A Novel Fuzzy Logic Pitch Angle Controller with Genetic Algorithm Optimization for Wind Turbines

by

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Keywords: Wind turbines, pitch angle, fuzzy logic controller, genetic algorithm, optimization, power production maximization, annual energy maximization

Abstract

As one of the most preferred renewable energy sources in the contemporary world, wind turbine technology has grown in importance.

Blades are among the most crucial parts of a modern horizontal-axis wind turbines. They extract dynamic energy from the wind and convert it to rotational mechanical energy for the turbine. Blades play a significant role in the safety, stability and control of the wind power plant. Blade pitch angles are controlled online via electrical or hydraulic actuators to safeguard the turbine from hazards of extreme wind conditions. The same actuation mechanisms are also active during power production for control purposes.

Turbines operate with prespecified generated power references. In order to keep the production at this reference pitch angles are position-controlled with feedback from the power output. Conventionally, linear control methodologies are applied. Recently, soft computing techniques and especially fuzzy logic controllers are applied in this field with promising success. The fuzzy rule base, the employed inputs and parameter values play important roles in the controller performance.

This dissertation presents the design of a novel fuzzy logic blade pitch angle controller. Power regulation is carried out by this system which evaluates power error, rate of change of power error and generator speed. This set of inputs, different from the majority of the studies reported in the literature, creates flexibility in the design of fuzzy rules which compute pitch angle references to be applied to the blade actuators. Tuning the many parameters of the three-dimensional rule base, however, proves to be an elaborate task. Evolutionary computing is applied in this thesis for the tuning of these parameters.

The controller is tested with dynamic simulations of a 2 MW wind turbine model under fluctuating wind profiles and over nominal wind speeds. The performance of the novel controller is contrasted to a number of traditional pitch angle control techniques. Also tested are these conventional techniques when they are tuned by genetic algorithms. Simulation studies and data from the literature indicate superior performance of the proposed technique. An energy production improvement of 1.1 % is achieved when compared with conventional pitch control technique.

Yenilikçi Rüzgar Türbini Kanat Açısı Denetleyicisi Bulanık Mantık Yöntemi ve Genetik Algoritma ile Tasarımı

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Anahtar kelimeler: Rüzgar türbinleri,kanat açısı denetleyicisi, bulanık mantık, eniyileme, genetik algorithma, yıllık enerji üretimi eniyilemesi, güç üretimi eniyilemesi

Özet

Günümüz dünyasında en çok tercih edilen yenilenebilir enerji kaynaklarından biri olan rüzgar türbini teknolojisinin önemi giderek artmaktadır.

Kanatlar, modern bir yatay eksenli rüzgar türbinlerinin en önemli parçaları arasındadır. Rüzgardan kinetik enerji toplayarak türbin için dönme mekanik enerjisine dönüştürürler. Kanatlar, rüzgar türbinlerinin güvenliği, stabilitesi ve kontrolünde önemli bir rol oynar. Kanat eğim açıları, türbini aşırı rüzgar koşullarının tehlikelerinden korumak için elektrikli veya hidrolik mekanizmalar aracılığıyla çevrimiçi olarak kontrol edilir. Aynı çalıştırma mekanizmaları, kontrol amacıyla güç üretimi sırasında da aktiftir.

Türbinler, önceden belirlenmiş güç referanslarıyla çalışır. Üretimi bu referans kanat açılarında tutmak için, güç çıkışından gelen geri besleme ile konum kontrollüdür. Geleneksel olarak, lineer kontrol metodolojileri uygulanır. Son zamanlarda, yenilikçi hesaplama teknikleri ve özellikle bulanık mantık denetleyicileri bu alanda umut verici bir başarı ile uygulanmaktadır. Bulanık kural tabanı, kullanılan girdiler ve parametre değerleri, denetleyici performansında önemli roller oynar.

Bu tez, yeni bir bulanık mantık kanat hatve açısı kontrol cihazının tasarımını sunar. Güç regülasyonu, güç hatasını, güç hatası değişim oranını ve jeneratör

hızını değerlendiren bu sistem tarafından gerçekleştirilir. Literatürde bildirilen çalışmaların çoğundan farklı olan bu girdi seti, kanat aktüatörlerine uygulanacak hatve açısı referanslarını hesaplayan bulanık kuralların tasarımında esneklik yaratır. Bununla birlikte, üç boyutlu kural tabanının birçok parametresini en iyilemek, ayrıntılı ve yenilikçi bir önerme konusu olduğunu kanıtlamaktadır. Bu tezde, bu parametrelerin ayarlanması için yenilikçi hesaplama uygulanmıştır.

Önerilen kontrolcü, 2 MW'lık bir rüzgar türbini için dalgalı rüzgar formları ve nominal hız üzerindeki hız profilleri ile dinamik olarak benzetim çalışmaları yapılmıştır. Yeni kontrolörün performansı, bir dizi geleneksel kanat açısı kontrol tekniğiyle karşılaştırılmıştır. Genetik algoritmalar tarafından en iyileme çalışması sonrasında bu geleneksel teknikler de test edilmiştir. Benzetim çalışmaları ve literatürden elde edilen veriler, önerilen tekniğin üstün performansını göstermektedir. Geleneksel tekniklere kıyasla % 1,1'lik bir enerji üretim arttırımı sağlanmıştır.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

Wind farms play an evergrowing role in the world's energy generation. In the past fourty years, wind energy has become incredibly popular all around the world. The utilization of wind energy has significantly expanded. The development of wind turbine technologies is being supported by numerous research teams from various fields.

Every year, thousands of wind turbines are built and put into service all over the world. Their primary objective is to assist the local power grid by generating electricity from renewable resources, which would raise the proportion of green resources used. The construction of larger and more powerful wind turbines that can gather significant amounts of wind energy results from the development of technology, manufacturing techniques, and economies of scale, which results in more competitive electricity production [2].

Wind turbines can be classified from a variety of view points based on the wind flow, axis of rotation, generator type and mechanical structure. They can be classified as upwind or back wind from the wind flow perspective. Figure 1.1 illustrates the classification of turbines based on wind flow. Turbines can be categorized as horizontal or vertical with respect to the rotational axis orientation. They have direct drive or gear boxed types.

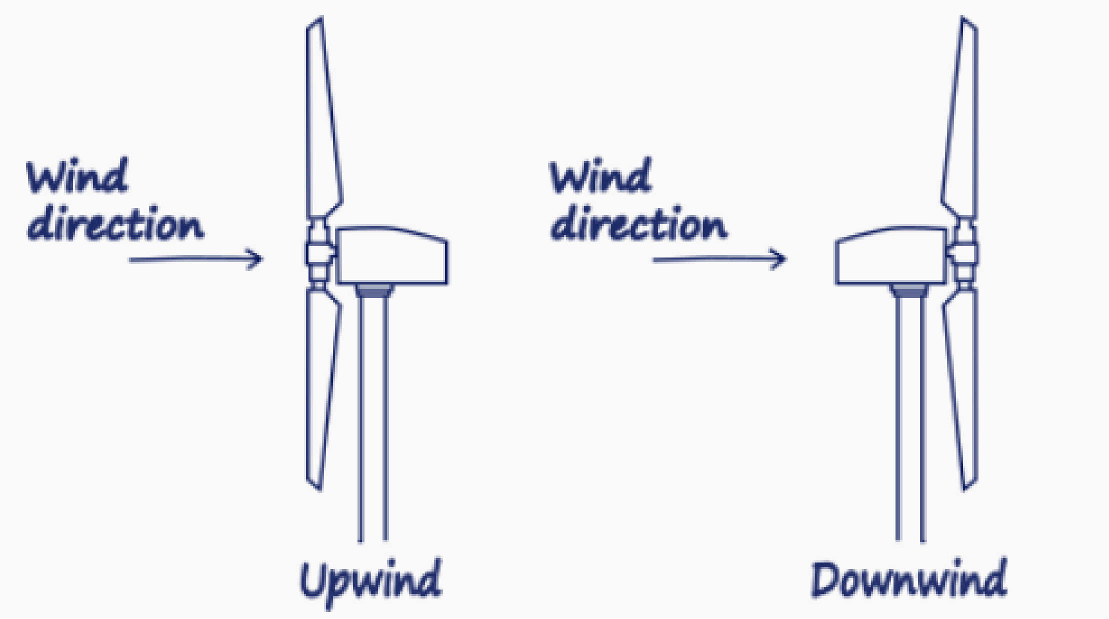

FIGURE 1.1: Upwind and downwind turbines

Rotational axis orientation can be considered as one of the most significant features which define the turbine mechanism. Research about wind turbines is mainly concentrated on horizontal axis wind turbines (HAWT). Moreover, the HAWTs are generally divided into two groups based on the main shaft's connection to the generator. If the main rotor is directly connected to the generator without a gearbox, the of configuration is referred to as "direct-drive" [1].

The components of a horizontal-axis wind turbine are blades, nacelle, hub, low speed shaft, gearbox, generator and electrical converters. Figure 1.2 shows the configuration of modern horizontal axis wind turbines. The rotor of a HAWT consists of generally three blades and a hub that transmits the rotational energy to the generator through a main shaft and gear box. The speed of the turbine is defined as the speed of the rotor. It depends on the absorption of wind's kinetic energy. The rotor blades of the turbine play a crucial role on speed regulation, safety and reliability of the turbine. They are mounted on the hub in a way that they can be rotated about a pitch axis. The rotation of blades is facilitated by pitch bearings between the hub and the blades and hydraulic or electric actuators. Each blade of the rotor can be controlled independently in order to set a certain blade angle called pitch angle [2]. The positioning of a blade with respect to the inflow direction has an important effect on overall wind turbine dynamics. Blades generate lift and drag forces which rotate the overall rotor and eventually generate electricity.

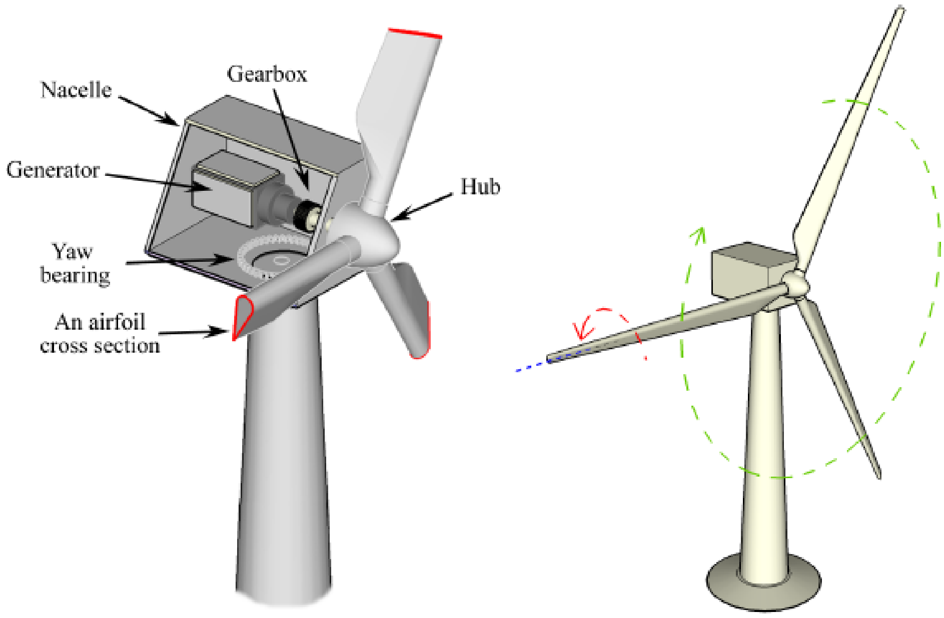

FIGURE 1.2: Configuration of HAWT [1]

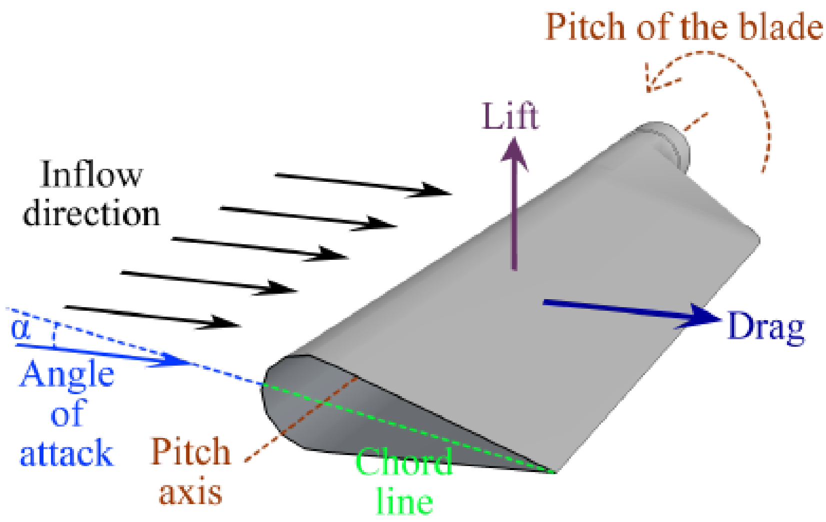

FIGURE 1.3: Section view of a wind turbine blade [1]

Figure 1.3 illustrates the general cross section view of a modern horizontal axis wind turbine's blade. By rotating the blade along the pitch axis, main speed of the turbine is regulated. Acceleration, deceleration and keeping the turbine speed steady can be achieved via pitch angle control in a state-of-the-art horizontal-axis wind turbine. Throughout the dissertation, design of pitch angle control techniques will be the main objective.

1.1 Motivation and Objectives

The constraints and shortcomings of the existing designs of wind turbine controllers serve as the motivating force behind the research activities reported in this document. Within the life span of a wind turbine, rotors encounter many dangers because of the faults of pitch angle controllers. Highly fluctuating wind profiles and extreme speeds of wind can affect the turbine's service life negatively. A defect of the pitch angle control system may degrade the reliability and safety of the turbine. By designing a suitable controller, the turbine operation can be optimized in many disciplines such as safety and power maximization. The objective of this study is to develop a pitch controller that achieves reliable power production under high wind speeds and fluctuating wind profiles. This would improve annual energy production of a wind turbine.

1.2 Contributions

A number of control methodologies are reported for blade angle control. PI, PID, PID with gain scheduling, Fuzzy Logic, robust control and neural network techniques are developed for a variety of wind applications. In today's modern and commercial wind turbines mainly PID controllers are employed for pitch angle control.

This thesis provides the following contributions in wind turbine pitch angle controller design:

- An innovative blade angle controller with fuzzy logic is designed. This design features the careful selection of three fuzzy system inputs.

- A detailed simulation environment is developed for a modern wind turbine with a doubly fed induction generator (DFIG).
- Genetic algorithm based parameter optimization is applied for the designed fuzzy controller.
- When tested under demanding wind conditions, the proposed fuzzy blade controller optimized by genetic algoritms outperfoms conventional and fuzzy system based blade controllers reported in the literature.

A 2 MW wind turbine in doubly fed induction generator (DFIG) configuration is modeled in software environment with included thermal and electrical systems. Simulations are run for several different wind cases. Compared to earlier models of wind turbines, our simulation environment is more detailed with respect to wind flow analysis, turbine modelling and control structures. Any kind of pitch angle controller with different control theories can be implemented and simulated.

With genetic algorithm based optimization the fuzzy logic controller, performance with more advanced results are obtained. Improved solutions in terms of settling time and maximization of power can be considered as the virtues of GA optimization.

1.3 Roadmap of this dissertation

The background information and associated works are presented in Chapter 2. Three major sections contribute to this chapter. In the first part, general definitions and summary of wind turbine history and technologies are covered. Second section of the chapter consists of six sub sections. Controller technologies of existing wind turbines are briefed. Existing P, PI and PID and feed forward controllers are described. Neural network based systems, sliding mode controllers, model predictive control and fuzzy logic controllers are discussed. Genetic tuning for wind turbines is covered.

Chapter 3 is on the mathematical modelling of horizontal axis wind turbines. The computer aided engineering software employed for modeling in this thesis is discussed in detail. Simulation characteristics and background disciplines are summarized.

In Chapter 4, PI and PID techniques for a pitch angle control are described with methodologies and theoretical background. This is followed by simulation results with the these control methods. A comparison between PI and PID applications and a general overview are presented.

Chapter 5 details the main topic of the dissertation. Fuzzy logic control design process is presented. The methodology and background theory is discussed. Simulation results with the 2MW wind turbine model under the novel fuzzy pitch angle controller are shown.

Chapter 6 improves Chapter 4 by adding genetic algorithm based controller parameter tuning. An overview of the genetic algorithm optimization is presented and the application results for the PI and PID controllers are given. A comparison study with the results of Chapter 4 is presented.

Similarly, Chapter 7 is an extension of Chapter 5 with genetic optimization of previously designed fuzzy logic pitch angle controller. In this chapter, applied techniques, simulation results and a discussion are presented. Majority of the contributions of the thesis are discussed in this chapter.

The final part of the dissertation is the conclusion chapter. This chapter presents the overall conclusion of the thesis and future work is discussed.

Chapter 2

Background and Related Work

2.1 General Background of Wind Turbines

Modern commercial wind turbines work with aerodynamic principles. The kinetic energy of the wind flow is converted to electric energy in many steps. As a result of wind moving toward the turbine blades, a wind turbine operates according to the principles of lift and drag forces. These forces cause the turbine to rotate, and as a result, the rotor of the generator that is connected to the turbine, provides electrical energy [3]. WTs are categorized as either horizontal axis wind turbines (HAWT) or vertical axis wind turbines (VAWT) depending on the arrangement and layout of the blades and their rotation plane (HAWT). HAWT is more expensive and sophisticated than VAWT, but because of how much more effective it is, it is more widely used. A WT can be categorized as either direct-drive, in which case the turbine's rotor is directly coupled to the electrical generator, or gearbox-based, in which case the power shaft is split into a low speed shaft on the turbine side and a high speed shaft on the generator side by the gearbox. In terms of number of blades there exits many configurations of wind turbines. The most efficient and commonly used configuration of modern wind turbines are with three blades however, there are still commercially available wind turbines with different numbers of blades.

Figure 2.1: Two and three bladed wind turbines

Climate change and environmental pollution will be mitigated by using renewable energy to meet the world's energy needs in the future. Most of the world's energy demand (around 80%) is met by fossil fuels, causing environmental and climate damage, despite the growth of energy demand at an average annual rate of around 2%. In light of this, and the growing safety concerns regarding nuclear energy, many countries have established ambitious targets for renewable energy sources that emit low greenhouse gases and pollutants, including wind energy [4]. According to REN21 (2017), in order to meet those targets, there will need to be a substantial increase in the amount of wind capacity installed worldwide over the next few decades. To achieve that growth, wind farms must be designed and installed in high-wind-energy regions and existing farms must be upgraded [4].

In the coming years, the energy industry sector will continue to focus on saving energy and making the best use of intermittent resources. More important than constructing new plants is utilizing the existing energy resources and operating industrial units to the fullest. Efforts should be made to evaluate existing waste heat-recovery systems and their characteristics as there is a compelling need for waste heat recovery from operating units. Wind farms (WFs) produce relatively low amounts of heat (approximately 90–150 °C), making them more suitable for use in heating than in energy generation. It is generally possible to recover waste heat and use it for space heating and process heating. The district heating (DH) sector can offer significant advantages such as the ability to utilize surplus waste heat from industrial processes and the use of renewable energy sources more efficiently. While district heating might be an apparent application, the agricultural and livestock sector can also benefit significantly by such an application. Greenhouse space heating, produce cooling (absorption cycle) and milk heating (pasteurization process) are just a few of the possible technical uses of the excess heat from WFs. The location of wind turbines (WTs) near rural and agricultural lands is an apparent advantage in this case. Engineering analysis and representative case studies will be performed to evaluate the overall benefits of such a system with the use of excess heat from WTs for additional heating [5]. Several researchers are working on waste heat recovery (WHR) applications and the number of researchers is increasing. According to Safaei et al. [6] compressed air energy storage (CAES) can cover district heating needs by enabling heat recovery. In a 25-km distance, a minimum gas price of $0.025/kWh renders heat recovery economically advantageous, while at 50 km, it makes no economic sense. Various energy carriers can serve industrial plants, residential areas, and the service sector by combining the supply and demand streams of independent users [7]. Local renewable energy sources with the ability to provide heating and cooling for a local area were examined by Perry et al. [8]. A combination of a solar/thermal (PV/T) system and heat recovery units was investigated by Alfagi et al. [9]. They found that as the temperature of air flow increased, so did the electricity produced by PV/T hybrid modules. In such systems, electricity and heat production should be optimized according to demand requirements.

It has been 20 years since Betz and Joukowsky [10] published seminal works in the field of wind-turbine aerodynamics, and especially in the optimization of horizontal-axis wind turbine (HAWT) rotors. Glauert (1935) revolutionized the field of physics when he formulated the blade-element momentum (BEM) theory. A theory such as this, which has later been extended with many "engineering rules", is the basis of all rotor design optimization codes currently used in the industry (e.g., reviews by Sørensen 2011 [11], and 2016 [12]). Using advanced aerodynamics, modern HAWTs have been able to achieve power coefficients of around 0.5 (based on aerodynamic efficiency), which is close to the maximum theoretical Betz–Joukowsky limit of 0.593, given the inevitable aerodynamic losses. Furthermore, if the incoming flow is known a priority, the performance of those turbines can be reasonably predicted. It remains difficult to predict wind-turbine and wind-farm performance under real conditions, which is one of the obstacles to optimizing wind farms' layout, operation, and control. Despite its turbulent nature and non-stationary nature (due to the diurnal cycle and synoptic forcing variability), the atmospheric boundary layer (ABL) interacts with wind turbines in complex ways. It is modulated by ubiquitous thermal effects and is often heterogeneous (due to topography and land surface heterogeneity). Furthermore, turbulent wake flows that form downwind from wind turbines result in substantial power losses, both because of reduced wind speed in wake flows and because of increased fatigue loads and associated maintenance costs [13] [14]. Thus, any improvement in the understanding and prediction of ABL flow interaction with wind turbines and wind farms could contribute to increasing wind energy's economic feasibility. Wind farms are affected by a wide range of atmospheric flow scales, as illustrated in Figure 2.2. At horizontal length scales wider than about 2000 km, and in the range of 2–2000 km, macroscale and mesoscale weather phenomena are responsible for the variability in free atmosphere flow. Using a combination of large-scale atmospheric motions, the Coriolis force, aerodynamic forces on the land or sea surface, canopy structures, buildings, topography, and wind turbines, as well as atmospheric stability, the ABL inside and around wind farms is structured and evolved. The continuous range of turbulence scales within the ABL, including the integral scale (on the order of 1 km and 100 seconds) and the Kolmogorov scale (on the order of 1 mm and 1 ms), plays an influential role in adjusting the ABL around wind turbines and farms (including wakes generated by turbines) and, ultimately, improving their performance. ABL flows and their two-way interaction with wind farms are particularly challenging because of the multi-scale nature of atmospheric turbulence. Figure 2.3 illustrates the properties of the wake behind the first turbine. For analytical wind farm models, the single turbine wake is one of the building blocks.

