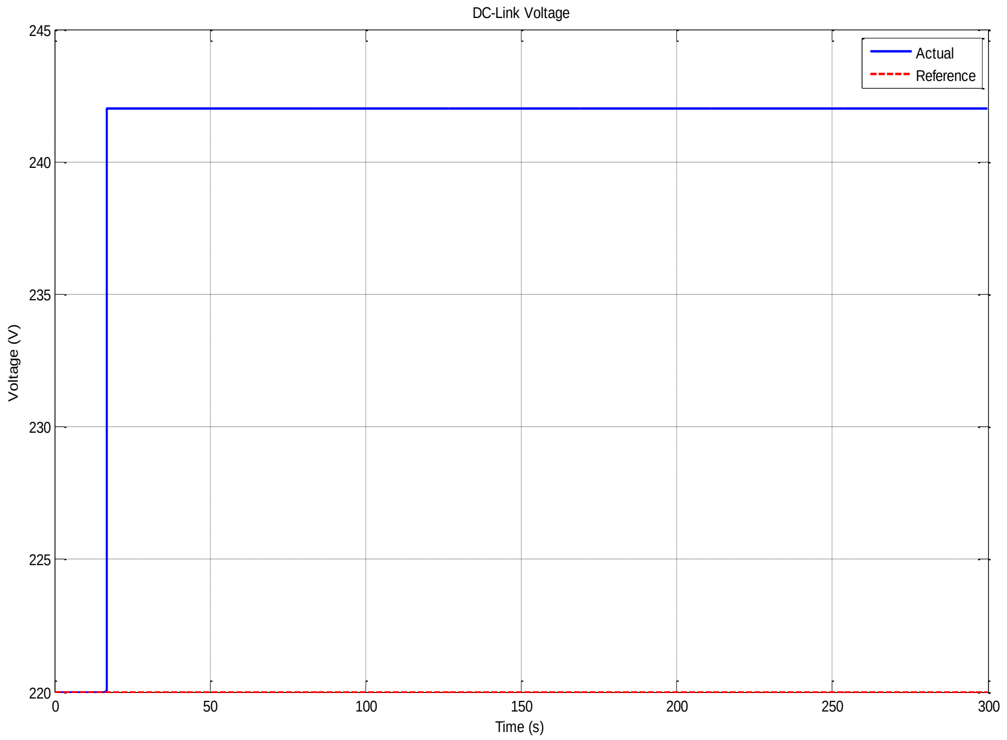

Figure III.6 : DC-Link Voltage.

The blue curve represents the actual voltage on the DC-link. Note that it rises rapidly from 220V to about 242 V at startup (in a fraction of a second), and then remains constant throughout and the red dashed curve represents the desired reference voltage (the target to be maintained), which appears to be constant at 220 V.

The actual voltage (blue) is very stable after the initial spike, meaning that the voltage control circuit works stably and succeeds in keeping the voltage at the desired level the lack of oscillations or vibrations after the initial spike indicates that the system is well-designed in terms of stability and dynamics, but there is a glitch in the tracking of the reference value and that's an error rate of about +10 %.