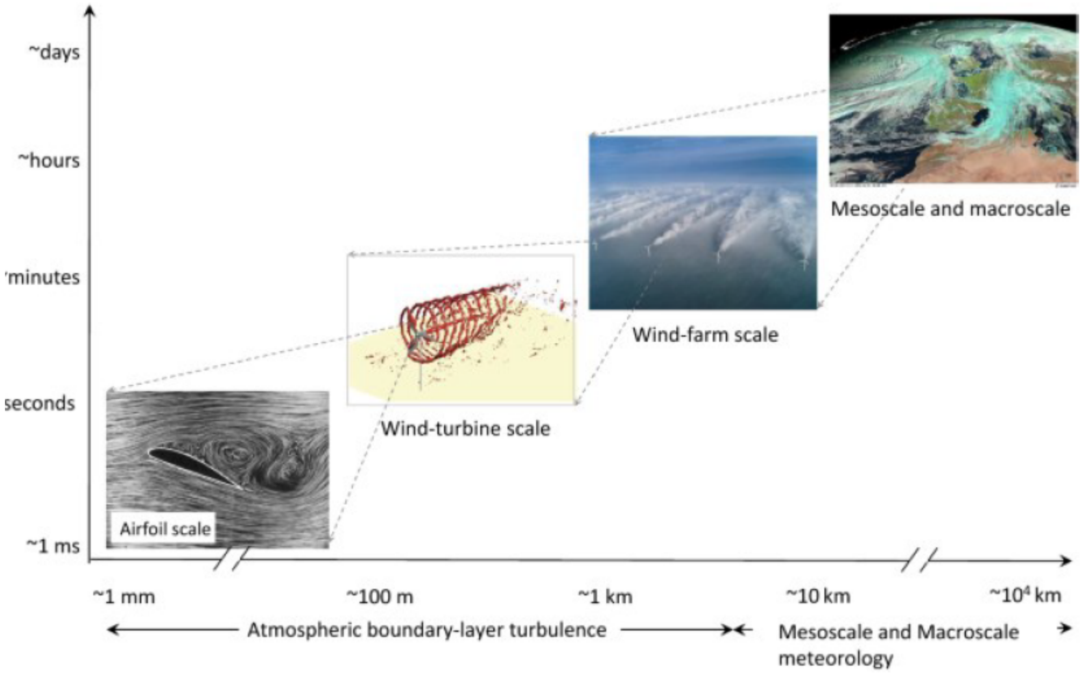

FIGURE 2.2: From turbine airfoil scale to meteorological effects

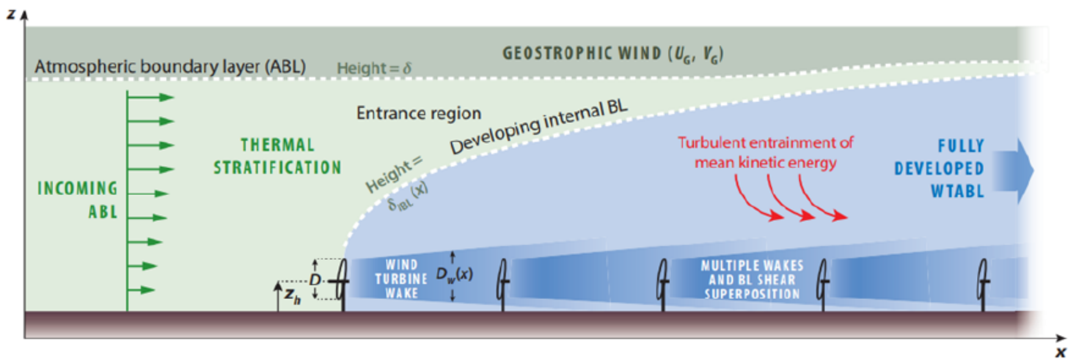

FIGURE 2.3: The dynamics of fluid mechanical flow in wind farms

2.2 Controllers of Wind Turbines

A growing need for alternative energy sources has prompted the rapid development of wind energy systems [15]. Figure 2.4 shows that, according to data provided by the global wind energy council (GWEC) [16], there will be about 651 GW of installed wind capacity in the world by the end of 2019. As compared to 2018, this represents an increase of 10 % in global wind capacity. As a result of the continuous demand for alternative energy sources, wind capacity is expected to increase exponentially over the next few years. Over the years, the designs of WTs have evolved from simple to complex. There is a need to incorporate control systems to ensure that wind turbines operate efficiently and that wind energy is effectively utilized. This is because of the complexity and dependence on weather and environmental factors of wind energy systems [17]. A control system is incorporated into wind turbines to make them more capable of coping with wind variability while producing energy in a cost-effective and reliable manner.

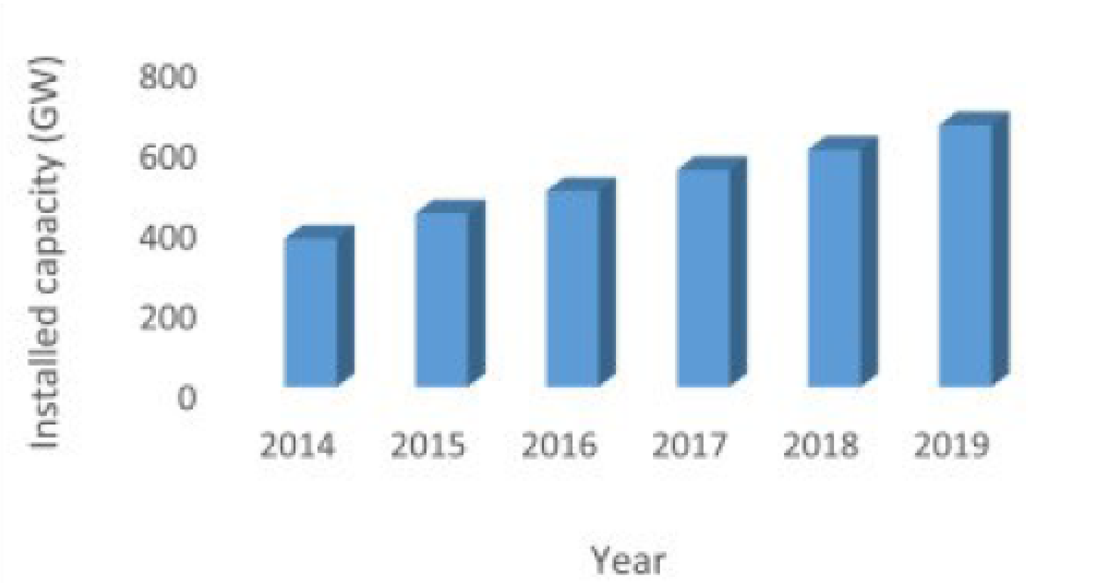

Figure 2.4: Capacity of wind installed around the world

In addition to providing grid integration stability, WT control schemes also mitigate static and dynamic mechanical loads, maximize power production, and maintain a continuous power supply to the grid [18]. The WT generator torque and blade pitch angle should be optimally controlled to achieve the aforementioned control objectives. The torque control of the generator allows the rotor speed of the turbine to be varied by employing MPPT strategies. This allows us to make use of as much wind power as possible. For the turbine to turn at optimum speed, the generator torque must be the shock absorber. In addition, pitch angle control ensures smooth power production by controlling the wind's input torque. As power electronics have advanced, WT systems have also been improved in various ways, particularly when considering the quality of the system. It is impossible to overemphasize the role played by power electronics components of the WT in stabilizing grid integration and enabling variable speed operation [19]. Several research papers have extensively explored individual control methods associated with wind systems, but few have attempted to review the various control strategies in one research paper. A recent review of these control techniques focused mostly on MPPT and pitch angle control of WTs [20] [21]. Rather than discussing the pitch control of wind turbines themselves, the authors in [21] discussed the pitch angle controller for WTs. WT operating regions were not discussed in [21] although the authors mentioned it. Pitch angle controllers were not addressed in [20], which focused on pitch control methods. Here, we review to fill the gap in this field. During the control of WT systems, power and speed control are two significant factors to consider. In most cases, WT extracts power in the form of 2.1:

$$P_w = 0.5\rho A C_p V^3 \tag{2.1}$$

where P_w indicates wind power, ρ represents air density, A is rotor area, the power coefficient C_p depends on tip speed ratio (TSR) λ and pitch angle β. The wind velocity is V, λ represents the relationship between V and linear velocity on the tip blade 2.2 :

$$\lambda = \frac{wR}{V} \tag{2.2}$$

w and R show the rotor speed and radius, respectively.

There are different control methods for each control system depending on the operational region and control objective. Any WT system operates in distinct regions, as shown in Figure 2.5. For the analysis of each WT control technique, it is essential to understand each of these operating regions.

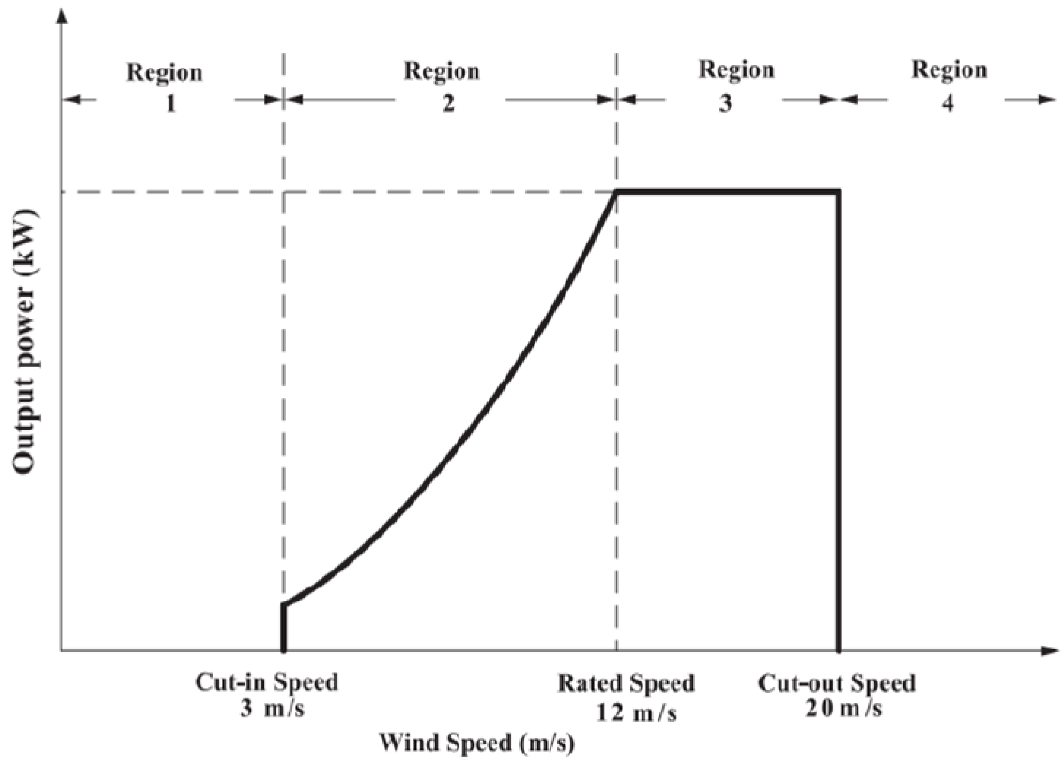

FIGURE 2.5: Operating regions for a wind turbine

The wind turbine does not generate power in region 1. The WT rotor cannot rotate in this region due to low wind speeds. When the wind speed exceeds the cut-in wind speed of the WT, the WT enters into idle mode. WTs can generate power in region 2 at a range of wind speeds, but not at nominal power. The primary focus is on maximizing power production. Wind power content varies with average wind speed as shown in equation 2.1. To ensure maximum power production, the rotor speed is varied to keep λ at an optimal level as the wind speed changes.

Maximal power can be achieved by operating the WT at an optimal tip speed ratio λ_{opt} with the rotor blades pitched at an optimal angle β_{opt}. Therefore, maximum power is generated by the generator torque controller τ_g which achieves λ_{opt} and is expressed as a function of rotor speed 2.3:

$$\tau_g = Kw^2 \tag{2.3}$$

Where w is rotor speed and K corresponds to aerodynamic constant of the WT, as 2.4:

$$K = 0.5\rho\pi R^5 \frac{C_{p_opt}}{\lambda_o pt^3} \tag{2.4}$$

$C_{p_{opt}}$ shows the coefficient of optimal power, and R indicates the blade radius [22] [23] [24] .

WT transits into region 3 as it reaches the rated wind speed. Often, region 3 is considered to be the full load region. The pitch angle controller controls the rotor rotation at nominal speed while the generator outputs rated power in this region where the wind speed is between the rated and cut-out speed. Region 3's control objective is to limit power production, in contrast with region 2's maximal power production goal. To ensure constant rated power from the wind, both torque and rotor speed are limited on the WT generator. Under varying wind conditions, proportional-integral-derivative (PID) control is used to regulate the WT speed with pitch blade control.

Wind turbines employ several control strategies before the cut-out speed to deal with high wind speeds that would otherwise threaten the turbines. Therefore, all WTs are designed with a power control technique. Controlling stalls or pitching can be done in this manner. Active stall control and passive stall control are two types of stall controls for WTs. These control methods are described in Figure 2.6, and Table 2.1 summarizes its advantages and disadvantages.

As the wind speed increases, the power generated by the wind energy conversion system (WECS) increases. The extracted power is highly affected by small variations in wind speed. The grid voltage must be constant in amplitude and frequency

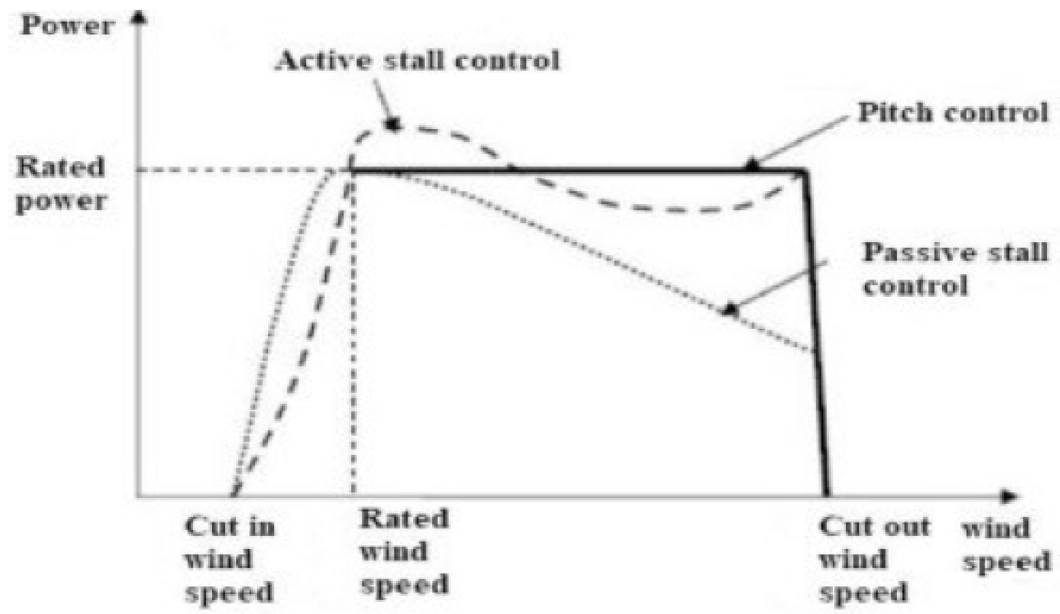

FIGURE 2.6: Controlling power of a wind turbine

TABLE 2.1: Control summary of wind turbine

Control Method	**Advantage**	**Drawback**
Passive Stall	Low Complexity	Suitable for small WT only
Active Stall	WT Blade angle is optimized according to wind speed	During high wind speeds the generator rotor speed is reduced
Pitch Control	Power control system that is efficient	Pitch mechanism adds complexity and cost

in order to be compatible with this power. Therefore, control strategies must be implemented to ensure maximum power and constant voltage in WECS [25]. The typical grid connected WECS is shown in Figure 2.7. Directly or through a gearbox, the wind turbine is connected to the generator. The wind turbine converts kinetic energy into mechanical energy. In order to convert mechanical energy to electrical energy, generators are used. The wind energy system is connected to the grid through converters. Depending on the wind speed, the wind turbine can produce its rated output.

Nonlinearity, rapid variations in wind speed, and uncertainty are challenges faced by wind power plants. In order to solve them efficiently, an advanced controller is needed. Integrating advanced controller into WECS in order to increase efficiency

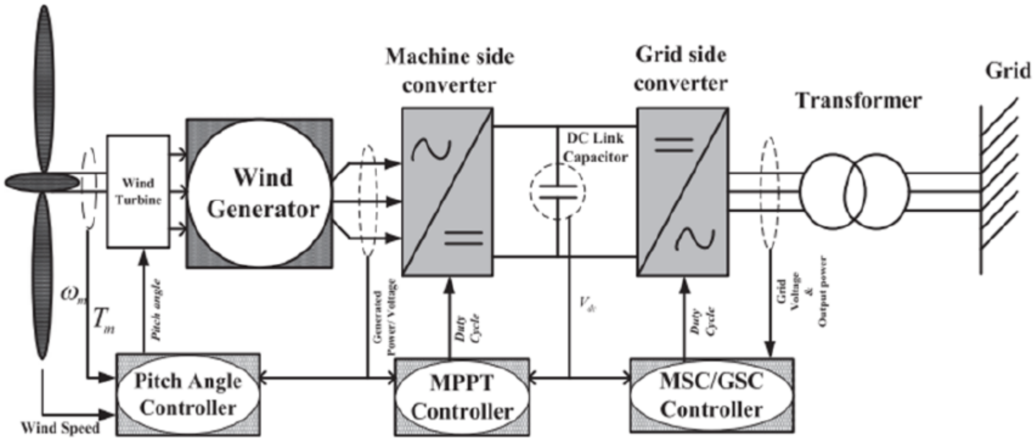

Figure 2.7: Wind energy conversion systems

in terms of power conversion and blade control design. Many researches have been conducted in order to develop a control strategy for WECS that can be integrated with grids. The controllers must be simple, reliable and cost-effective in order to be able to withstand the fluctuation caused during its operation. A comparison of WECS's different control strategies is shown in Figure 2.8.

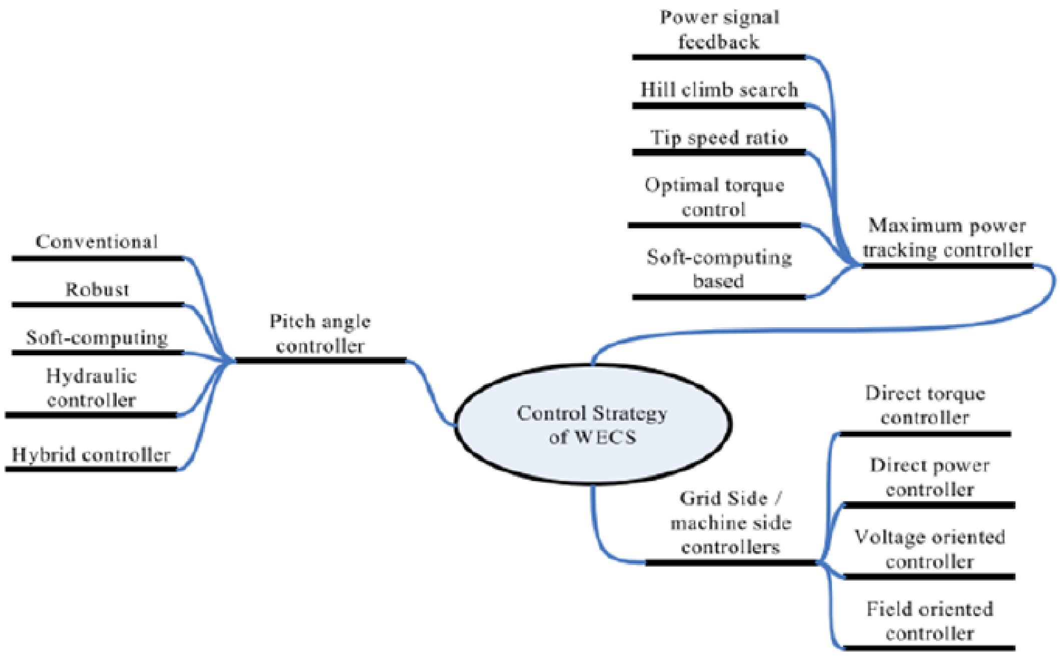

Figure 2.8: Wind energy conversion schematics

2.2.1 Pitch Angle Controllers

The pitch control WT senses the output power several times every second using an electronic controller. When the power level exceeds the prescribed safe level, an electronic signal is generated to pitch the turbine blades out of the wind. When the power level drops, the turbine blades are tucked into the wind or turned backward to catch the wind. By pitching the WT blades, a minimum power loss can be achieved, resulting in a capture of power equal to that produced by the wind generator. WTs with pitch controlled turbine blades have an active control system that reduces torque and rotational speed by changing the pitch angle of the blades. High rotational speeds and aerodynamic torques can damage equipment when using this type of control in high wind speeds. A WT's pitch control and stall control differ primarily at high wind speeds. For pitch-controlled turbines, active pitch control is used to control the rotational speed of the blades at high wind speeds, whereas stall-controlled turbines rely on the aerodynamic design of the blades. When the wind speed exceeds the rated wind speed, pitch controlled systems maintain a constant power output, but stall controlled systems cannot. The rotation of the WT blades is used for both pitch control and active stall control. WT blades operate differently because they turn. Active stall control of the WT turns the turbine blades into the wind instead of away from the wind so the lift force on the blades is reduced. Two types of pitch control are available for WTs: collective pitch control (CPC) and individual pitch control (IPC) [26] [27]. Electric or hydraulic controllers can implement both control methods [28].

Power output is regulated mechanically by the pitch angle controller. Angular speed is controlled by the wind turbine's output torque, and mechanical output power is controlled by the torque. Wind turbines with high rated generators are designed to protect the wind generator from sudden gusts of wind [29]. Low wind speeds increase the power of the machine by adjusting the pitch of the blades. If the pitch angle controller is unable to limit the rotor speed below the optimal speed, it acts as a brake system and protects the generator during higher wind speeds [30]. Variations in wind speed are used to determine the pitch angle control and rotational velocity control. Wind turbines generate aerodynamic power by adjusting their pitch angle. Due to blade pitching, there is a minimal loss of power, so the power captured is the same as the power generated by the wind generator [31]. In order to control the rotor's speed, the pitch angle controller continuously monitors the operation and adjusts the blade pitch. In order to enhance the efficiency and stability of wind energy conversion systems, pitch angle controllers are essential and useful controllers. The pitch system generally consists of a motor and an electromechanical actuator. Electric pitch controllers and hydraulic pitch controllers are the two types of pitch systems [28].

2.2.1.1 P, PI, PID Controllers

Wind turbine blades are controlled collectively by the same control method in the majority of commercial wind turbines [14]. There are no differences in pitch between WT blades regardless of the existence of independent servomechanisms. A CPC uses traditional proportional-integral (PI) control laws and its main goal is to limit wind power capture by adjusting pitch angles as the rotor speed is regulated. It is the difference between the nominal rotor speed reference and its actual value that determines the controlled variable in this case. As shown in 2.5,

$$\beta_c = K_p(1 + \frac{k_i}{s})(w_{ref} - w) \tag{2.5}$$

Where β_c represents the collective demand on blade pitch angles, for the proportional controller K_p is utilized, the integral gain is K_i, w_{ref} is to reference the rotor speed and w is speed measured at the rotor axis. Region 3 is responsible for implementing this control. The CPC has been the subject of several researches [32] [33] [34]. As described in [35], Schlipf demonstrated that CPC was effective for controlling WTs. CPC has traditionally been implemented using PI control with gain scheduling, but the constant need for load reduction has motivated the development of various modern approaches to CPC. To overcome modeling uncertainties, adaptive and robust techniques have been introduced. Adaptive CPC is described in [36][37] to address disturbance rejection in WTs. As a result of turbulent wind conditions, this adaptive technique was further explored. WT blades are erroneously assumed to receive equivalent aerodynamic loads under the CPC strategy. This causes unbalanced loads on the rotor disk, which can result in stress on the WT and eventually failure [37].

In small wind energy conversion systems, conventional controllers are most commonly used. The PID/PI controller controls the rotor speed and generated power. Smaller WT systems can benefit from these controllers. Typically, conventional controllers determine pitch angle reference based on wind speed, generator power, and rotor speed [38]. Research on conventional controllers can be found in [39] [40] [41]. Although these controllers are simple, accurate wind speed measurements cannot be obtained [42]. This controller has a slow response time compared to other controllers. A rotor speed and generator power based pitch angle controller is the most efficient and reliable conventional controller. Gain scheduling can improve the control performance of a system with non-linear characteristics. This method is often used to counteract the sensitivity of the aerodynamic torque to pitch angle since it is based on how the output power changes with pitch angle. In a conventional controller with gain scheduling, the relationship between the controller gain and the system sensitivity is inversely proportional, which makes it more reliable than one without it.

An ordinary pitch angle controller uses PI/PID controllers to control rotor speed or power generation. For conventional controllers, pitch is determined by input parameters such as rotor speed, generator power and wind speed. PI/PID controller is fetched with the error signal and the wind turbine is supplied with the generated pitch angle reference. Using conventional converters with gain scheduling, non-linear systems can be controlled more effectively. Aerodynamic torque is sensitive to pitch angle, which is to overcome with gain scheduling [43]. Variations in output power with pitch angle determine the aerodynamic sensitivity of the system. There is an inverse relationship between the sensitivity of the system and the controller gain. Therefore, gain scheduling-based conventional controllers are more reliable than non-gain scheduling-based controllers. With gain scheduling, PI-based pitch angle control is illustrated in Figure 2.9.

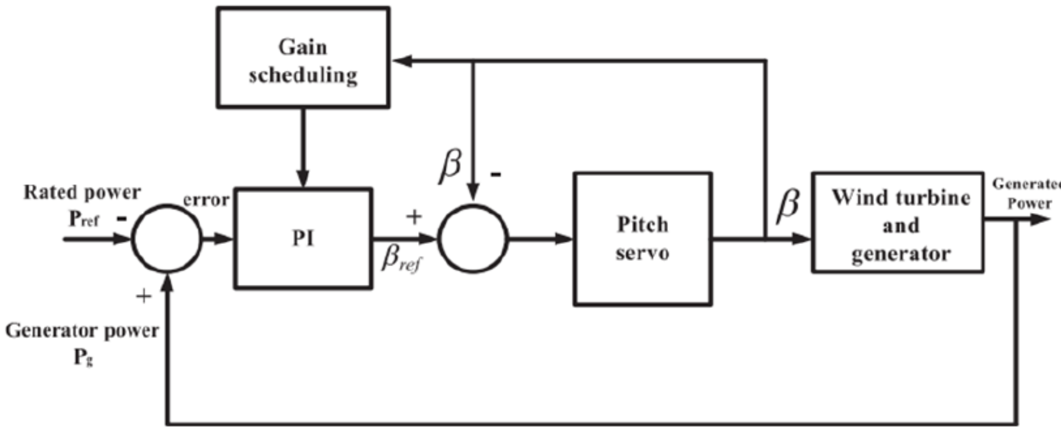

Figure 2.9: Gain scheduling based on PI-based pitch control

According to Muljadi et al. [31], the wind turbine's power can be maintained at an optimal level using pitch control and generator load control. Optimal power is maintained by monitoring power versus rotor speed and maintaining rotor acceleration. Pitch rate is controlled according to wind speed with the controller. A smoothness factor depends on rotor speed variation and inertia. Based on the operating characteristics, the effects of slow and fast pitch rates were examined for different wind speed regions.

A PID-based pitch controller was developed and analyzed using root locus techniques by Jauch et al. [44]. A short circuit fault near the wind turbine is used to analyze and test the controller's performance. By stabilizing the power system, grid integration can be achieved. Power system oscillations can be dampened by the pitch actuator. There is an investigation of the turbine's grid frequency and active stall and a suitable inference is drawn.

PI controllers with fuzzy logic control(FLC) were proposed by Zhang et al. [45]. The complexity of the system increases due to the PI based controller's requirement for system knowledge. Wind speed nonlinearity prevents the PI controller from achieving the dynamic characteristics of wind turbines. A gain schedule is used to overcome the disadvantages of conventional PI controllers. This work implements and compares FLC-based control strategies with PI-based systems and the results show that FLC-based systems have a low fatigue load.

A PI controller was proposed by Junsong Wang et al. [40] to provide a time delay to hydraulic-based pitch controllers. PI controller gain is determined using a graphical approach. The stabilizing region of wind generation system is analysed and the strategy does not require linear programming. By using MATLAB/Simulink, the controller is validated and the results show that it is efficient at reducing computation time and complexity.

Hwas et al. [39] discuss the method of calculating the gain of PI-based pitch controllers. To calculate the gain of the system at different wind speeds, the authors specify both analytical and simulation methods. Quadratic control law is implemented in below wind speed region for selection of operating point. Using a 5 MW wind turbine, the system is validated using simulation based calculation method that is simpler and faster than analytical method.

Qian et al. [41] proposed a prediction-correction pitch angle control strategy. Using the wind speed data, the moving average method predicts pitch value, while the PI controller associated with it analyses control error. Consequently, this method can reduce the influence of wind speed fluctuations on pitch angle. The cost and complexity of the system are high since the wind speed measuring sensor is incorporated into the controller.

Zhang et al. [46] developed a PI-resonant pitch controller for the mitigation of unbalanced loads. In this technique, individual pitch controllers (IPCs) are used. In this controller, a PI controller with two resonant controllers is implemented. The proposed method reduces the load on wind turbines. Pitch error is used to determine and minimize the unbalance of the system. Conventional pitch controllers have the major disadvantage of failing to track the system's non linearity.

An adaptive and fault-tolerant wind turbine control scheme is developed by Habibi et al. [47] using a PID-based fault-tolerant controller with a nussbaum-type function. The proposed controller offers several advantages over available methods, including the capability to handle nonlinear dynamics of wind turbines, including model uncertainty, the ability to ensure system stability through the use of an adaptive self-tuning gain algorithm, and resilience to variations in wind speed. Furthermore, an unknown direction of control can be accommodated and unexpected actuator faults can be accommodated.

To control the pitch of a wind turbine, Wang et al. evaluated the performance of a fractional order PID (FOPID) controller with an anti-windup strategy. Pitch control is coupled with active tower damping control to prevent undesired oscillations on the tower caused by pitching activity. FOPID-based control system results in an improvement in the wind turbine's control performance, according to simulation results. Compared to other techniques, conventional controllers have a very high response time. For conventional controllers, prior knowledge of the system is required. They are therefore suitable for small-scale wind power systems.

2.2.1.2 Feed Forward Controller

Commercial wind turbine blade pitch control algorithms typically rely solely on feedback, as shown in Figure 2.10.

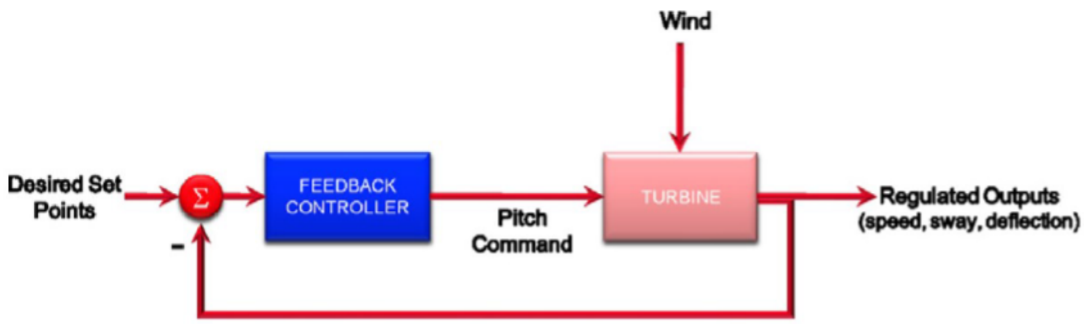

FIGURE 2.10: WT control with only feed back

An error in generator speed is often used to control blade pitch by a proportional-integral (PI) based collective blade pitch controller. There has been recent evidence that more advanced feedback controllers can reduce structural fatigue loads [48] [49]. In addition to the generator speed, these advanced controllers use strain gauges and position encoders for individual pitch control. It is possible to measure wind speed remotely using LIDAR (Light Detection and Ranging). It is now realistic to measure the wind speed upstream of a turbine using LIDARs that are smaller, more cost-effective, and more reliable. By using disturbance feedforward control, we can take advantage of additional information such as wind speed measurements. Figure 2.11 shows how this feedforward control can be combined with either standard or advanced feedback controls.

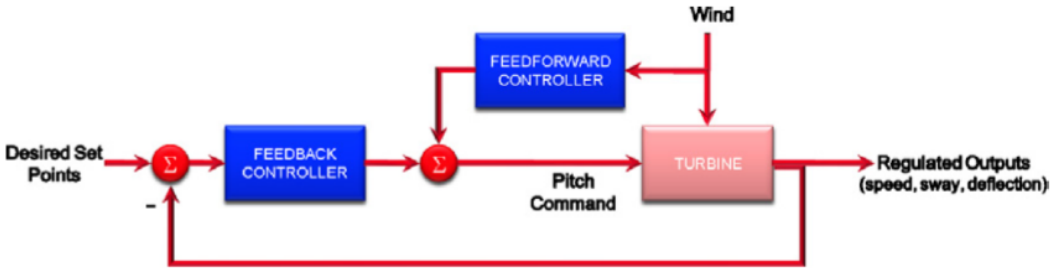

FIGURE 2.11: Combined feedback/feedforward control

This type of wind speed measurement is being actively researched for its use in reducing fatigue loads on turbines. An approach to disturbance accommodating control with inputs from a Lidar simulator has been studied by Harris et al. [50]. In combination with preview wind speed inputs, Laks et al. [51] studied feedforward/feedback MIMO control. Kühn and Schlipf [52] studied feed-forward control, which is composed of a static gain schedule coupled to a low pass filter. There were two feed-forward designs studied by Dunne et al.[53]: collective-pitch model-inverse feed-forward using a non-causal series expansion and individual pitch gain-scheduled shaped compensator. A feed-forward controller uses LIDAR to measure incoming wind speed as an input. By reducing structural loading, three of the designs are more efficient than standard feedback control. Recently, Ren et al. combined feedback controllers with feed-forward controllers. PID controller parameters are adjusted using fuzzy algorithms in the feedback loop. In addition, variable universe theory is proposed for optimizing fuzzy algorithms to overcome large variation in input wind speed. Using feed-forward loop, he proposes feedback linearization to solve nonlinear problems. The sliding mode algorithm improves the robustness of feedback linearization. The feed-forward loop can thus compensate for the time-delay deficiency of wind turbines. Using the proposed controller, the system can be controlled more accurately and robustly [54]. Gain-scheduled feedforward controllers were designed by Bao et al. [55] to augment baseline feedback controllers in wind turbine loads above rated operation, using pseudo-LIDAR (light detection and ranging) wind speed measurement. By employing gain scheduling strategy, the feedforward controller was first developed using a linearised model at a wind speed above rated. It was then expanded to the full operational envelope above rating. Simulation studies have demonstrated that the proposed control strategy can reduce rotor and tower loads for large wind turbines.

A variable-speed wind turbine (VSWT) output feedback controller was proposed by Jabari Asl and Yoon [56] to increase turbine efficiency. In designing the controller, both the electrical and mechanical dynamics of the turbine are taken into account. For the full dynamic, the rotor acceleration is a damping term, which is not highly accurate compared to previous studies, this paper's approach uses an observer to estimate this information in order to increase the system's reliability. The dynamic model of the turbine is also robust against structured and unstructured uncertainties. A numerical simulation is presented and compared with an adaptive controller available on the market. The system performs better than other methods in terms of its response and performance. Using disturbance feedforward control, Laks et al.[57] investigated load mitigation through preview-based control. A more realistic comparison is made between performance based on highly idealized rotational wind measurements and that of more realistic stationary wind measurements. With reasonable pitch rates, excellent performance gains can be obtained with idealized, "best case" measurements. A more realistic wind measurement, however, indicates that errors in determining the shear local to each blade, without further optimization of the controller and/or better data processing, can negate any advantages obtained by utilizing preview-driven feed-forward. Figure 2.12 illustrates preview, a feed-forward control variation that uses advance knowledge of imminent disturbances (or commands). Because LIDAR measures wind approaching the turbine rather than at it, this technique is feasible using LIDAR technology. Hence, measurements of wind perturbations can be taken before they hit the turbine.

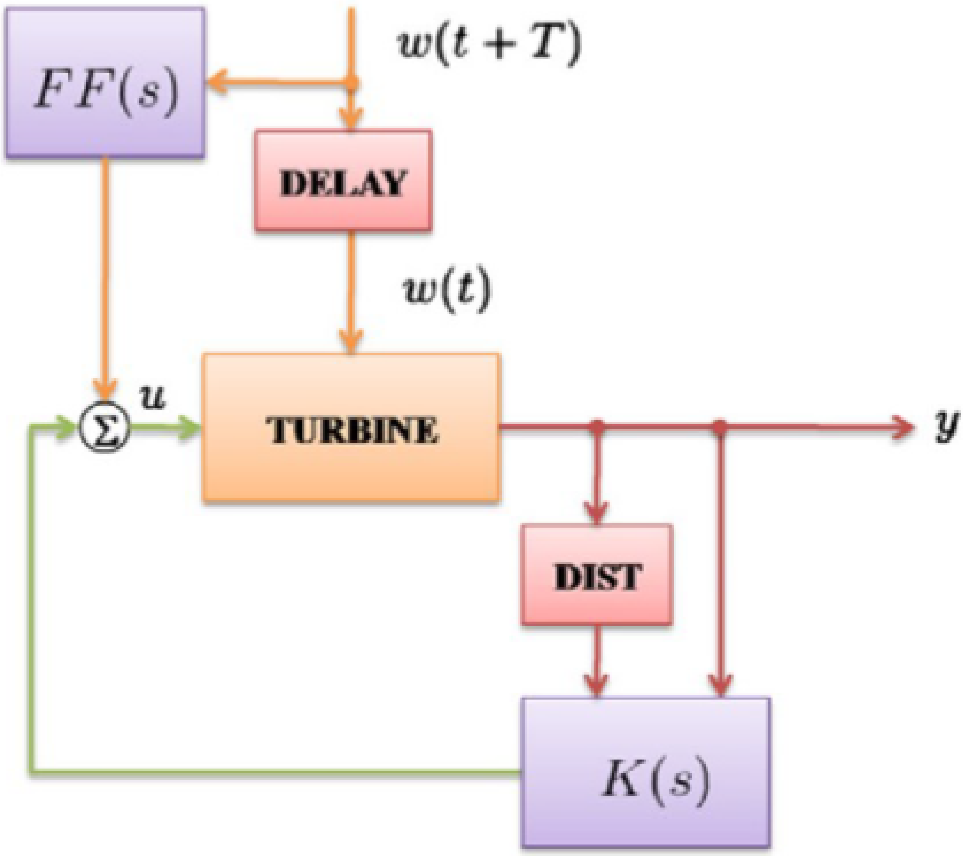

FIGURE 2.12: Feedback preview control

2.2.1.3 Neural Network Controlled Wind Turbines

With soft computing controllers, uncertainties in wind energy systems may be overcome quickly, predictably and efficiently due to variations in environmental conditions. They are based on artificial techniques. A metaheuristic algorithm, fuzzy logic controller (FLC) and artificial neural network (ANN) are the most commonly used techniques with these controllers. In a variety of control systems, ANN is also a popular control technique [58]. A controller can be controlled by rotor speed, output torque, wind speed, pitch angle or a combination of these variables. If the purpose of the WT control is to optimize power at winds above the rated wind speed, ANN is suitable. An ANN can also be used to estimate the nonlinear characteristics of the WT. To maximize power extraction during wind speed variations, a neural network approach is proposed to control (WECS) mechanical speed. A four-layer ANN controller with feed-forward architecture is described in Figure 2.13 [59]. The input variables of the ANN are the desired speed and the generated speed. ANN controllers produce torque as their output [59]. To achieve the required precision of the proposed approach, the number of hidden layers and their neurons is determined empirically [60] [61]. Repeated learning algorithms were used. To search for the optimal synaptic weights, the Levenberge Marquardt algorithm was applied to train the ANN. Due to its fast convergence properties and robustness, it is an excellent algorithm for optimizing quadratic errors. Approximately %70 of the setpoints were used for training, and %30 for testing [62].

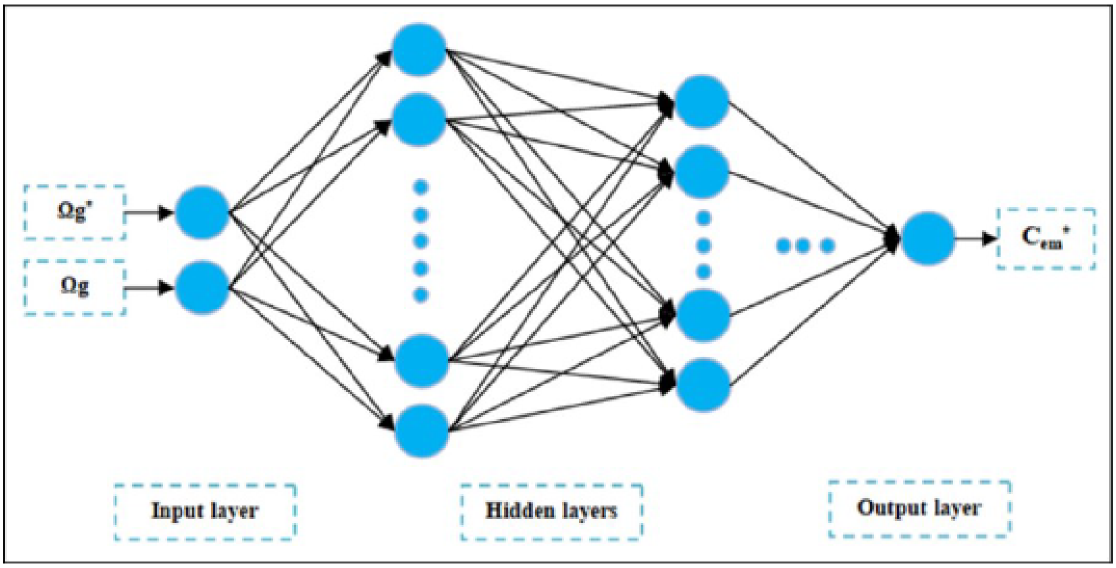

FIGURE 2.13: ANN schmeme

Using artificial neural networks and evolutionary algorithms to control plants is a method that does not require a dynamic model of the plant under control. Instead, it only requires input and output data. Evolutionary algorithms are a subset of evolutionary computation and are categorized as artificial intelligence. In artificial neural networks, the obtained knowledge is used to calculate the output responses of complex systems using machine learning and knowledge representation. An RBF neural network-based collective pitch control (CPC) controller was developed by Poultangari et al. [63] for 5 MW wind turbines. An evolutionary algorithm called particle swarm optimization (PSO) is used to provide an optimal data set for training the RBF neural network in Figure 2.14. System complexity, non-linearity, and uncertainty are not required for the proposed method. According to the simulation results, the proposed controller performs satisfactorily.

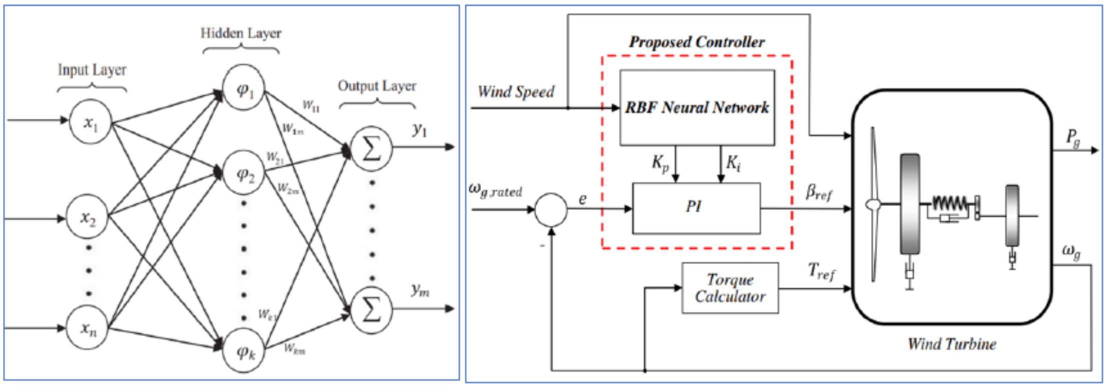

FIGURE 2.14: RLB neural network scheme

2.2.1.4 Sliding Mode Controlled Wind Turbines

A well-performed perturbation compensation-based sliding mode control (SMC) was proposed in [64] for optimal power extraction of Permanent-Magnet Synchronous Generator (PMSG)-based WTs. The system non-linearities and not modeled dynamics, uncertain parameters, and stochastic wind speed variations were aggregated into a perturbation and estimated by developing a sliding mode perturbation and state observer. Accordingly, the proposed control scheme effectively compensated the perturbations, avoided the being over-conservative of SMC, and delivered a robust control performance. Due to its fast dynamic response, good transient performance, stability, and robustness to matched parameter variations and external disturbances, sliding mode control has been proven to be an effective and suitable control strategy for various nonlinear control problems [65] [66] [67] [68]. Nevertheless, despite the satisfactory tracking performance of conventional SMC techniques in practical applications, some of its shortcomings remain, such as its vulnerability to measurement noise, the difficulty of attaining asymptotically stability under mismatched perturbations, generating unnecessary control signals to overcome parametric uncertainties, as well as the chattering phenomenon associated with discontinuous switching control, which causes high-frequency oscillations [69] [70]. It is impossible to estimate the effects of chattering on real-world applications due to the lack of a component that can switch to an infinite frequency [71]. Therefore, it is usually important to mitigate the consequences of this phenomenon by reducing it [72]. Due to WT's highly nonlinear behavior and the fact that they operate in harsh environments, SMCs are known to play an important role in power control and performance enhancement [73] [74].

Under high uncertainty conditions, sliding mode control is effective [75][76]. By using discontinuous control signals, the sliding mode strategy drives the system states toward pre designed surfaces in state space. Designing a SMC consists of two steps: (i) designing a stable sliding surface to obtain the desired dynamics, and (ii) designing a control law to ensure reaching the chosen sliding surface in finite time and staying there. There are two modes of state dynamics in a system controlled by an SMC: reaching mode and sliding mode. When states reach the sliding surface, the controller forces them to slide and as they slide, the controller transitions to the sliding mode. Nonlinear systems have recently been commanded robustly using SMC methodology. In order to satisfy the sliding condition, a discontinuous command signal is added across the sliding surface. Although this type of command has an essential inconvenience, which is that the discontinuous command action causes chattering. It has been proposed to modify the usual command law in order to resolve this problem. In most cases, boundary layer analysis is used. In order to command doubly fed induction generator (DFIG), fuzzy logic regulators and SMC regulators are combined [77] and in order to control the DFIG, a neuro-second order sliding mode controller (NSOSMC) is proposed [78].

A grid-connected DFIG based WT with bounded uncertainties and disturbances was proposed in [79] with an improved SMC controller with reduced chattering.

An effective disturbance rejection component was developed to mitigate chattering effects. To deal with the chattering phenomenon, [80] proposed an exponential reaching law. As reported, the proposed approaches effectively reduced the chattering problem and minimized the machine losses. According to [81], DFIG-based WTs with various uncertainties were investigated using the SMC approach for calculating APC and RPC. As the authors reported, although some minor chattering still exists in the developed SMC, the errors are acceptable due to the decreased tracking error and the higher performance of the developed SMC in the transient time response in terms of overshoot and settling time compared to the H_∞ robust control method.