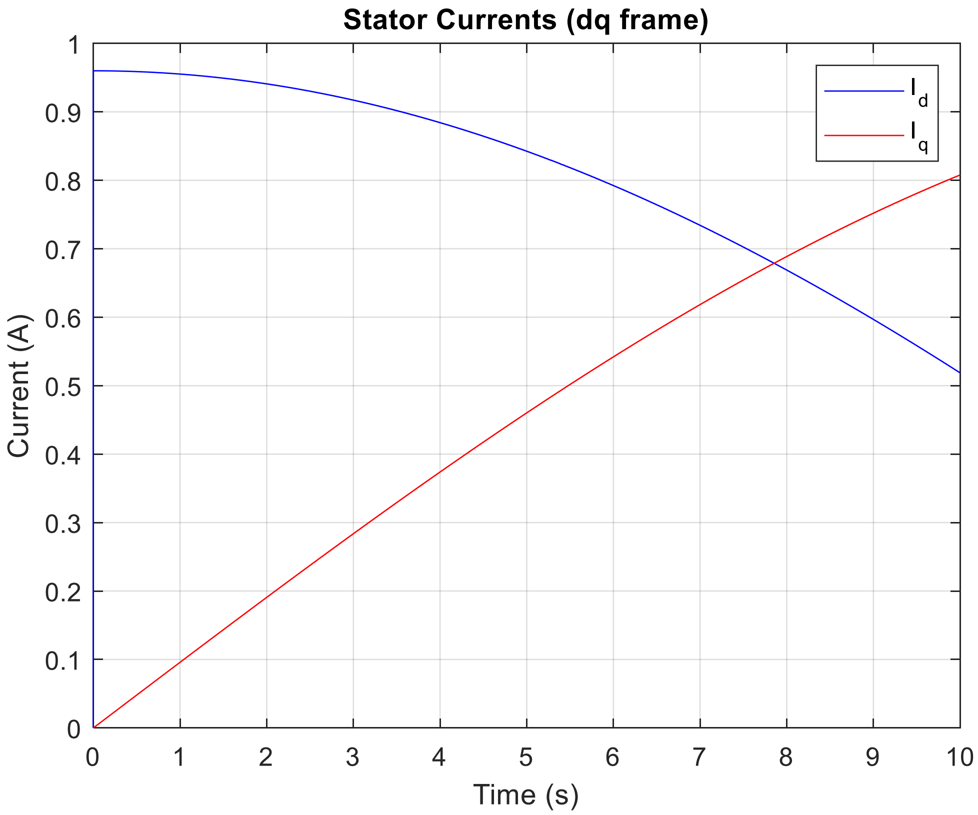

Figure III.7 : Stator Currents.

The blue line represents the current Id starts from 0.98 A and decrease to 0.53 A and the red line represents the quadrature current component Iq starts from 0 to 0.81 A. The current Id is responsible for generating magnetic flux and the current Iq is responsible for generating electric torque.

III.5 Conclusion

This chapter presented a simulated model of wind power systems using MATLAB, based on artificial intelligence "ANN" to estimate the speed of an induction generator rotor without mechanical sensors as the system achieved high accuracy under variable operating conditions, enhancing efficiency and reducing costs. The results prove the feasibility of this practical solution for autonomous power systems.

General conclusion

The objective of this thesis was to study a wind power system based on a three-phase squirrel cage type Asynchronous Generator, focusing on the estimation of two key variables that directly affect the system performance, namely Rotor Flux and Rotor Speed. To achieve this, two smart technologies were combined : Adaptive Kalman Filter for estimating Rotor Flux and Artificial Neural Network for estimating Rotor Speed. A model is also included to simulate electric power production, maximum power point tracking (MPPT), and DC-link dynamics associated with a storage battery.

firstly, we discussed general concepts about the wind energy, including its definition and the classification of wind turbines, main components, operating principle, and key applications. We also examined the factors affecting power production and wind turbine modeling then we moved to the estimation methods in wind energy systems including Kalman filter and artificial neural networks also we discussed Maximum Power Point Tracking (MPPT) techniques and their different types and lastly we presented a simulated model of wind power systems using MATLAB, based on artificial intelligence "ANN" to estimate the speed of an induction generator rotor.

Throughout these chapters, we have explored both the theoretical and practical aspects of wind energy systems-from their physical and electrical modeling to intelligent estimation techniques using the Adaptive Kalman Filter and Artificial Neural Networks. Moreover, we examined how MPPT algorithms contribute to optimizing energy output, Simulation results showed the effectiveness of the proposed system in tracking wind changes and estimating dynamic variables with reasonable accuracy, reflecting the importance of using AI tools and adaptive filters in optimizing the performance of renewable energy systems.

This work opens up promising prospects towards the development of wind energy systems by integrating artificial intelligence techniques and modern estimation filters. In the future, this system can be expanded to include more sophisticated algorithms to improve the accuracy of estimation and control, as well as the possibility of integrating it with smart grids or testing it on real application models. The methodology can also be generalized to other energy systems, enhancing the efficiency and sustainability of renewable energy production.

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Appendix A

The rotor flux estimator is developed using the Kalman filter applied to the discretized model of the induction generator. The discrete state space model is expressed as :

$$\begin{cases} x(k+1) = A(k).x(k) + B(k).u(k) + w(k) \\ y(k) = C(k).x(k) + v(k) \end{cases}$$

where k is the step , x= $[i_S\alpha \quad i_S\beta \quad \psi_{r\alpha} \quad \psi_{r\beta}]^T$, u=$[u_{S\alpha} \quad u_{S\beta}\,]^T$, y=$[i_S\alpha \quad i_S\beta\,]^T$, w and v are independent measurement noises with covariances.