An innovative sliding-mode control system for WT with nonlinear perturbation observers was presented by Yang et al. [82], which DFIG to achieve an optimal power extraction with improved fault ride-through (FRT). A sliding-mode state and perturbation observer (SMSPO) estimates the online perturbation by taking into account the strong non-linearities originated from the aerodynamics of the wind turbine together with generator parameter uncertainties and wind speed randomness. An efficient sliding-mode controller fully compensates the perturbation estimate to provide considerable robustness against various modelling uncertainties and consistent control performance under stochastic wind speeds. A further advantage is that the proposed approach is integrated and only requires measurement of rotor speed and reactive power, eliminating the classical auxiliary dq-axis current regulation loops. In four case studies, a more optimal wind power extraction and an enhanced FRT capability are demonstrated as compared to conventional vector control (VC), feedback linearization control (FLC), and sliding-mode control (SMC).

2.2.1.5 Model Predictive Controller

Model predictive control (MPC) has been explored for various objectives, including maximizing wind energy capture, mitigating fatigue loads, and smoothing wind power [83]. Standard MPCs optimize the economic costs of the plant operation before selecting optimal steady-state set-points. By optimizing a tracking cost function, the MPC tracks such set-points whilst directly handling input and state constraints. The separation of economic cost optimization and optimal tracking controllers undermines the overall performance when the operating plant deviates from its predefined set-point. A dynamic economic MPC approach has been developed to improve the control system's dynamic economic performance [84]. Economics MPC combines set-point tracking and information management into a single economic cost optimization step, compared to standard MPC that takes two steps [85]. Hence, the MPC is "economic" because the control system directly optimizes the economic cost function online. Recent applications of the economic MPC include power systems [86], building climate control [87], and wind energy [83]. There are, however, several issues that need to be addressed so that economic MPC can be successfully implemented for wind turbine control in order to achieve success.

In order to perform MPC calculations, a turbine model must be accurate which is a methodology issue. Low-order nonlinear models or linearized models are typically used. According to [87], the nonlinear MPC achieves better results when operating away from the linearization points of the linear MPC. It is costly to solve with no guarantee of a global optimal solution if a nonlinear MPC is implemented. The dynamics and operating constraints of nonlinear wind turbines are convexified to avoid this issue. Globally optimal solutions can be obtained by using convex optimal control algorithms.

The optimal control problem within the economic MPC framework can be seen as a convex optimal control problem with linear dynamics and convex constraints. An integrated turbine and energy storage system effectively smooths the wind power supplied to the grid. However, this method ignores the effect of control actions on turbine fatigue loading, which can lead to premature failures. Optimum wind power supply as well as turbine fatigue can be mitigated with a more comprehensive control system. A standard MPC algorithm for wind turbines assumes no model-plant mismatch. Standard MPC methodologies generally achieve the anticipated objectives with this assumption. This includes smoothing wind power [88], reducing fatigue loads, and managing severe constraints on actuators [89].

An economic MPC framework with adaptive control based on light detection and ranging (LIDAR) was developed by Shaltout et al. [90]. An analysis of wind turbine fore-aft dynamics is presented, including both drivetrain and tower dynamics. The convex optimization approach is used to propose an economic MPC controller based on this model. For wind speed previewing ahead of the wind turbine, a LIDAR system is used. In order to overcome model-plant mismatches, the authors introduced an adaptive algorithm. The developed controller maximizes wind energy capture and mitigates fatigue loads acting on the wind turbine tower while rejecting the effect of model-plant mismatches. Based on results in [91], the proposed framework is compared to the performance of a baseline controller (BLC) incorporating a variable-speed generator torque control and gain-scheduled proportional-integral blade pitch control. Zhang et al. [92] studied the merging effect of wind turbines on the system frequency of multi area power system. The first control area includes an aggregated wind turbine model of 60 wind turbine units beside the thermal power plant. According to the distributed Reliable load frequency structure, the dynamics model of the four-area interconnected power system is established.

The MPC was tested by Jassmann et al. [93] in co-simulation with Simpack, a framework that simulates multibody systems (MBS) for detailed load analysis. The analysis was performed using the IME6.0 MBS WT model described in this paper. As shown in figure 2.15, based on NREL's 5MW WT rotor, it includes a detailed representation of the drive train. As well as a supporting flexible main frame, this model encompasses a flexible main shaft, its main bearings, and a planetary gearbox. Simpack has been modified to implement the NREL Aerodyn v13 code for simulating wind loads. Using this modeling approach, wind loads and drive train dynamics can be investigated nonlinearly. As a result, it is possible to assess and investigate the effect of the MPC on specific loads not covered by standard simulation tools.

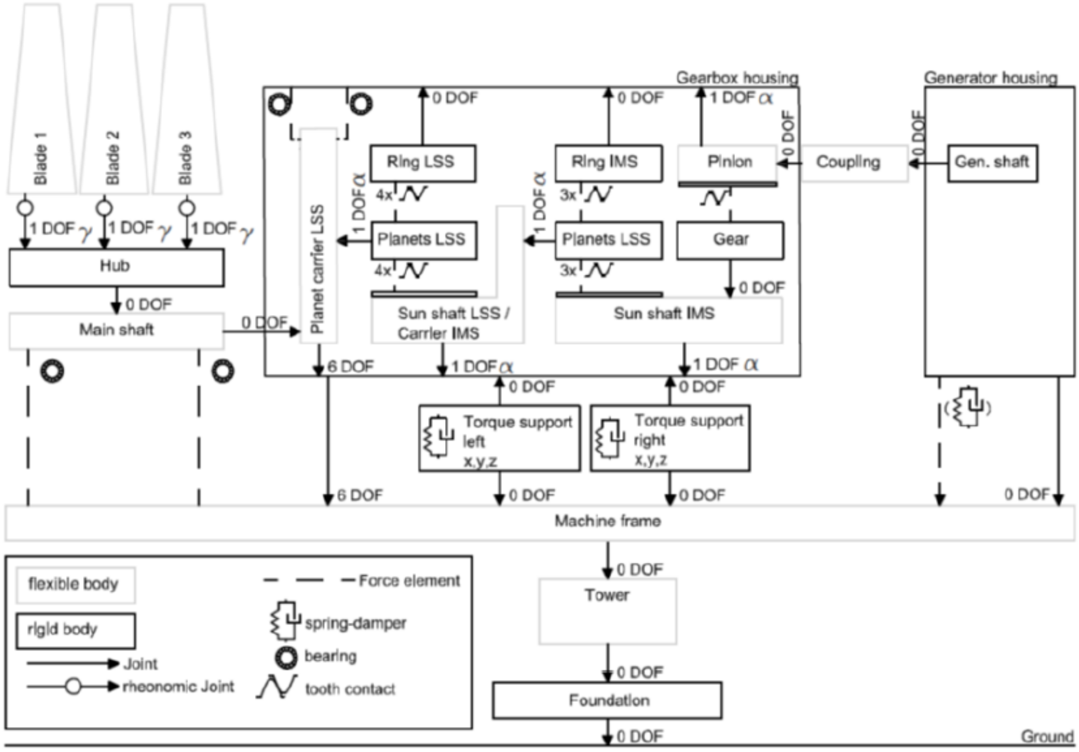

FIGURE 2.15: Baseline IMB6.0 model for WT

Soliman et al [94] propose a multiple model predictive controller to cope with non-linearities in WT and continuous variation in operating point across the entire operating range. MPC is based on the following basic concepts. The first step in controlling a system is to identify its dynamic model and the physical constraints on the variables of the system. Predictions of future outputs are made at each sampling time within a predefined prediction horizon. Solving a constrained optimization problem involving the constraints of the system and a performance index that reflects the performance of the system results in the set of future control signals. At subsequent control intervals with shifted prediction horizons, the system calculates the optimal sequence using the first input. Figure 2.16 illustrates this idea [94].

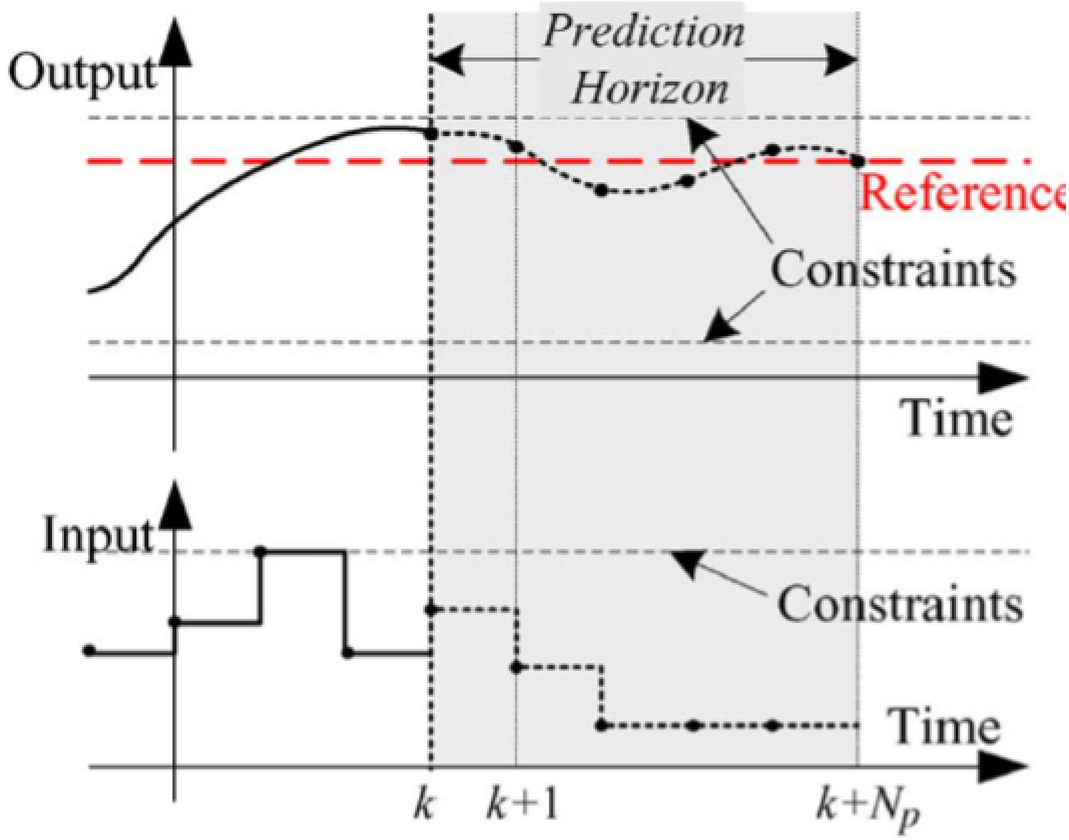

Figure 2.16: MPC concept with shifted prediction

2.2.1.6 Fuzzy Logic Controlled Wind Turbines

The field of engineering has many applications for fuzzy logic. With fuzzy logic algorithm, Civelek et al.[95] studied PID parameters for blade pitch angle controllers of wind turbines. There were three different control methods used to control the pitch angle of wind turbines. A conventional PI, a fuzzy PI, and a fuzzy PID are all examples of these control methods. In high wind speed regions, these control methods prevented possible harm to the system and maintained the nominal output power. Simulating controllers with Matlab/Simulink software was used to control the blade pitch angle of wind turbines at different wind speeds and hold output power constant at set points. Performances of control systems have been measured and compared by evaluating the steady state power of output power received from simulation results and steady state errors. From these simulation comparisons, it is evident that fuzzy PID controllers perform better than PI controllers.

The control of wind turbines involves a number of factors that need to be mentioned. An implementation of fuzzy logic pitch control for a wind turbine mounted on a semi-submersible platform is shown in the paper by Rubio et al. [96]. The model is used for the WT OC4 wind turbine, which represents a 5 MW power plant. Fuzzy controllers have as inputs instantaneous wind speed values filtered and normalized according to nominal speed, as well as pitch references.

As a result of a typical wind patterns, the authors of [97] developed a hierarchical fuzzy logic pitch controller. In this case, it is compared to a PID pitch-control system. An alternative approach to turbine selection utilizes fuzzy logic in [98]. With the proposed methodology, several scenarios are analyzed along with a turbine selection model. According to [99], the estimated wind speed is used to design a robust observer-based fuzzy controller. Wind turbines with variable pitch and variable speed are modeled by a Takagi-Sugeno fuzzy model with nonlinear consequential parts. A study published by Arturo Soriano et al.[100] investigates the characteristics and applications of wind turbine models in the market and lab. It focuses on nonlinear, fuzzy, and predictive methods of wind turbine control. Figure 2.17 illustrates fuzzy control for a wind turbine.

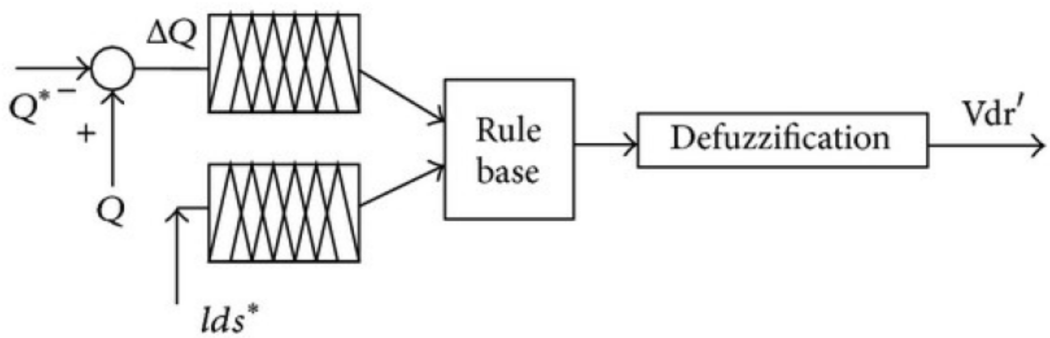

Figure 2.17: A fuzzy controller for a reactive power

In a wind turbine application, Adzic et al. [101] describe fuzzy logic control of induction generator speed. With fuzzy controllers, wind power can be delivered to the grid at its maximum potential. The cost of a fully-controlled wind turbine, which includes an induction generator and a back-to-back converter, is underestimated. With this configuration, the electrical torque, the speed, and reactive power compensation are all fully controlled. Simulations in MATLAB/Simulink have been conducted to validate the fuzzy logic control algorithm.

A great variety of applications of fuzzy logic theory have been found in control engineering, power systems, telecommunications, consumer electronics, information processing, pattern recognition, signal processing, machine intelligence, and so on. There are a number of heuristic control rules and fuzzy sets that make up the fuzzy control algorithm. Fuzzy rules are primarily based on IF-THEN rules [102]. An operator's control action or knowledge is often used to obtain fuzzy control "IF-THEN" rules. A fuzzy rule approach is used to improve tracking of the system, which adjusts the PID parameter when the wind turbine generator is running [103]. PID controller performance can only be improved by adjusting PID parameters. The servo motor is controlled by the fuzzy controller to improve the resolution. MATLAB toolbox is used for developing fuzzy rules and for designing and developing fuzzy controllers. In proportion to the number of rules, the wind turbine head's rotation angle becomes more precise. It is therefore always facing the maximum wind direction. A yaw controller is illustrated in Figure 2.18. A fuzzy logic controller was used to track maximum wind speed directions by Bharani and Jayasankar [104]. In order to measure maximum wind speed and direction, anemometers and wind vanes are used. An error is calculated based on the present wind direction and the current wind turbine head direction. A fuzzy controller uses the error signal to correct the error and turn the wind turbine head towards the maximum wind direction. Generators produce maximum power this way.

In wind turbines with variable speeds, pitch angle control is well supervised by a PID controller due to its easy structure, gain-scheduling, and implementation. Nevertheless, control system literature presents a fractional order PID (FOPID) controller as an improvement on a conventional PID controller. By providing fractional power of an integrator and differentiator, the FOPID can meet the specifications of a complex system with five tuning gains and a sufficient range of flexibility. FOPID controllers have been described in a number of research

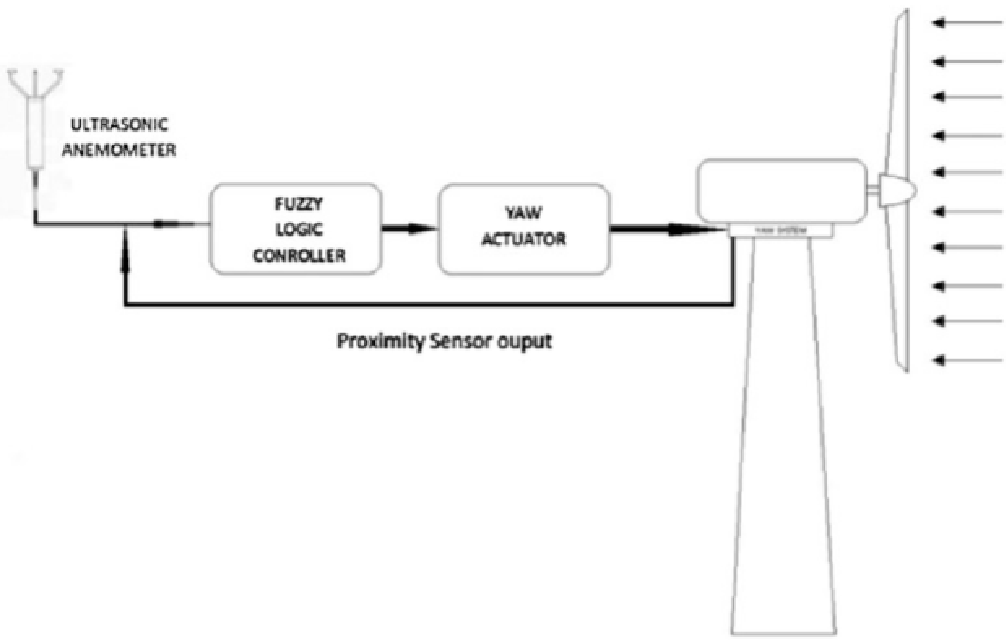

FIGURE 2.18: A basic FLC on WT schematic

articles [105] [106]. A 2 MW direct-drive WECS with a fractional order fuzzy-proportional-integral-derivative controller was developed by Pathak and Gaur [107] for maintaining output power at rated values under dynamic wind conditions. A comparison of the proposed controller's rise time, fall time, settling time, overshoot and total harmonic distortions is conducted with other intelligent controllers and conventional controllers to evaluate its performance. A teaching-learning based optimization (TLBO) algorithm is also used to fine tune the proposed controller. Figure 2.19 depicts the effectiveness of the TLBO, its performance is compared to that of the genetic algorithm.

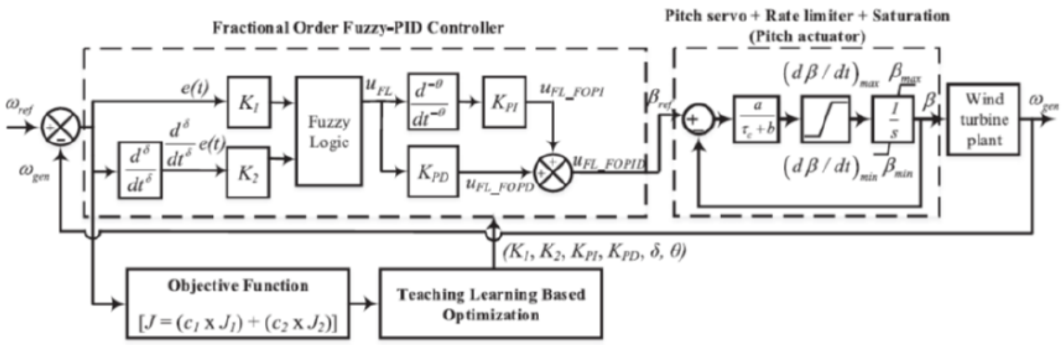

FIGURE 2.19: A fuzzy PID controller with fractional order

2.3 Genetic Tuning on Wind Turbines

Genetic algorithms are based on natural selection and genetic mechanisms. Each solution represents a solution to the problem, called chromosome, which is actually a string of symbols. The proposed search starts with the initial solutions of a group of random populations. During the subsequent iteration called heredity, these chromosomes continue to evolve. The fitness of each chromosome is assessed in each generation and the offspring is formed by crossover or variation. To maintain a constant population size, some offspring are chosen and others are weeded out based on their size. Choosing high-fit chromosomes is easy. After a number of generations, the algorithm will converge on the most suitable chromosome that probably is the optimal or second-best solution [108].

Using genetic algorithms (GAs) to solve aerodynamic optimization problems for horizontal axis wind turbines has been successful [109]. Using the blade element momentum theory (BEM) to calculate the power performance of the blade, Liu et al. [110] linearized the chord and twist angle radial profiles for a fixed-pitch, fixed-speed horizontal axis wind turbine. AEP was used as the optimization criterion with constraints on the maximum power output of the wind turbine for a specific wind speed. Based on both BEM and GA, Ceyhan [111] developed an aerodynamic design and optimization tool for horizontal axis wind turbines. Power output was optimized for given wind speeds using blades. Airfoil sectional profiles, chord, and twist angles were all taken into account in the design.

Based on genetic algorithms and blade element momentum theory, Polat and Tuncer [112] developed an aerodynamic shape optimization methodology for horizontal axis wind turbine rotor blades. The researchers looked at how to maximize power production at specific wind speeds, rotor speeds, and rotor diameters. Several variables were taken into account when designing the blade, such as the length of the sectional chord, the twist, and the profile of the blade at the root, middle and tip regions. Based on an objective function to satisfy the maximum annual energy output on specific winds, Liu et al. [113] examined an optimization model based on the extended compact genetic algorithm (ECGA) for rotor blades of

1.3 MW stall-regulated wind turbines. A genetic algorithm was used by Mendez and Greiner [114] to illustrate the optimal wind blade shape. According to the IEC classification, this work focused on optimizing wind turbine applications in particular wind conditions.

Most of the research has examined and reported on the optimization of twist and chord rates. Tahani et al. [115] considered the placement of different types of airfoils along the blade in their research. An aerodynamic analysis of the Vestas 660 kW wind turbine blade is conducted. The methodology is implemented within an integrated GA method and modified BEM developed by computer code for this complex wind turbine blade. Optimum chord and twist rates and the optimal placement of airfoils along the blade length are the key factors in optimizing power generation. To increase the annual energy production (AEP) of an NREL 5MW wind turbine and a wind turbine designed for site-specific wind conditions, Yashin et al. [116] optimized the aerodynamic parameters (airfoil chord lengths and twist angles smoothed using Bezier curves) of these wind turbines. NREL's FAST Modularization Framework is used to optimize this process using a GA developed in MATLAB. AEP was improved by 5.9 % of the baseline design AEP after optimizing the NREL 5MW wind turbine design, compared with 1.2 % for a site-based design based on Schmitz equations. Based on these results, it can be observed that optimizing wind turbine blade aerodynamic parameters for site-specific wind conditions leads to a reduction in the rate of AEP and hence a reduction in the cost of generating energy.

2.3.1 P,PI,PID with GA

To achieve optimal output from a wind power generation system, the control parameters must be continually changed due to the system's instability. Using the optimization of the PID controller, the optimal index is determined by deciding the group of K_p, K_i, and K_d, with the common error performance indexes being integral of square error (ISE), integral of absolute error (IAE), integrated time and absolute error (ITAE), and integral of time square error (ISTE). Among these performance evaluation indices [117], the ITAE provides the best engineering practicality and selectivity.

Li et al. proposed an online PID parameter optimization control for wind power generation based on a genetic algorithm. To begin with, the anti-saturation PID control strategy considers the instability and complexity of wind power sources. They introduce a genetic algorithm for optimizing the PID parameters online. Simulating wind power using MATLAB simulation system is used in the simulation study. This control strategy solves the integral saturation problem, suppresses harmonics in the output waveform, and improves the power factor of the system in addition to solving the integral saturation problem. A study of ITAE error performance is conducted in this paper. ITAE is used in this paper because of its practicality and selectivity [118]. A definition of ITAE is as follows:

$$ITAE = \int_0^\infty t|e(t)|dt \tag{2.6}$$

It is necessary to select an appropriate algorithm to optimize the PID controller parameters to manipulate a wind power system optimally. Currently, many optimization algorithms exist, including GA, particle swarm optimization (PSO), fuzzy self-adaptation (FS), expert algorithms (EA), and iterative learning (IL). To optimize the parameters, genetic algorithms encode them into chromosomes instead of focusing on the parameters themselves. Therefore, it is not constrained by function. Furthermore, the GA is characterized by implicit parallel search, which minimizes the possibility of falling into a local minimum. In addition, GA is particularly suitable for solving large-scale nonlinear optimization problems. In Figure 2.20 a GA was applied to the optimal design of an anti-saturation PID controller.

An algorithm-based controller based on genetics has two parts, namely, a PID controller that controls a wind power system in a close cycle using dynamically optimized K_p, K_i, and K_d parameters, and a GA that adjusts the parameters of

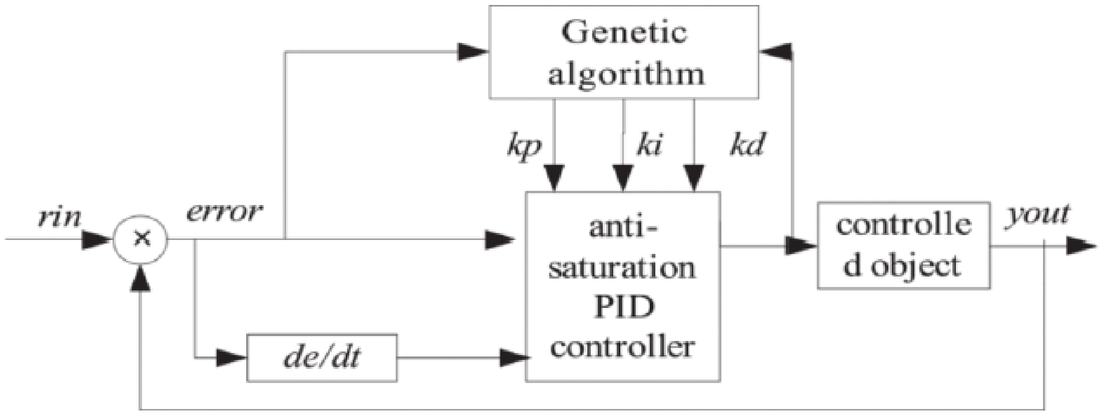

FIGURE 2.20: A structure of GA optimizing PID controller parameter

a PID controller according to the system's state [119] [120]. Implementing the GA-based optimization of PID parameters is accomplished in four steps.

1. A certain scale initial group is generated based on an even-crossing design method, which controls three parameters with a Z-N method [121].
2. The fitness of each unit in a group is calculated using the reciprocal of 2.6
3. Crossing selection and mutation generate distinct populations.
4. Fitness is calculated for new populations using the method described in step 2. An optimal parameter will be found if a new population achieves the terminal condition. Otherwise, go back to step 3.

Figure 2.21 shows the structure of genetic optimization cycle for a PID controller parameters.

By using a PID controller and particle swarm optimization, Zahra et al. [122] presented a new control strategy for wind turbines by regulating pitch angle to capture the maximum power. The problem is to identify the parameters of the PID controller by applying the particle swarm optimization or PSO technique. To control the power characteristics of the turbine, a mathematical model is developed, which is compared to a proposed strategy and genetic algorithm PID controller. The simulation results show that the proposed approach results in less

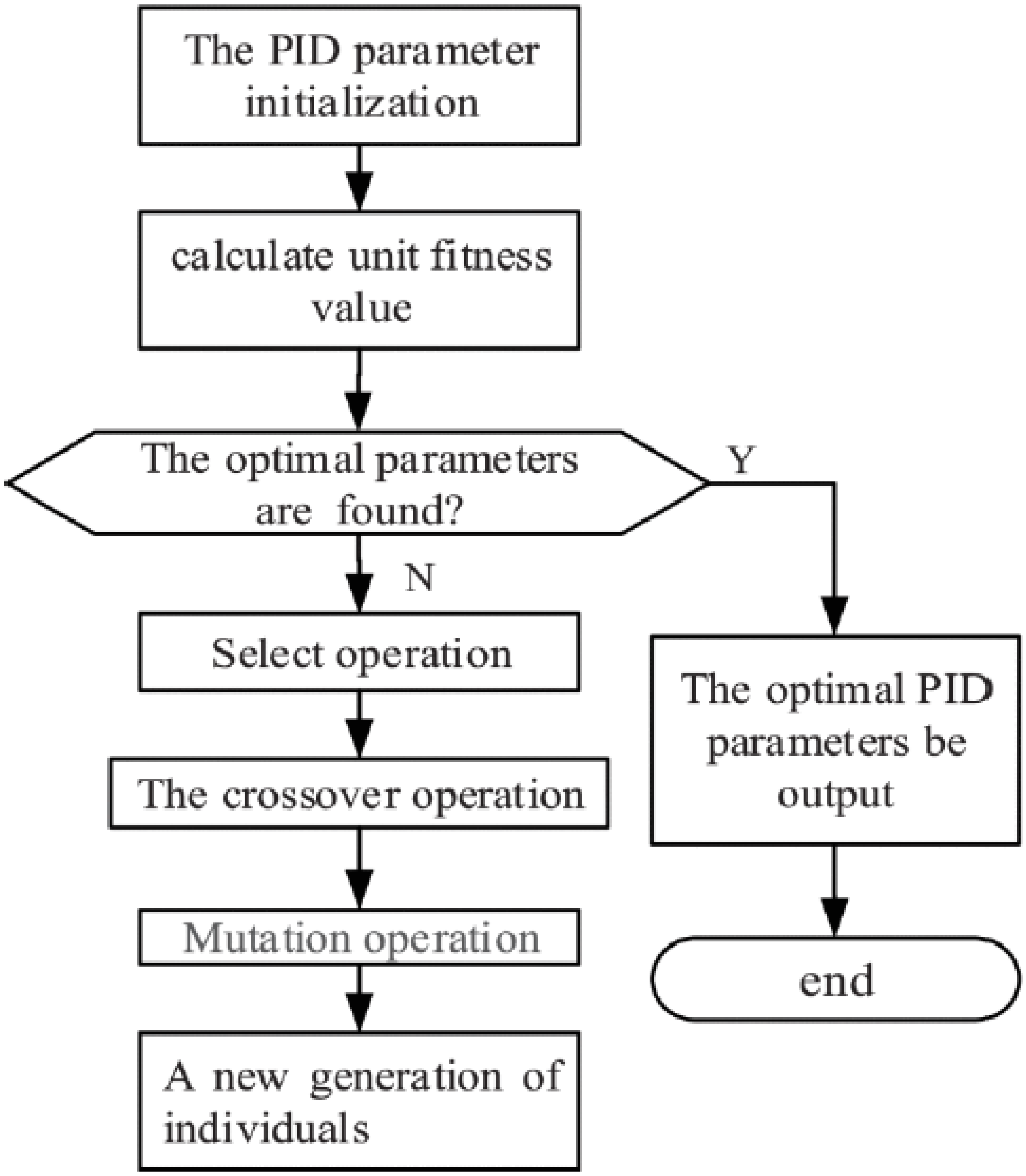

FIGURE 2.21: A structure of GA optimizing PID controller parameter

pitch action and better power regulation. This strategy is easy to implement and robust. Using an IGA algorithm to optimize the PID parameters of the blade pitch controller was proposed by Civelek et al. [95]. The mutation rate and the crossover point number were rearranged according to the algorithm progress first. The new IGA approach has also been tested and validated by using MATLAB/Simulink software. A comparison of the other genetic algorithms (GAs) has then proven its superiority. Thus, the new IGA approach has been more successful in adjusting the blade pitch of a WT at higher wind speeds than other GA approaches.

2.3.2 Fuzzy blade controller with GA

Due to the nonlinear nature of wind turbines, the blade pitch angle controller must also be able to handle these situations. The fuzzy controller is an appropriate candidate for wind turbine blade control because it is capable of accommodating such non-linearities. As part of Civelek's study [123], a fuzzy controller is optimized with a genetic algorithm that improves the control of wind turbine blades. Advanced Intelligent Genetic Algorithm's or AIGA's performance has been improved with new features. The concept of acceptable error (AEC) is one of these. According to the amount of this acceptable error, binary and decimal conversions are performed. It may not be possible to accurately convert a decimal to a binary value, especially for the digits following the decimal. Small errors may occur during back conversion from the binary back into decimal in IGA due to these inaccuracies. As a result of the AEC implemented in AIGA, this is no longer an issue. The number of crossover points in AIGA is also determined by the length of the chromosome. Implementation of this algorithm improved its performance. As a result of optimization, the output power is even higher.

To enhance the ride-through capability of grid-connected wind turbines (WTs) with doubly fed induction generators (DFIGs), Vrionis et al. [124] proposed a computational intelligence-based control strategy. In order to support the grid voltage, grid codes around the world require that its supply reactive power to the grid during and after the fault. When grid faults occur, conventional crowbar-based systems are intended to protect the rotor-side converter. However, they do not meet this requirement, because the DFIG behaves like a squirrel cage machine when it is connected to the crowbar, absorbing reactive power. A control system that eliminates or reduces the need for the crowbar was developed to solve this problem. This paper proposes a coordinated control strategy for the DFIG converters to achieve the above-mentioned requirement without the use of any auxiliary hardware during a grid fault. Genetic algorithms are used to tune a fuzzy controller that coordinates the two controllers. DFIG with a 1.5-MW power output supplying relatively weak electrical infrastructure is simulated to verify the proposed control strategy.

A new methodology for controlling the frequency and power of a system was presented by Elsayed Lotfy et al [125]. A decentralized fuzzy logic-based control scheme for a wind–diesel system with high penetration is studied. Figure 2.22 depicts the double configured controller for fuzzy logic. First, one is used in conventional generator governors to dampen frequency oscillations, while the other is used to control wind turbine pitch angle systems to smooth power fluctuations and enhance power system efficiency. Fuzzy logic controllers are tuned and optimized using GAs in order to achieve optimal performance. Three wind farms are included in the IEEE nine-bus three-generator test system to validate the effectiveness of the proposed controllers. During normal and faulty operations, the robustness of the power system is assessed.

The pitch angle of wind turbines was the target of Zheng et al. control study [126]. Parameter tuning has a strong correlation with fuzzy pitch angle controller performance. A good parameter tuning can even determine whether the output converges. An analysis of how parameters are tuned affects the controller's output. Using a GA to optimize the variable pitch system and a sub-fuzzy controller to tune the parameters of the main fuzzy controller, this study aimed at improving controller performance. Based on simulation results, the double fuzzy controller designed was able to handle input signals of different pitch angles. Mechanical losses associated with blade starts were reduced. As shown in Figure 2.22, the dual fuzzy controller has an overall structure.

2.3.3 Other GA applications of Wind Turbines

Using a genetic algorithm approach, S.A.Grady et al. [127] obtain optimal placement of wind turbines while reducing the number of turbines and the acreage

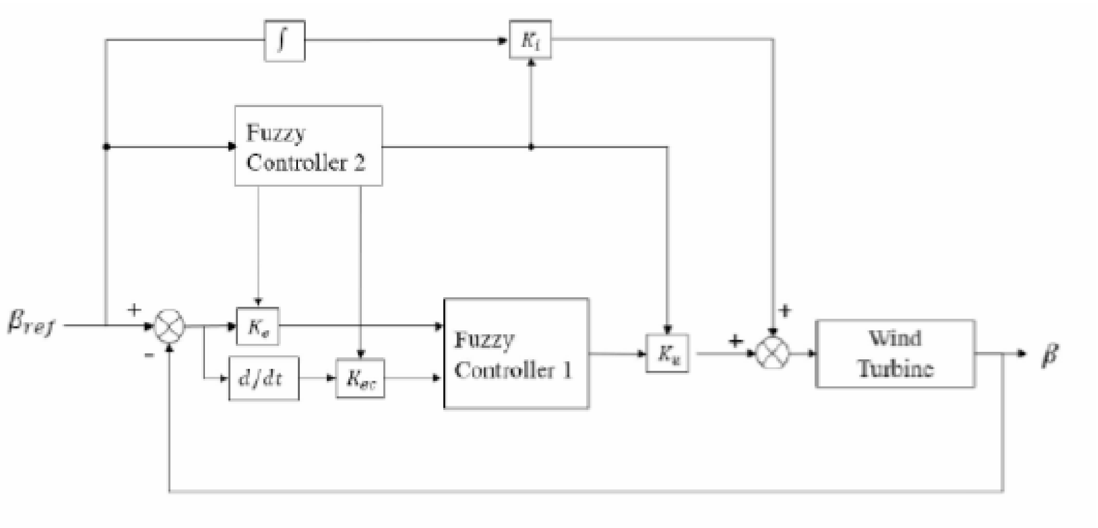

FIGURE 2.22: A structure of GA optimizing PID controller parameter

of land occupied by each wind farm. Specifically, three types of wind are considered: (a) unidirectional uniform wind; (b) uniform wind that rotates and (c) non-uniform wind that rotates. The 600 individuals in case (a) are initially distributed among 20 subpopulations and evolve over 3000 generations. An initial population of 600 individuals divides into 20 subpopulations and evolves over 3000 generations in case (b). 2500 generations are required to evolve 600 individuals over 20 subpopulations in case (c). Results also include fitness, total power output, power output efficiency, and the number of turbines per configuration in addition to optimal configurations. A possible explanation is provided for the discrepancy between the results of an earlier study and the results of this study.

G.Mosetti et al. [128] optimized the wind turbine distribution at a given site so that the maximum amount of energy is extracted with the lowest installation costs. Using a wake superposition simulation model and genetic search codes, the wind farm simulation model is optimized. Using some simple applications, the paper demonstrates the feasibility of the method. The optimization method is applied to the number and position of turbines for three wind cases: single direction, the constant intensity with variable direction, and variable intensity with variable direction, using a square site subdivided into 100 square cells as a test case.

Among intelligent optimization algorithms in electrical system design, the genetic algorithm (GA) is the most widely used. Researchers at the National Renewable Energy Laboratory (NREL) presented a study on the design and optimization of airfoils for a 20 kW wind turbine using a multi-objective GA and HARP-opt Code [129]. To improve the electromagnetic performance of the flux-switching permanent magnet motor [130], sensitivity analysis and design optimization are performed using the non-dominated sorting GA-II. Based on the GA method, an optimal design is developed for a PMSG used in a wind power conversion chain to maximize energy input and minimize PM volume [131]. Optimizing the distribution network's total cost by using the GA method minimizes power losses and maximizes voltage profile [132]. According to the annual wind speed, an optimization method of generator structure and control for SWT power plants is described using GA [133]. In order to optimize the design of PMSGs inserted in small wind turbines, a multi-objective GA is coupled to the fast finite element analysis (FEA) to calculate electromagnetic torques and field distributions [134]. The GA optimization method is used to control the auxiliary damping on the rotor side converter of a doubly-fed induction generator found in wind farms [135].

According to Zorgani Agrebi et al. [136], PMSGs can be designed using a DIO approach. This study has two purposes. As a first step, effective analytical models of PMSG are created and compared to design specifications to come up with a feasible generator structure. Models are developed for PMSGs with radial flux and surface magnets. Even though structural modeling represents only %5 of the total design activity, it fixes %75 of the lifetime costs. In order to develop the optimization model, further information about generators is provided, including parameters and performance. In contrast, a GA code with eight mixed variables and six constraints is formulated. The design by optimization of the generator is mono-objective due to the multi-physical nature of the system (thermal-mechanical-electrical-and magnetic disciplines). Its active components (iron, copper, and especially PMs) are designed to minimize their mass. By reducing the cost of the materials, construction costs are reduced. Using simulation results to validate the approach used, the theoretical problem is supported by simulation results. There are three main analysis methods for PMSG electromagnetic design analysis, according to the literature: analytical, magnetic circuit, and finite element. As a result of these analyses, the material and multi-physics aspects of the thermal structural system are fixed. FEA produces accurate results despite taking a long time to run [82].

Chapter 3

System Modeling and Control Methods

3.1 Aeromechanic Modeling and airfoils

3.1.1 Airfoil Designs

Among the concepts of aero-mechanical challenges of modern wind turbines, airfoil design can be considered one of the most significant ones. Airfoils are two-dimensional, narrow structures that are intended to be used in fluid flows such that, through their interaction with the flow, they can produce forces. The typical characteristics of subsonic airfoils are a rounded leading edge and a somewhat sharp trailing edge. Since the geometry of airfoils is essential to how well they operate, a universal communication nomenclature has been established that enables accurate shape reproduction of airfoil shapes based on several fundamental dimension features[2].

The main properties of airfoils as shown in Figure 3.1 can be mentioned as listed :

- Upper Surface: Can be considered as "suction side" is the low pressure region of the airfoil.

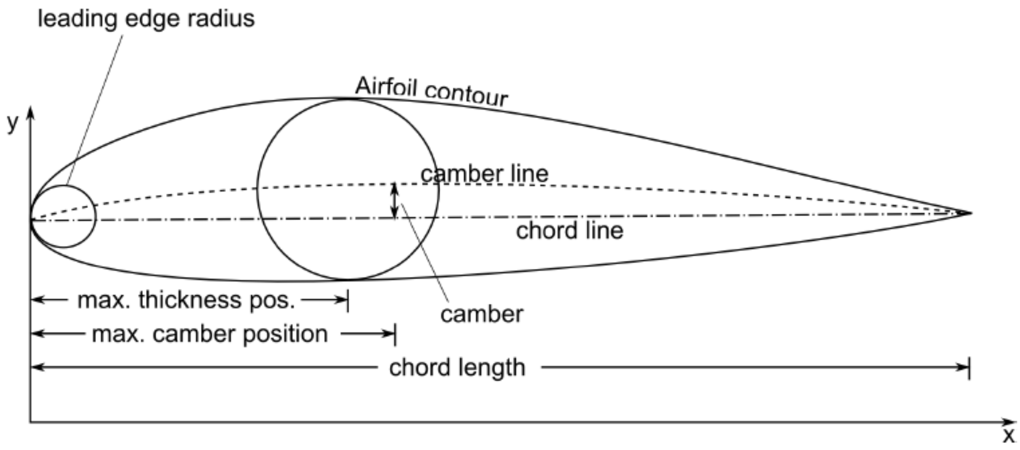

FIGURE 3.1: Airfoil design parameters

- Bottom Surface: Also known as "pressure side" is the high pressure region of the airfoil.
- Chord Line: Can be described as a line that connects the leading edge to trailing edge.
- Mean Line: Can be defined as a line that extends from leading edge to trailing edge of the airfoil and its equal distance between suction and pressure sides.
- Leading edge radius: It is a virtual circle that defines the curving properties of airfoil .
- Trailing edge distance: Thickness of trailing edge of airfoil.

All of the aforementioned airfoil design parameters are expressed in terms of relative length, more specifically as a percentage of chord line length percentage "c". This makes it possible to describe general airfoil forms without using dimensions, which simplifies the handling of information exchange about multiple distinct airfoil shapes [2].

3.1.2 Aeromechanical characteristics of airfoils

As mentioned previously, the concept of airfoils can be stated as most crucial concept for any aero mechanical devices. Air crafts, helicopters and wind turbines work with similar aerodynamic principles in which all engineering products use the similar airfoils. Mostly NACA standards are being used for aero mechanical devices.

The literature on fundamental fluid mechanics provides a very good foundation for and explanation of the lift and drag concepts of infinite span airfoil sections [137]. Most often, non-dimensional coefficients are used to characterize and explain the airfoil performance, which can be computed or measured for a variety of airfoils with variable absolute dimensions and tested using various techniques.By establishing airfoil performance curves, it is possible to choose the best airfoils for each type of wind turbine blade design [137]. The lift, drag, moment coefficient, and glide ratio over angle of attack curves are the most practical performance curves for HAWT applications [2](C_l/AoA,C_d/AoA,C_m/AoA,$C_l/C_m/AoA$).

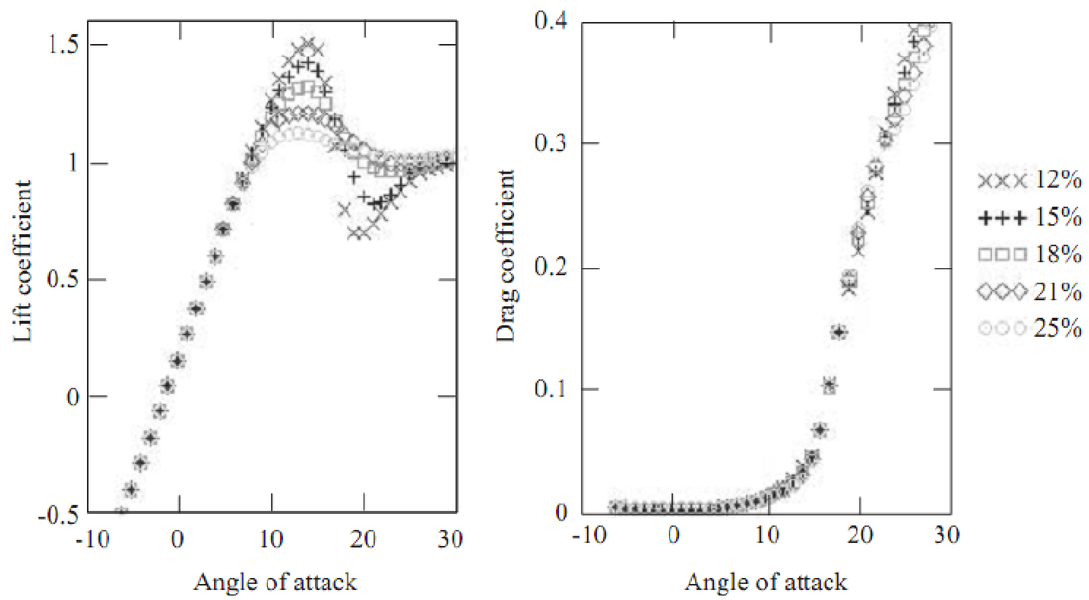

FIGURE 3.2: Lift and drag coefficients vs angle of attack

3.2 Aerodynamic Modeling of a Rotating Wind Turbine Blade

Horizontal axis wind turbine blade aerodynamics are largely the same as the traditional finite wing aerodynamics encountered on fixed wing aircraft. Rotor aerodynamics and aeroelasticity is a very difficult topic, yet there are certain differences that cause various impacts and complexities. In this section of the text, a short introduction of HAWT aerodynamics is made [2].

Figure 3.3: Wind flow directions of rotational wind turbine axis

Both a lift force (normal to the inflow direction) and a drag force (parallel to the inflow direction) are produced by a finite wing revolving around an axis in Figure 3.3 and Figure 3.4. The lift and drag components each contribute to the thrust and torque of the rotor, depending on the local angle of attack. Naturally, only the torque is used by wind turbines to produce power; the thrust is absorbed as a load by the wind turbine frame. Each airfoil segment on a HAWT blade's angle of inflow consists of a real wind velocity component and a peripheral wind velocity component brought on by the rotation of the rotor and the separation of the airfoil segment from the rotation axis. This implies that the attack angle changes continuously along the blade [2]. As a result, the structural twist in the blades is intended to account for this fluctuation in the AoA.

FIGURE 3.4: Aerodynamic forces along wind turbine rotation axis

3.3 Modeling of a Wind Turbine

Modeling of a wind turbine is a critical part of wind turbine engineering as it affects many disciplines. There are several simulator options employed in research and development. There are two major types of wind turbine models in the literature: A doubly-fed induction generator (DFIG) type with gearbox and a direct drive type without a gearbox. In this study the controller algorithm is designed and optimized for a 2MW wind turbine with DFIG type generator. The system is modeled for controller design and observation of the effects of many different engineering aspects. The mathematical model is generated in the Matlab Simulink environment. The model can simulate thermal and electrical grid aspects, power output and controller effects.