$$E\{w(k)w(k)^T\} = Q, E\{v(k)v(k)^T\} = R$$

the matrices A, B and C are given by :

$$\mathrm{A} = \begin{vmatrix} 1 - T_S\gamma & 0 & \frac{T_S\mathrm{K}}{\tau_r} & Tsp\mathrm{K}w(k) \\ 0 & 1 - T_S\gamma & -Tsp\mathrm{K}w(k) & \frac{T_S k}{\tau_r} \\ \frac{T_S L_m}{\tau_r} & 1 - \frac{T_S}{\tau_r} & 1 - \frac{T_S}{\tau_r} & -Tsp\mathrm{K}w(k) \\ 0 & Tspw(k) & Tspw(k) & 1 - \frac{T_S}{\tau_r} \end{vmatrix}$$

$$\mathrm{B} = \begin{vmatrix} \frac{T_S}{\sigma L_s} & 0 & 0 & 0 \\ 0 & \frac{T_S}{\sigma L_s} & 0 & 0 \end{vmatrix}^T$$

$$C = \begin{vmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{vmatrix}$$

Where Ts is the sampling time, $\sigma = \frac{L_m^2}{L_S L_r}$, $\gamma = \frac{1}{L_{S\sigma}}\left(R_S + \frac{R_r L_m^2}{L_r^2}\right)$, K $= \frac{L_m}{\sigma L_S L_r}$ and w is the rotor speed.

The rotor flux estimation is expressed by :

$$\psi_{rKF} = \sqrt{\psi_{r\alpha KF}^2 + \psi_{r\beta KF}^2}$$

ملخص

تهدف هذه الدراسة إلى تطوير نظام ذكي لتقدير سرعة دوار المولد في نظام توليد طاقة الرياح دون الحاجة إلى استخدام أجهزة الاستشعار الميكانيكية مباشرة، وذلك باستخدام تقنيات متقدمة مثل مرشح كالمان والشبكة العصبية الاصطناعية. تُعد سرعة الدوار متغيرًا حيويًا يؤثر بشكل مباشر على عملية التحكم في المولد ، لذا فإن الحصول على تقدير دقيق لها يساهم في تحسين كفاءة النظام وزيادة كمية الطاقة المستخرجة من الرياح. ويوفر هذا النهج بديلاً منخفض التكلفة وأكثر موثوقية من أجهزة الاستشعار التقليدية، التي قد تتلف أو تتطلب صيانة دورية، خاصة في البيئات القاسية. ومن خلال هذا النموذج، يمكن تحسين الأداء العام للنظام الكهروميكانيكي بشكل عام، وتقليل التكاليف التشغيلية، وتحقيق إنتاجية أفضل للطاقة في أنظمة الطاقة المتجددة.

كلمات المفتاحية : طاقة الرياح ، تقدير سرعة الدوّار ، MPPT ، مرشح كالمان ، الشبكة العصبية الاصطناعية .

Abstract

This study aims to develop an intelligent system to estimate the generator rotor speed in a wind power generation system without the need to use mechanical sensors directly, using advanced techniques such as Kalman Filter and Artificial Neural Network. The rotor speed is a vital variable that directly affects the generator control process, so obtaining an accurate estimate of it contributes to improving system efficiency and increasing the amount of energy extracted from the wind. This approach provides a low-cost and more reliable alternative to traditional sensors, which may be damaged or require regular maintenance, especially in harsh environments. Through this model, the overall performance of the electro-mechanical system can be improved, operational costs can be reduced, and better energy productivity can be achieved in renewable energy systems.

Keywords : Wind power, rotor speed estimation , MPPT , Kalman filter, artificial neural network.

Résumé

Cette étude vise à développer un système intelligent pour estimer la vitesse du rotor du générateur dans un système de production d'énergie éolienne sans avoir besoin d'utiliser directement des capteurs mécaniques, en utilisant des techniques avancées telles que le filtre de Kalman et le réseau neuronal artificiel. La vitesse du rotor est une variable vitale qui affecte directement le processus de contrôle du générateur de sorte que l'obtention d'une estimation précise de cette vitesse contribue à améliorer l'efficacité du système et à augmenter la quantité d'énergie extraite du vent. Cette approche constitue une alternative peu coûteuse et plus fiable aux capteurs traditionnels, qui peuvent être endommagés ou nécessiter une maintenance régulière, en particulier dans les environnements difficiles. Grâce à ce modèle, il est possible d'améliorer les performances globales du système électromécanique, de réduire les coûts d'exploitation et d'obtenir une meilleure productivité énergétique dans les systèmes d'énergie renouvelable.

Mots-clés : Puissance éolienne , estimation de la vitesse du rotor , MPPT , filtre Kalman , réseau neuronal artificiel.