The mathematical model of a wind turbine can be defined by the torque equation of its rotor 3.1 expresses the main dynamics of a turbine rotor [138].

$$T_\tau = \frac{1}{2}\rho\pi R^3 \frac{C_p(\lambda,\beta)}{\lambda} V_w^2 \tag{3.1}$$

here ρ denotes the air density $[kg/m^3]$, R stands for the radius of the motor(m), v_m is the wind speed $[m/s]$, β is the pitch angle, and λ is the tip speed ratio [138].

Power coefficient (C_p) is one of the most crucial parameters for wind turbines. The function converts the parameters pitch angle and the tip speed ratio to a constant between 0 and 0.6. The constant that function yields affects the generated aero mechanical power of a turbine. The power coefficient is calculated as,

$$C_p(\lambda,\beta) = C_1(C_2\frac{1}{\kappa} - C_3\beta - C_4)\mathrm{e}^{\frac{-c5}{\lambda}} + C_6\lambda \tag{3.2}$$

where

$$\frac{1}{\kappa} = \frac{1}{\lambda + 0.008\beta} - \frac{0.035}{1+\beta^3} \tag{3.3}$$

and C_1=0.5,$C_2 = 116$,$C_3 = 0.4$,$C_4 = 5$,$C_5 = 21$,$C_6 = 0.0068$ [138]

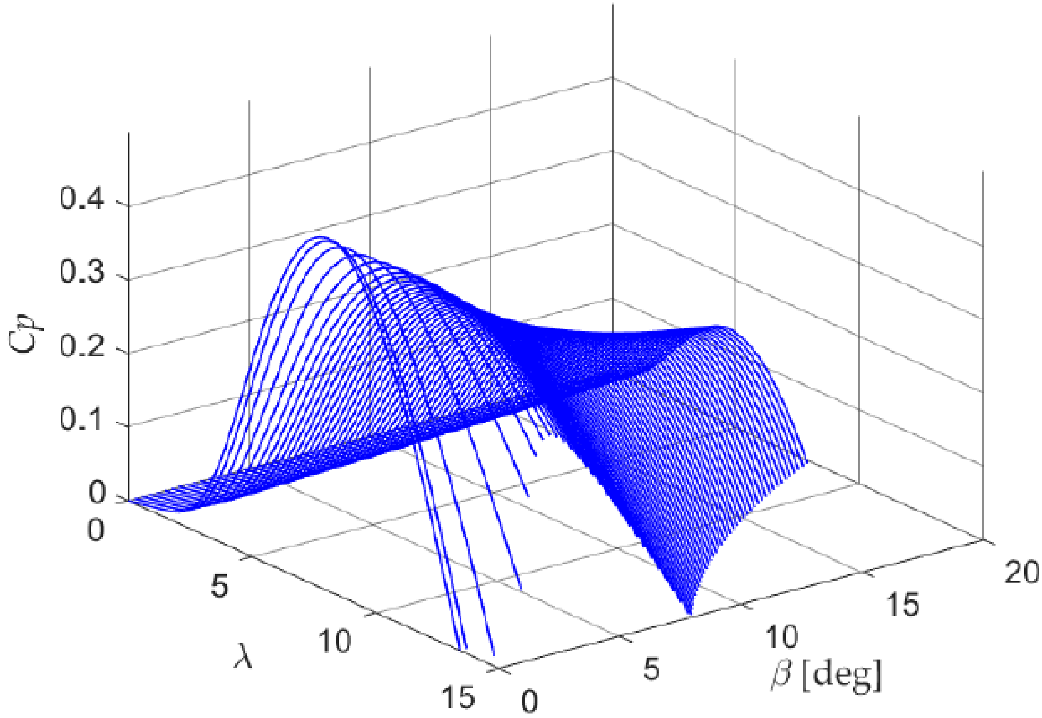

FIGURE 3.5: Power coefficient diagram

Figure 3.1 denotes the curve for the power coefficients for a modern horizontal axis wind turbine. They are the functions of pitch angle and tip speed ratio [139].

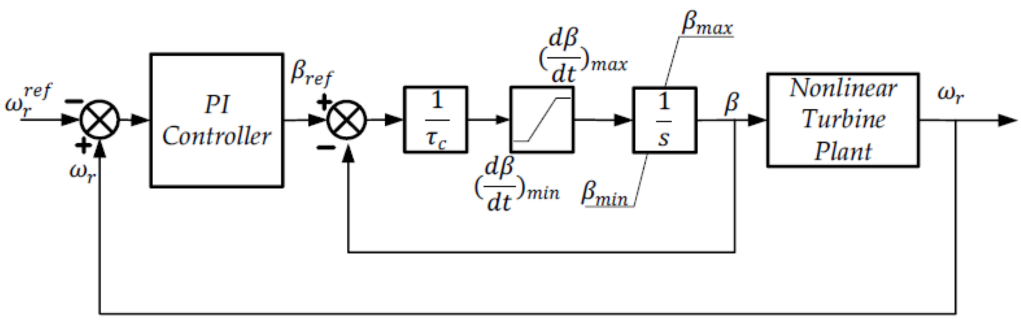

FIGURE 3.6: Block diagram of a pitch angle controller

Figure 3.2 illustrates the block diagram of a conventional wind turbine. As can be seen from the figure, pitch angle reference is supplied for a nonlinear turbine plant where the output is generally the rotational speed of the generator [139].

3.3.1 Pitch Angle Controller

In medium-sized to large wind turbines, the pitch angle controller is typically used to restrict the power output of the turbine. The blades' rotation around the longitudinal axes can be modified by the actuator. For the pitch actuator in turbines with high power ranges, hydraulic or electromechanical devices are frequently utilized. A nonlinear servo called the pitch actuator often rotates all or a portion of the blades. The pitch servo is described as an integrator or a first-order delay system in the closed loop with a time constant τ_c. The pitch servo's dynamic behavior is represented by the expression 3.1.

The actuators are mainly controlled with servo electrical motors and gear boxes without backlashes. Generally cycloid gearboxes are used in order to obtain precise pitch angle positioning in which the output of the controller is generally position control.

$$\frac{dB}{dt} = \frac{-1}{\tau_c}\beta + \frac{1}{\tau_c}\beta_{ref} \tag{3.4}$$

which is subject to ;

$$\beta_{min} \leq \beta \leq \beta_{max} \tag{3.5}$$

$$(\frac{dB}{dt})_{min} < \frac{dB}{dt} < (\frac{dB}{dt})_{max} \tag{3.6}$$

where β_{min} and β_{max} are the minimum and maximum pitch angles. Generally, in modern horizontal wind turbines the interval can be stated as -5 and 90 degrees.

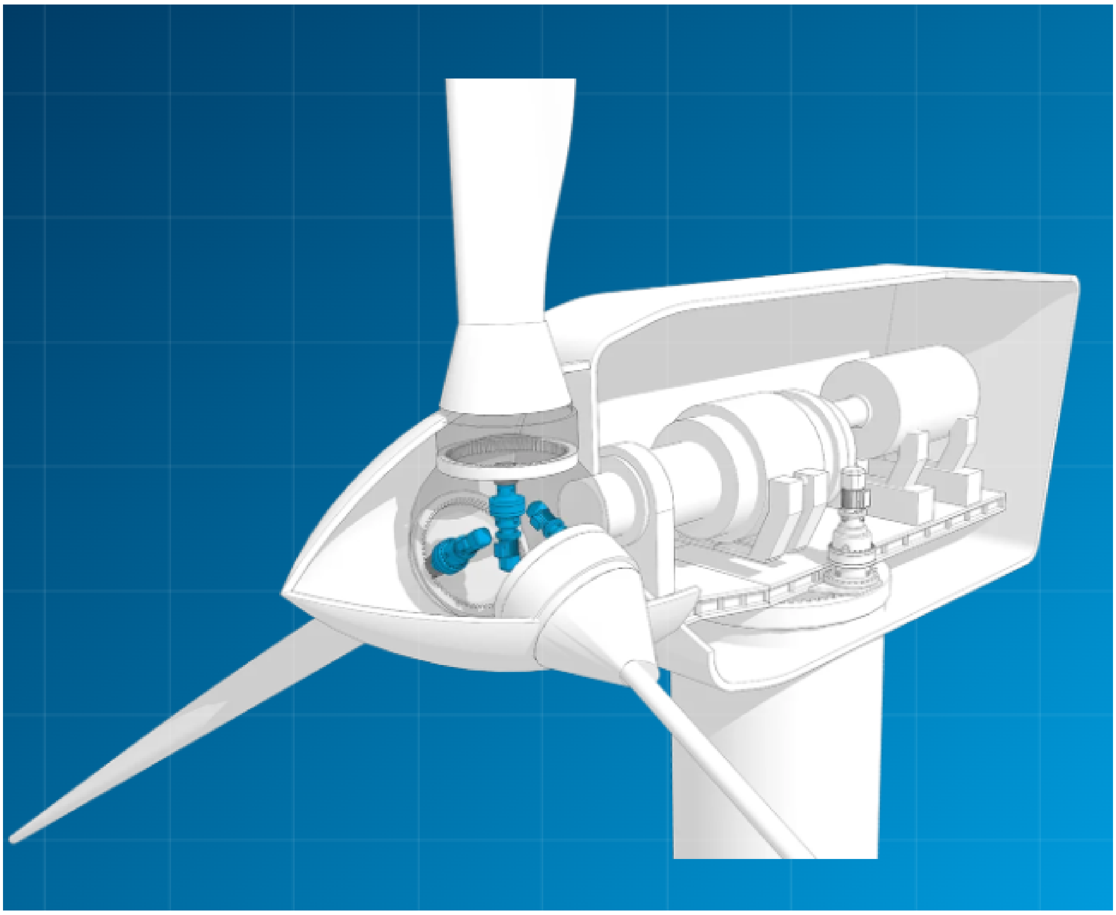

FIGURE 3.7: Pitch angle mechanism

3.4 DIFG Type Wind Turbine Configuration and Modelling

Aerodynamic, mechanical, electromechanical, and electrical subsystems are all parts of a wind turbine. For each of the aforementioned subsystems, a separate control system is built. The most important ones, nevertheless, can be regarded as the torque and pitch controllers.

As shown in Figure 3.8, wind turbines comprise a variety of subsystems from many technical disciplines and most of them require distinct controllers. Torque controllers are often used to adjust the power of DFIG type generators, whereas pitch controllers are utilized to control the rotor speed. The classification of operating regions is significant for wind turbine technologies since wind regime graphs provide many critical descriptions for the turbine, including operating speed, maximum

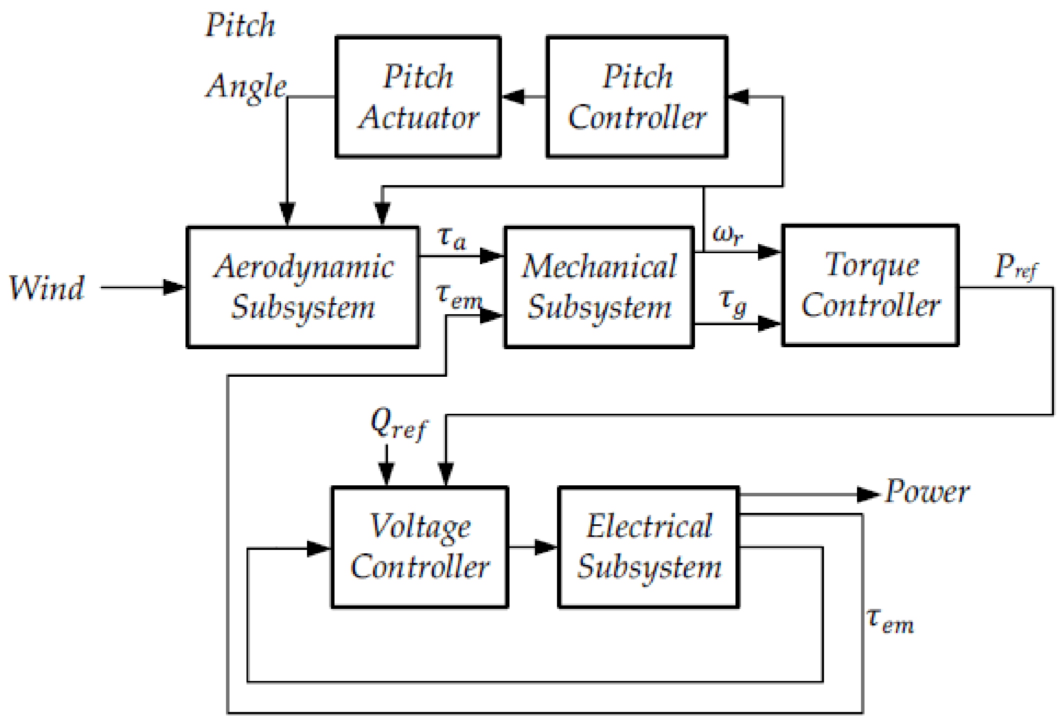

FIGURE 3.8: Wind Turbine Block Diagram

power, and maximum attainable aeromechanical power. The operating zones of the 2MW wind turbine employed in this investigation are shown in Figure 3.9. In this figure, the wind profile is separated into three regions based on wind speed. Regions 1, 2, and 3 are referred to as cut-in, rated and cut-off, respectively. Wind turbines typically begin to generate power when the wind speed reaches a certain threshold. The pitch mechanism runs in Maximum Power Point Tracking (MPPT) state with 0 degrees of the pitch until the rated wind speed is reached. As the wind speed increases, the pitch mechanism maximizes the power generation from the accessible aeromechanical power. Region 2 is a partial load zone where the pitch system may begin to become active to achieve more reliable power output performance. The pitch mechanism activates when the wind speed exceeds the rated speed. However, rotational speed and power are limited as the wind speed escalates. Region 3 is an active pitch location where the power is managed by active pitching over the specified wind speed. The automation system uses the pitch angle to halt wind turbines when the wind speed exceeds or approaches the

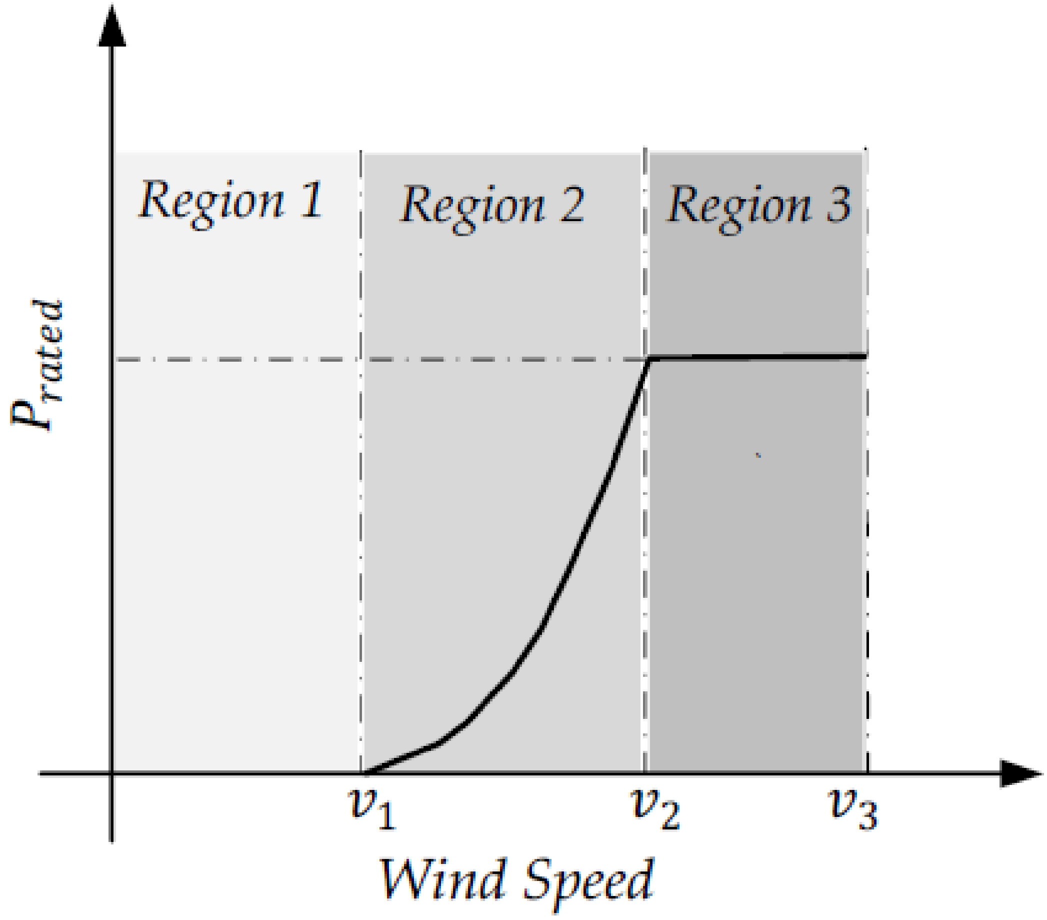

Figure 3.9: Wind speed regions

cut-off speed for mechanical safety reasons [140]. Modeling aerodynamic, mechanical, electromechanical effects, and grid side converters in a simulation environment is significant in the performance comparison of controllers. A 2MW DFIG type variable speed and variable pitch wind turbine in Matlab/Simulink environment is used with a wind regime above its rated speed through-out the study. This particular wind regime aims to observe the effect of pitching under abrupt changes in wind speed and the power regulation characteristics. Table 5.1 shows the parameters for the wind turbine simulated throughout the controller design study.

Table 3.1: Wind turbine system parameters

Simulated System Characteristics			
Nominal Output Power	2MW	Nominal Rotor Speed	15.8 rpm
Working Mode	Grid Connected	Gear Box Rate	1:94.7
Cut-in speed	3m/s	Generator Pole Pair	2
Nominal wind speed	12m/s	Generator Type	DFIG
Cut-out speed	25m/s	Generator Synchronous Speed	1500 rpm
Rotor Diameter	82.6m	Generator Voltage	690 V
Rotor Swept Area	5359m^2		

Chapter 4

P, PI and PID Control Implementation for Wind Turbine Blade Angle Controllers

In this dissertation study, it has been mentioned before that a modern horizontal axis wind turbine consists of many different subsystems. It is evident that a wind turbine can be considered a mechatronics problem due to its fact about multidisciplinary systems. Among the other structural, electrical, mechanical and electromechanical systems of wind turbines, control systems play the most vital effect for the complex power production system. A survey of literature on advanced control strategies for wind turbines indicates the following as the main design challenges:

- Wind disturbances affect the performance of the closed loop system.
- Unmodeled dynamics impact the stability and performance of the closed-loop system.
- The main source of the non-linearity in wind turbines such as the function is unknown, and changes during the course of operation of a wind turbine

- Wind turbine dynamics indicate wind dependent behavior, which means that the parameters of a wind turbine model are different at different wind speed operating points.
- Faults may occur in the components of the wind energy conversion system (WECS).

The P, PI and PID methods used in the research study to tackle some of these problems are briefly mentioned in the remaining sections of this chapter. A detailed comparison work among the controller methodologies applied to the wind turbine power plant will be shown.

It is simple to demonstrate the resistance of a proportional integral derivative (PID) controller to steady-state perturbations. PID has thus been frequently utilized to manage WTs on the presumption of piecewise constant wind disturbances. WT PID-based control is covered in depth in [141]. The parameters of a wind turbine model would change from one wind speed operating point to the next, though, as the linearized WT model depends on the wind speed parameter even in the absence of any unmodeled dynamics. As a result, a PID control would not be able to guarantee the linear wind energy conversion system's overall stability [3]. This issue has been resolved by using gain-scheduled PID control to regulate the WT [142, 143].

The fundamental concept is to create various PID controllers at various wind speed linearization points and then identify a scheduling function based on interpolation of the controllers in order to effectively modify the loop gain. Pitch angle and wind speed can be thought of as the scheduling parameters in this method. Although this controller performs better than the standard approach, the design, like the PID method, would be subject to unmodeled dynamics [3].

4.1 The Methodology of P, PI and PID Controller

One of the most important subsystems of a wind turbine can be pitch control since it affects the mechanical strength, aeromechanical power, rotation dynamics and consecutively electrical power regulation. Pitch controllers are actively used in the full load-operating region in order to prevent any kind of mechanical damage from excessive loading at high wind speeds. Moreover, in order to regulate the power with the aid of speed regulation, different pitch controlling techniques are used in modern commercial wind turbines. Throughout this study, PI and PID controllers are implemented and simulated for 2MW DFIG wind turbine as mentioned above. The pitch controller uses the rotor angular speed as an input and error is regulated with the PID controller. In this study, the normalized error is calculated and applied to the controller as per unit (p.u).

In conventional control methods, PID controllers have feedback structures. After an error is passed through proportional, integral and derivative actions, the error is applied again to the system input in accordance with and the system output is controlled as desired [95]. Clarification of the continuous equation of the PID controller is as in 4.1. Where $u(t)$ is the controlled output, K_p is the proportional gain, K_i is the integral gain, K_d is the derivative gain and $e(t)$ is also the error signal between the system output and the system input value [95]. The discrete version of the PID controller can be stated as follows in 4.2.

$$u_t = K_P e(t) + K_I \int_0^t e(t)dt + K_D \frac{d(e(t))}{dt} \tag{4.1}$$

$$\Delta u(k) = K_p[e(k) - e(k-1)] + K_i T_s e(k) + \frac{K_d}{T_s}[e(k) - 2e(k-1) + e(k-2)] \tag{4.2}$$

4.2 Simulation Results

As has been mentioned in the previous chapter of this research study, 2MW wind turbine power plant is being used to simulate different conditions. In the simulations of PI and PID controllers, real wind data for 2MW wind turbine has been used. The power plant model has been modified for many iterations and an optimization study is also applied.

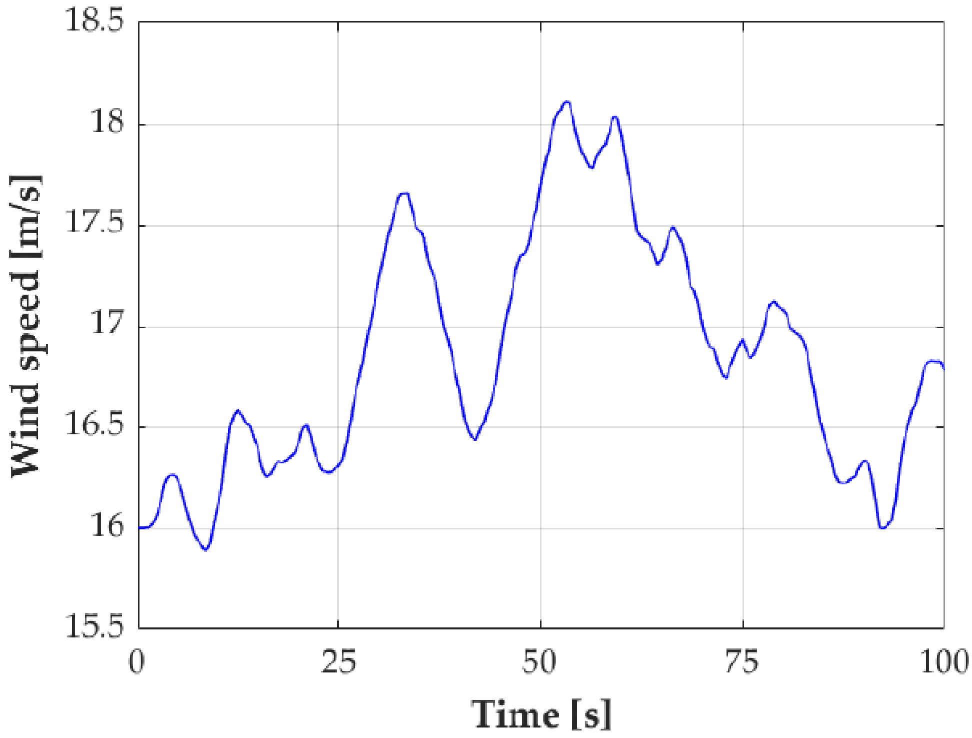

FIGURE 4.1: Wind speed For 100 second

Figure 4.1 shows the wind speed data applied throughout the controller design. The data is real wind data collected from the field. The wind speed curve is specially selected to observe the over nominal speed regions. The PI and PID controllers were implemented for the plant under the wind data shown at Figure 4.1. Transient and steady-state dynamics with the arguments of overshoot, rise time, settling time, steady-state error and power productions are compared.

As shown in Figure 4.2 a PI controller is simulated. The transient region of the result is the important part in order to compare the performances. The arguments

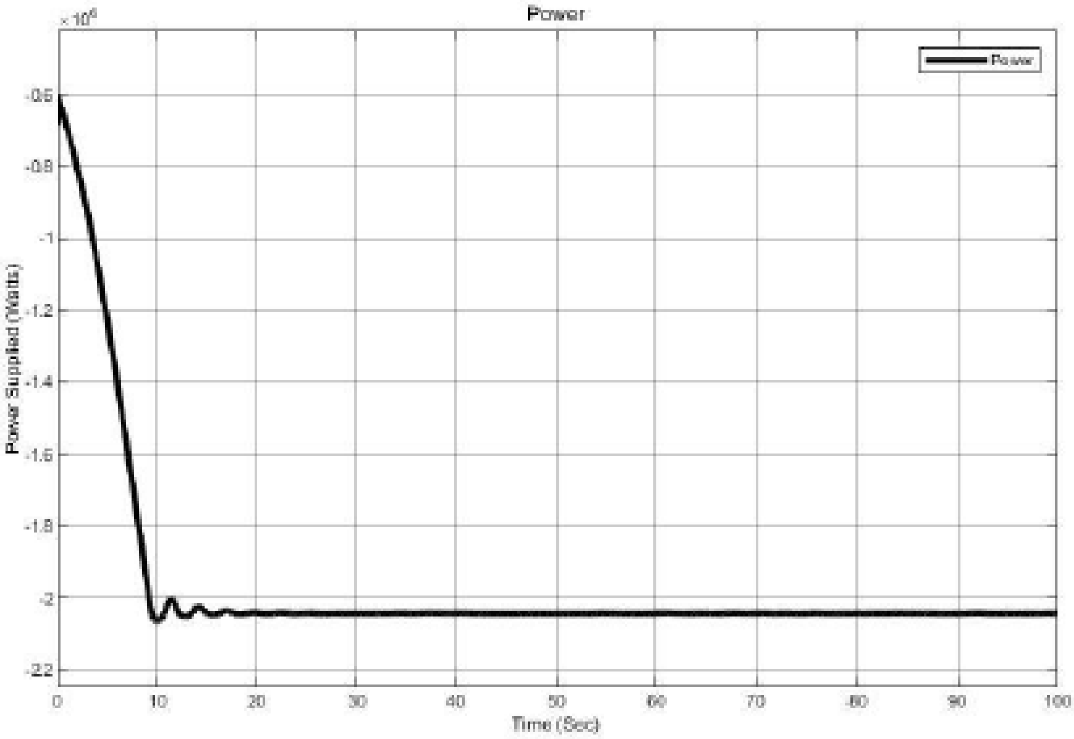

FIGURE 4.2: Power output for 100 second

of overshoot, rise time, settling time, steady-state error, and power productions are used to compare transient and steady-state dynamics. Wind speed has abrupt increases to observe the response of the controllers. Under the depicted wind profile several simulations were conducted to compare the performances of both PI and PID controllers for transient and steady-state situations.

As Figures 4.2 and 4.3 show, the main aim of the controller is to maximize the power output by keeping the generator rotational speed steady at 220 rad/sec. As previously mentioned, pitch controllers aims to regulate the rotational speed of the turbine and consecutively regulate the power while full-load wind regions. As wind speed fluctuates and abruptly changes overrated speed, the pitch angle of the blades also changes drastically. Figure 4.4 shows the simulation results of a PID controller configuration.

The pitch angle result changes show the effectiveness of the controller. As the pitch angle changes, power stabilization is achieved. The maximization of power production is aimed and will be declared in other chapters of this study.

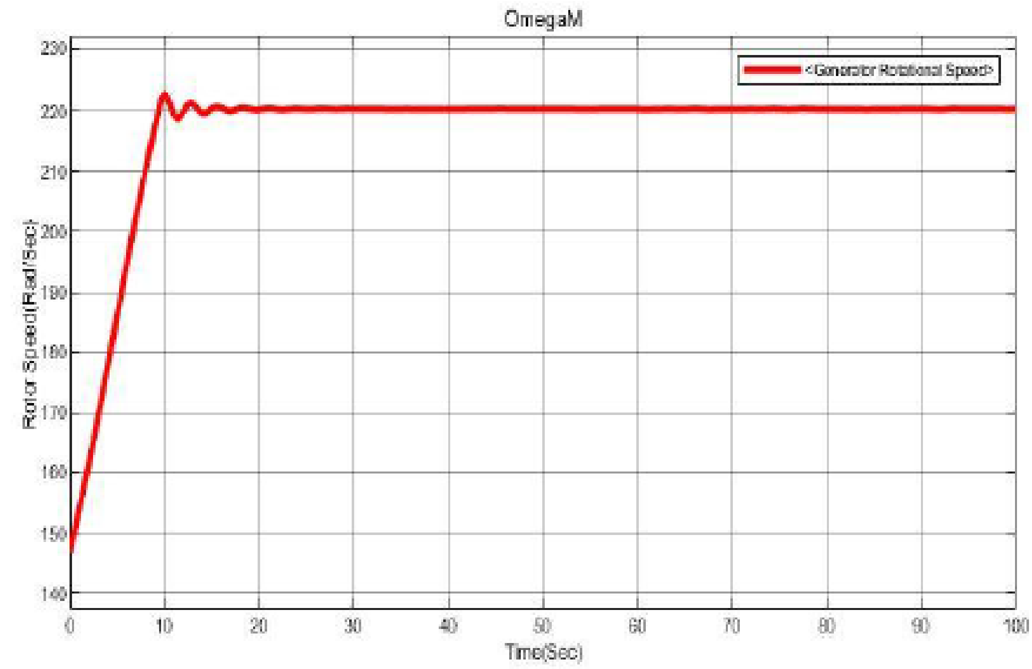

FIGURE 4.3: Generator speed results for 100 seconds

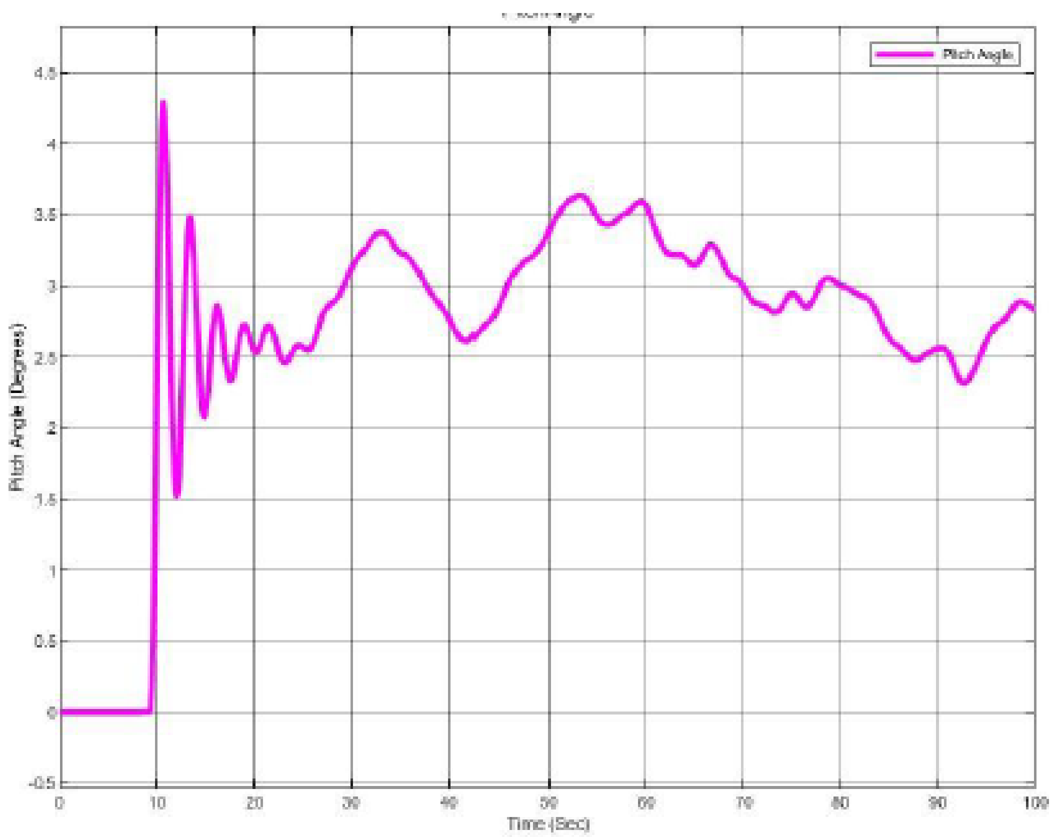

FIGURE 4.4: Pitch angle change for 100 second

4.3 Discussion

In this study, both PI and PID configurations of pitch controllers were compared initially with transient responses. Successively, steady-state responses for both controllers are also shown. Both controllers perform successfully as they have stable outputs in terms of reaching maximum power output and generator speed stability. However, their transient dynamics alter in terms of overshoot and settling time. In this manner, PI controller performance can be more efficient.

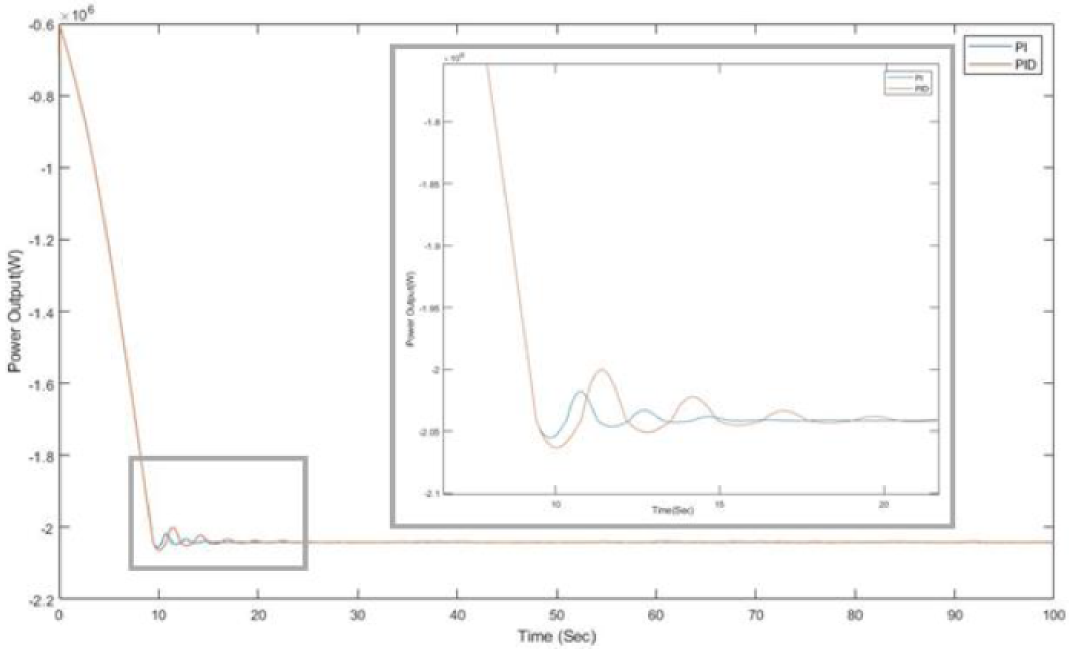

FIGURE 4.5: PI & PID controller comparison study for transient response

As denoted in figure 4.5, both controllers perform successful operations for 100 second simulation for steady-state characteristics. However, transient response performances vary. PI and PID controllers denote different transients as overshooting is more stable for PI controller. In addition, rise time, overshoot and settling time for PI and PID controllers are tabulated in Table 4.1 that is shown below.

Unlike the previous transient response, the PID controller yields better results than the PI controller under steady state in terms of both steady-state error and

TABLE 4.1: PI-PID results

Controllers	**PI**	**PID**
Overshoot (Δ_h)	2%	4.5%
Rise Time (t_r)	10s	11s
Settling Time (t_s)	20s	25.8s

total power production. Necessary results for comparison are tabulated in Table 4.2.

TABLE 4.2: Steady state results

Controllers	**PI**	**PID**
Steady State Error (e_{ss})	0.002	0.001
Total Power Production		2.4% (More than PI)

As a consequence of this attempt at controller design, controller performances were observed for two different concepts of pitch angle controllers. PI and PID controller types were observed and compared. The simulation studies were conducted to seek the performance of the controller under difficult wind situations. For example, a highly fluctuating wind manner at the third region was conducted. Gust wind environment was also applied to challenge the controller designs. As a future study proposal, PI and PID studies with gain scheduling techniques can be considered.

Chapter 5

Fuzzy Logic Controller Implementation for Wind Turbine Blade Angle Controller

This section presents a controller design approach for wind turbine controllers with a fuzzy logic control technique. There exists a couple of different attempts for pitch angle controller with fuzzy logic techniques. Our proposed methodology has novelties in terms of the number of inputs.

5.1 The Methodology of Fuzzy Logic Pitch Angle Controller Design

The advantage of a fuzzy controller is its remarkable inference capability based on fuzzy information. Changes to the control rules and suitable membership functions, reasoning processes, and choices can enhance the features of the controlled system. Fuzzy control has been frequently utilized in variable pitch control to reduce the negative impacts of nonlinear components and the challenge of changing system parameters. The design of the control scheme is crucial, including the selection of input and output variables and membership function parameters. Figure 5.1 shows the fuzzy control system block diagram.

Power error, change in power error, and generator speed are chosen as controller inputs. The primary purpose of the controller is to keep the generator speed steady. Power error and change in power error are selected as inputs since the aim is to maximize the power output. Therefore, it is essential to keep power error steady at zero. Power error and change in power error are defined as

$$e_p[k] = P_{ref}[k] - P_{gen}[k] \tag{5.1}$$

$$\delta e_p[k] = e[k] - e[k-1] \tag{5.2}$$

Here $e_p[k]$ is power error, $P_{ref}[k]$ is generator power reference, k is time step, $P_{gen}[k]$ is generator power and $\delta e_p[k]$ is the change in power error. A third input variable is also used, namely, the deviation of the generator speed from its nominal value $d_{w_g} = w_{g_{nominal}} - w_g$. Any modification on the pitch angle β will affect the generator speed. The generator speed, on the other hand, determines the turbine power. The inclusion of our third variable provides the controller with the freedom of tuning its action with the instantaneous generator speed. When the power error requires an increase in generator speed, and when this speed is already excessive, a moderate action on pitch angle variation can be taken. If instantaneous generator speed is not considered in the control output decision, however, a large pitch angle would be commanded. Triangle membership functions with overlaps are utilized to build the fuzzy sets of inputs, as shown in Figures 5.2, 5.3 and 5.4. The membership functions of power error and change in power error can be seen in Figures 5.2 and 5.3. The membership functions of generator speed are presented in Figure 5.4. Negative Big (NB), Negative Medium Big (NMB), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM), Positive

Medium Big (PMB), and Positive Big (PB) are the linguistic variables. Membership function variables are unknown and calculated with the GA. The membership functions of the output are presented in Figure 5.5. Fuzzy outputs are negative big (NB), negative medium big (NMB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM), positive medium big (PMB) and positive big (PB). The centers of output membership functions are at -0.4, -0.3, -0.2, -0.1, 0, 0.1, 0.2, 0.3 and 0.4 respectively. FLC rules are chosen as in Table 5.2. For instance, if the generator power error value is NB at the FLC membership function, the change in generator power error is NS and the change in generator speed is PB, the FLC output is PS which means $\beta[k]$ is equal to 0.1 (Table 5.2).

Fuzzy logic rules are of the following structure:

R_i: If $e_{w_g}(k)$ is A_i and $e_p(k)$ is B_i and $\delta e_p(k)$ is C_i then $\delta\beta(k)$ is D_i

where A_i, B_i, C_i are fuzzy sets of input variables and D_i is a fuzzy singleton corresponding to a rule strength. The fuzzy system computes the necessary change $\delta\beta(k)$ in the pitch angle in the next computational step. The final value of this angle is obtained by cumulatively adding the fuzzy system outputs each cycle. The FLC rule base is presented as in Table 5.2. It reflects 75 rules (R1, ... R75) in the structure described above. For instance, if generator power error value is NB, change in generator power error is NS and deviation of generator speed from its nominal value is PB, the FLC output is PS which means $\beta[k]$ should be increased by 0.1 deg. For each rule a truth value Ti is computed with the product inference technique.

$$T_i = \mu_e p(e_p(k))\mu_{\delta e_p}(\delta e_p(k))\mu_d w_g(d_{w_g}(k)) \tag{5.3}$$

The necessary change in the pitch angle β is computed by the center average defuzzification rule:

$$\delta\beta = \frac{\sum_{i=1}^{75} T_i D_i}{\sum_{i=1}^{75} T_i} \tag{5.4}$$

The output of the fuzzy logic controller is multiplied by a tuning coefficient to obtain the pitch angle :

$$\beta_{ref}[k] = K_p \beta[k] \tag{5.5}$$

Here, β_{ref} is the pitch angle reference, K_p is a proportional constant, and β is FLC output. The main feature of the rule base in Table 5.2 is to increase β when the power is below the reference value, and to lower it when there is excess power. This action is, however, moderated by two factors: change of power and deviation of generator speed. If power is to be increased and the change of power is positive, β is increased less when compared with the case with zero or negative change of power. Also, if the generator speed is in excess of the nominal value, power increase is targeted with a very small increase in β. The overall rule base acts as a dual goal control mechanism, aiming to keep power in generator speed at their reference and nominal values, respectively.

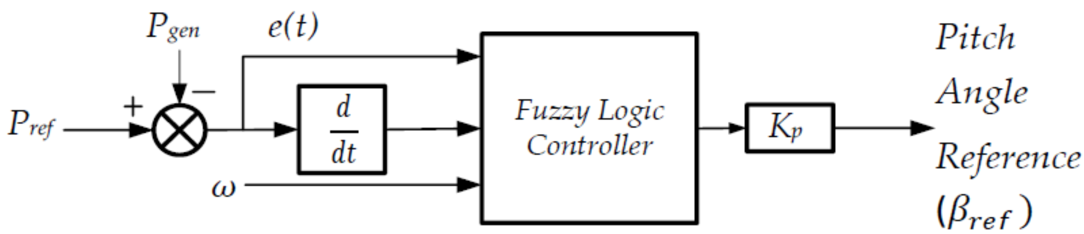

FIGURE 5.1: Fuzzy logic control block diagram

5.2 Simulation Results

The controller is simulated with significantly fluctuating wind data obtained from a wind field for 100 seconds. As shown in Figure 5.6, region three wind speed 5m/s over the nominal speed is simulated and controller response is observed. Another

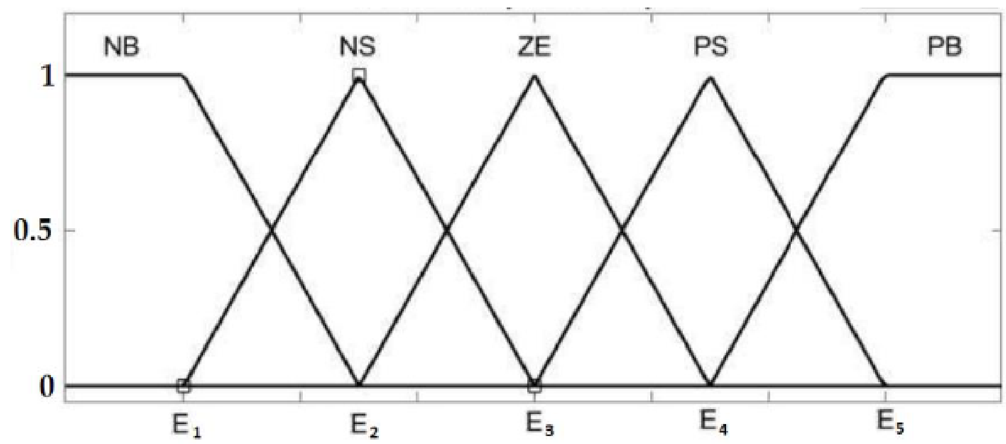

FIGURE 5.2: Fuzzy control membership functions for generator power error

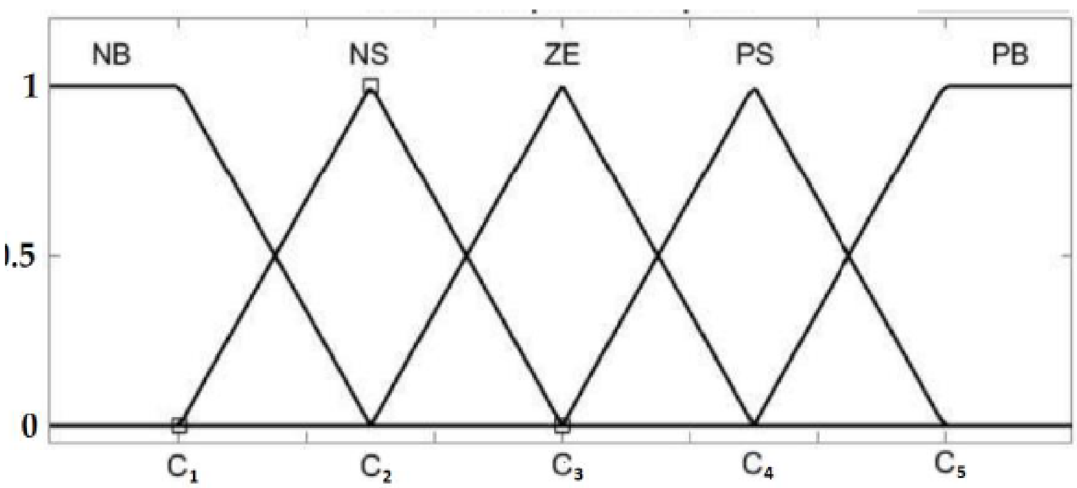

FIGURE 5.3: Fuzzy control membership functions for change in generator power error

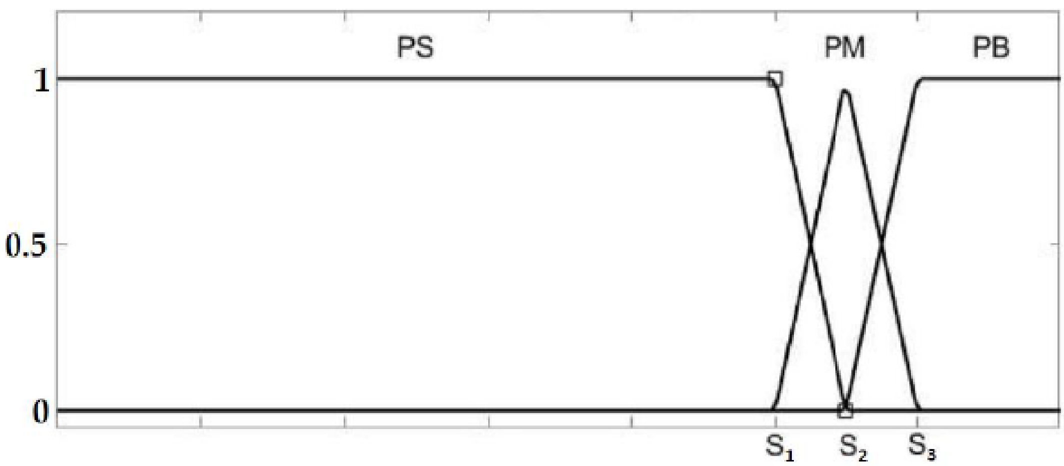

FIGURE 5.4: Fuzzy control membership functions for change in generator speed

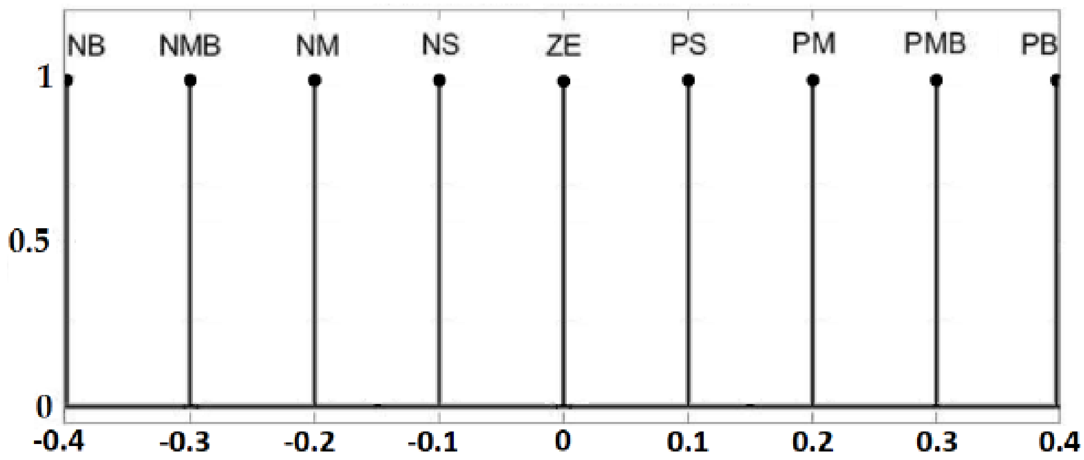

FIGURE 5.5: Fuzzy control membership functions for output pitch angle

TABLE 5.1: Simulated system characteristics

Nominal Output Power	2MW	Nominal Rotor Speed	15.8 rpm
Working Mode	Grid Connected	Gear Box Rate	1:94.7
Cut-in speed	3m/s	Generator Pole Pair	2
Nominal wind speed	12m/s	Generator Type	DFIG
Cut-out speed	25m/s	Generator Synchronous Speed	1500 rpm
Rotor Diameter	82.6m	Generator Voltage	690 V
Rotor Swept Area	$5359m^2$		

purpose of the controller is to achieve the desired power output in the shortest time and the most prolonged duration.

The controller performance is measured with criteria such as settling time, overshoot, rise time and steady-state error. As presented in Figure 5.7, the system reaches steady state around 10th second with the maximum power output. The magnitude of the power fluctuations without genetic tuning is 0.015 MW. With genetic tuning, this magnitude drops to 0.005 MW. Similar previous studies were not conducted in region three with wind speeds over 50 percent above the nominal wind speed [138] [123]. This, however, is the case in the presented work. In this research, the controller performs under highly fluctuating wind speeds, whereas previous similar studies [138] [123] had more steady profiles.

In Figure 5.8, the maximum power is achieved after the transient phase is completed and the change in power error is decreased by approximately 50 percent with the genetic algorithm. In study [138] which employs fuzzy logic control without genetic algorithm optimization, there are significant errors in power and power error rate of change.

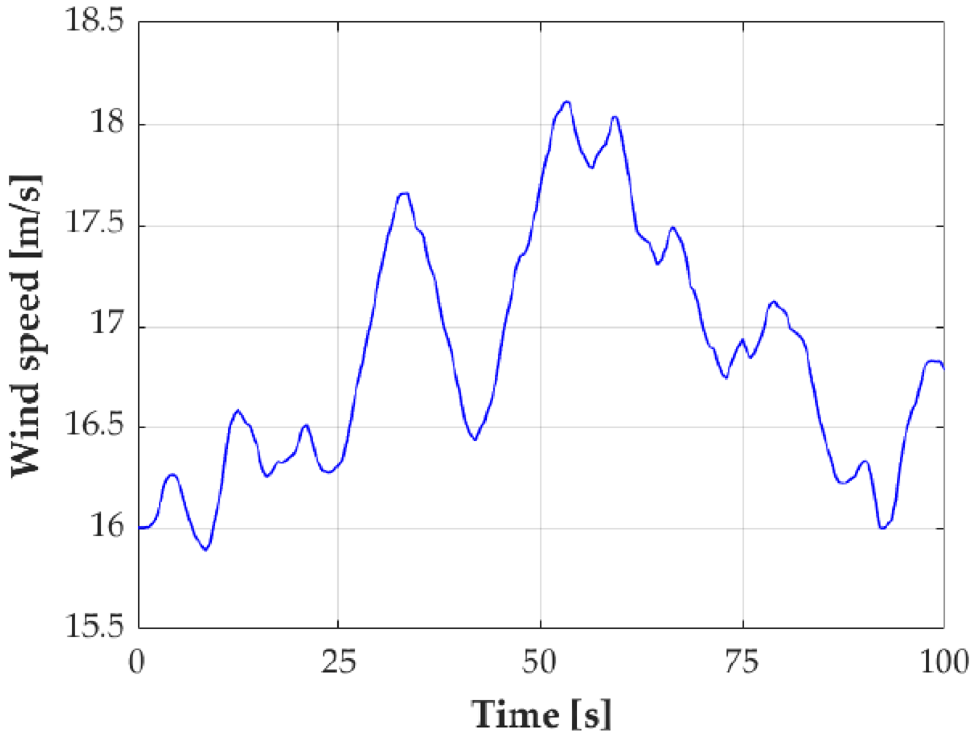

FIGURE 5.6: Wind profile for region 3

5.3 Discussion

The fuzzy logic controller is applied with novelties. In this chapter, the process of design is explained for the pitch angle controller. Three different inputs are applied for the controller and 75 different rule basis were implemented. The fuzzy logic controller design is carried out on a 2MW wind turbine model with DFIG layout. Inputs include generator speed, power error, and power error rate. Control settings for fuzzy logic are modified by a genetic algorithm. The genetic algorithm study

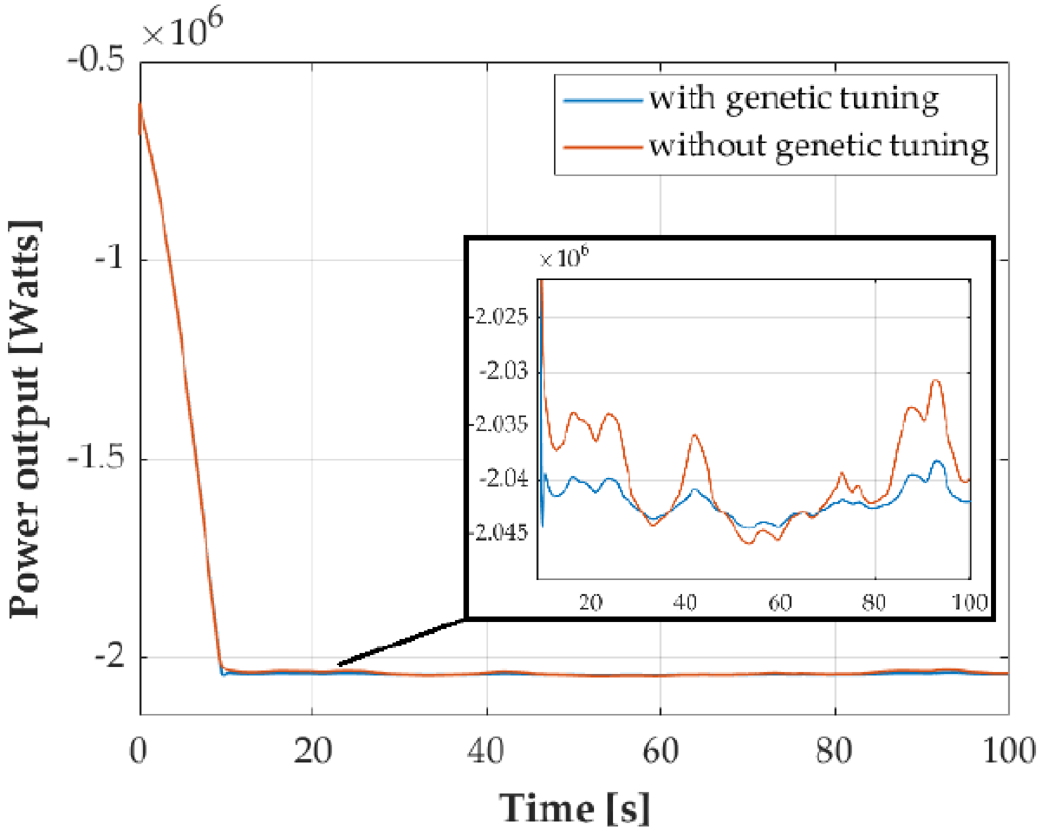

FIGURE 5.7: Power output of Fuzzy logic control with blue line

TABLE 5.2: Fuzzy Logic Control Table

e_p		NB			NS			ZE		
d_{w_g}		**PS**	**PM**	**PB**	**PS**	**PM**	**PB**	**PS**	**PM**	**PB**
Δe_p	**NB**	NB	NS	PS	NB	NS	PS	NB	NS	PM
	NS	NB	NS	PS	NB	NS	PS	NB	ZE	PMB
	ZE	NB	NS	PS	NB	ZE	PM	NMB	ZE	PMB
	PS	NB	NS	PM	NMB	ZE	PM	NMB	ZE	PB
	PB	NMB	ZE	PM	NMB	ZE	PM	NM	PS	PB

e_p		PS			PB		
d_{w_g}		**PS**	**PM**	**PB**	**PS**	**PM**	**PB**
Δe_p	**NB**	NB	PM	PMB	NMB	PMB	PB
	NS	NMB	PM	PMB	NMB	PMB	PB
	ZE	NMB	PM	PB	NM	PMB	PB
	PS	NM	PMB	PB	NM	PMB	PB
	PB	NM	PMB	PBPB	NM	PMB	PB

will be explained in future chapters. Multiple simulations conducted in MATLAB/SIMULINK show optimized FLC performance. Controller performance is

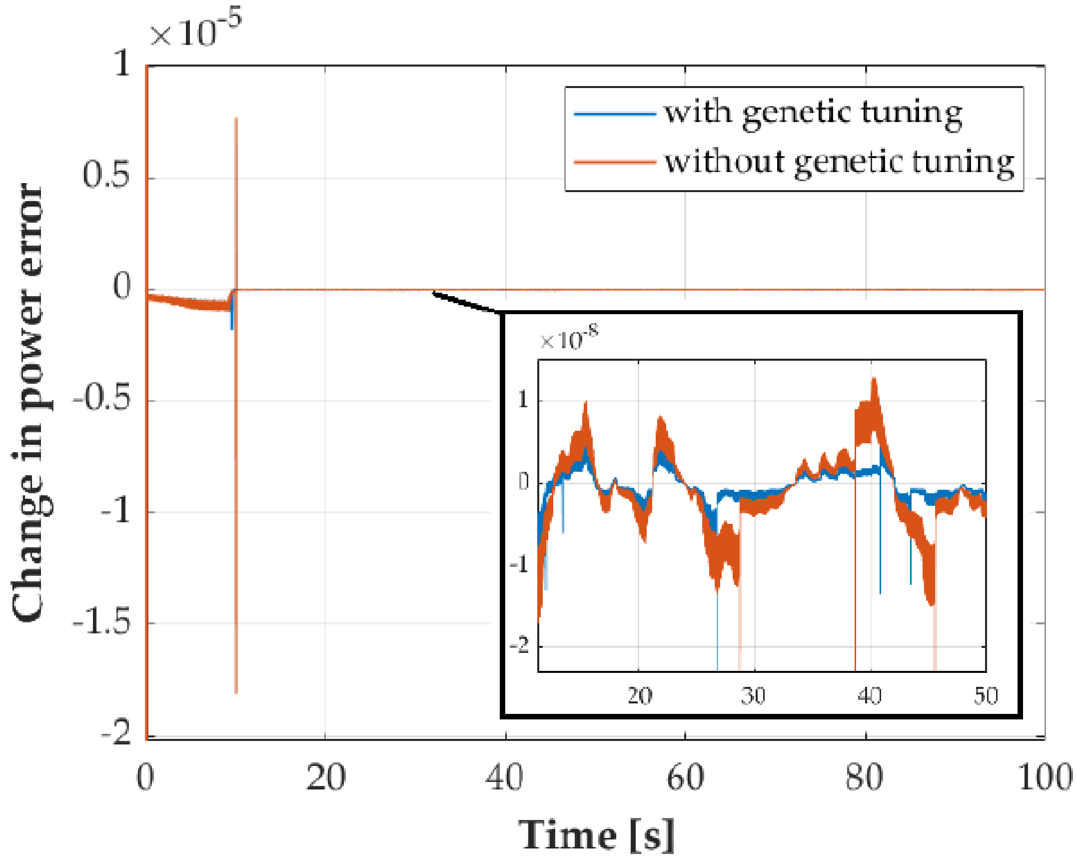

FIGURE 5.8: Power output of Fuzzy logic control with blue line

one of the most important topics in order to maximize annual energy production.

Chapter 6

P, PI and PID controllers with Genetic Algorithm

6.1 The Methodology of the P,PI and PID controllers with Genetic Algorithm Optimization

In this chapter, the optimization part of the PI and PID controller attempts will be discussed. Among the many optimization methodologies, the genetic algorithm was selected. As described previously in chapter 4, PI and PID controllers were developed for the defined power plant of 2MW wind turbine. A typical type of feedback is the proportional, integral and derivative (PID) controller [144]. Because of its straightforward structure, which is simple to comprehend and put into practice, it has been widely employed in process industries [144]. The PID controller needs to be tuned for it to function effectively. The majority of researchers are examining the genetic algorithm, a contemporary optimization tool, to find the ideal PID settings [145]. Genetic algorithm theory is based on Darwin's theory of evolution, which claims that the rule "the stronger species survives" has an impact on an organism's chances of surviving [145]. Darwin also claimed that the processes of reproduction, cross-pollination, and mutation can ensure an organism's survival. Darwin's theory of evolution is then applied to a computing algorithm to naturally solve the problem of the objective function. Chromosomes are solutions produced by genetic algorithms, while populations are collections of chromosomes. A chromosome is made up of genes and depending on the issue at hand, its value may take the form of a number, a binary code, a set of symbols, or even a character. The fitness function will be applied to these chromosomes to evaluate how well the GA-generated solution fits the challenge [145]. Through a process known as crossover, certain chromosomes in a population will mate, giving rise to new chromosomes called children, whose genes are a combination of their parents. A few chromosomes will also mutate in their gene during the course of a generation. The value of the crossover rate and mutation rate determines how many chromosomes will experience crossover and mutation. According to the Darwinian evolution rule, the chromosome in the population that will survive for the following generation will be chosen; the chromosome with the higher fitness value will have a higher likelihood of being chosen once more in the following generation. The chromosome value will eventually converge to a specific value which is the best way to solve the issue after several generations [145]. The steps of the algorithm can be listed below:

- Step1: Determine the number of chromosomes, generation, mutation rate, and crossover rate value
- Step2: The population's chromosome-chromosome number should be generated, and the initialization value for each gene's chromosome should be chosen at random.
- Step3: Until the desired number of generations is reached, carry out steps 4–7.
- Step4: By computing an objective function, chromosomal fitness is evaluated.
- Step5: Chromosomes selection

- Step6: Crossover
- Step7: Mutation
- Step8: Solution

To find the best control settings for PID controllers, a variety of strategies have been developed over the last few years. Numerous innovative methods for tuning PID controllers have been created by the academic control community. They have been weak to try to use the new techniques founded on evolutionary ideas. One such direct search optimization method that is based on the principles of natural genetics is a GA. The GA for autotuning has the benefit that it can operate to minimize naturally specified cost functions without requiring sophisticated mathematical procedures because it does not require gradient information [146].

Figure 6.1 shows the flowchart of the genetic algorithm methodology. Optimization is one of the most important concepts in a post-design study to get an advanced controller for the plant. For the genetic algorithm optimization, it is very critical to determine the parameters of the initial population, crossover rate and other parameters in order to have the convergence of the optimization.

As has been shown in figure 6.2, with error calculation, the optimization study is carried out for minimizing the error. The objective function for the PID controller gain tuning can be stated as minimizing the error with special constants as illustrated in figure 6.2. Integral square error (ISE), integral absolute error (IAE), and integrated time absolute error (ITAE), respectively, are often used error criteria to achieve optimized PID tuning values. The equations for ISE, IAE and ITAE are shown respectively below. The objective function to minimize the steady-state error (e_{ss}) is depicted at 6.4. In the research study, the ITAE methodology is implemented in the simulations.

$$ISE = \int_0^\infty [e(t)^2]\,dt \tag{6.1}$$

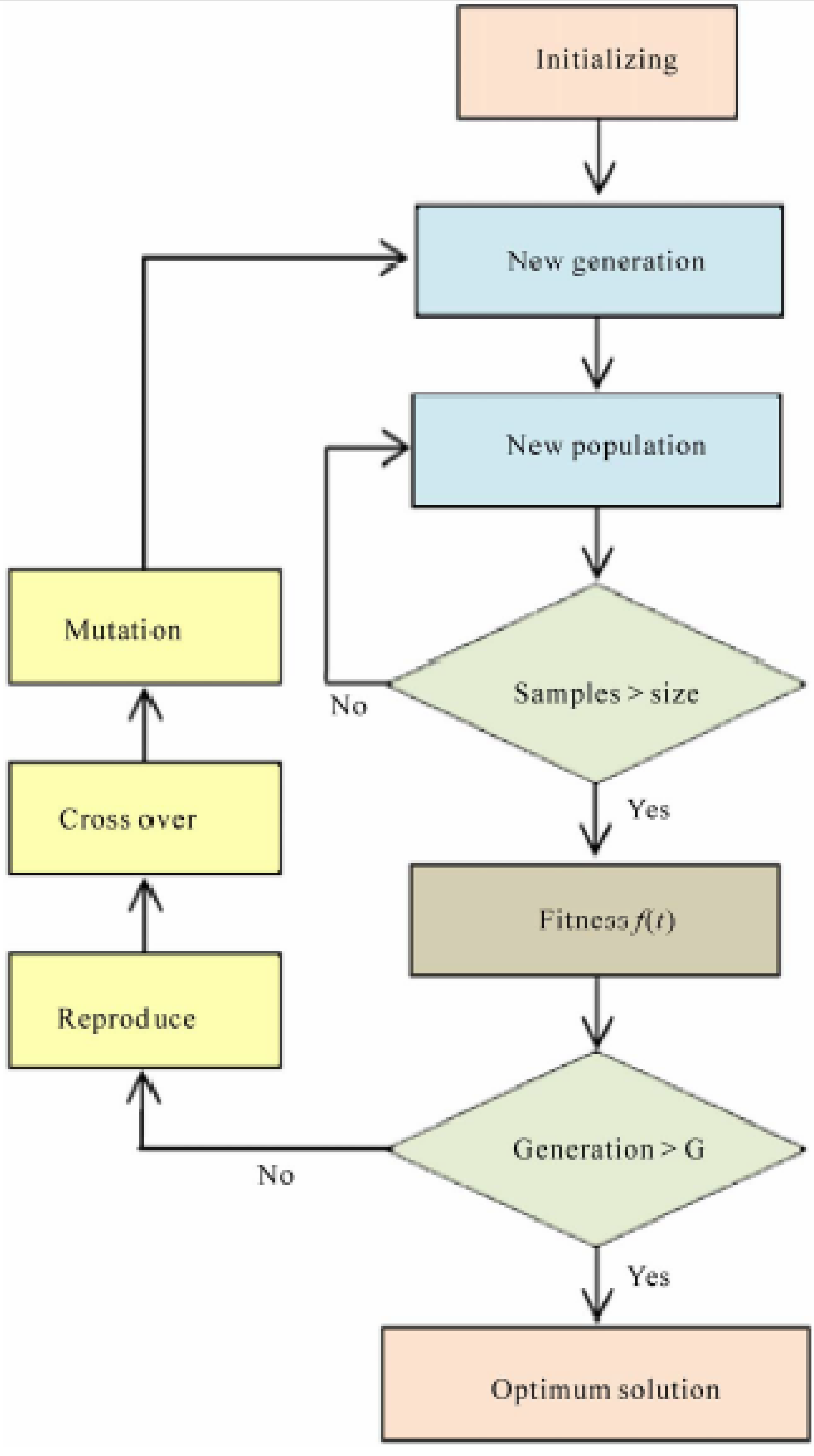

FIGURE 6.1: The flowchart of genetic algorithm technique

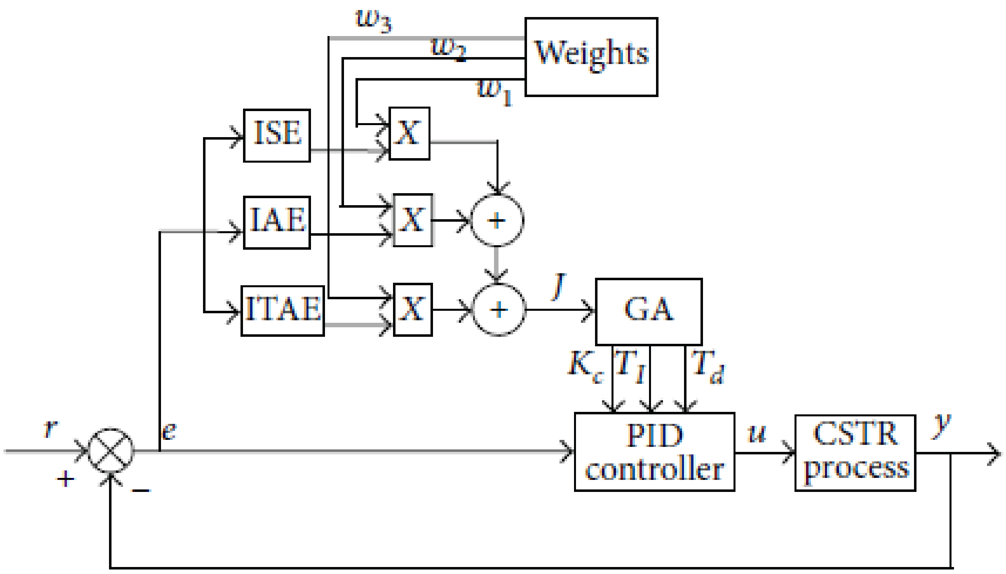

FIGURE 6.2: The PID controller block diagram with optimization

$$IAE = \int_0^\infty |e(t)| \, dt \tag{6.2}$$

$$ITAE = \int_0^\infty t\,|e(t)| \, dt \tag{6.3}$$

$$J(K_p, K_i, K_d) = w_1(ISE) + w_2(IAE) + w_3(ITAE) \tag{6.4}$$

In this dissertation study, the PID controller was designed for the described plant for a 2MW wind turbine. The coefficients of K_p, K_i and K_d were optimized within the lower and upper boundaries. In this research, the coefficients are optimized with the ITAE technique to minimize the steady-state error (e_{ss}). For lower and upper boundaries of the coefficients are selected as [10,10,10] and [1000,1000,1000] respectively. After the genetic algorithm optimization study minimization of steady-state error for the controller is achieved in order to maximize the power production of the turbine. The optimum solution for coefficients is reached as [384,256,24] for K_p, K_i and K_d respectively.

6.2 Simulation Results

As mentioned previously at the beginning of this chapter, the simulation runs for the genetic optimization were conducted in order to find the optimum solution of the PID controller for the above-rated mean wind speed performance. The wind speed input is applied to observe the performance results of the region 3 wind speeds. At the beginning of this part of the chapter, the initial coefficients of the PID controller which is introduced as a lower boundary will be shown.

After the initial coefficients results, the optimum solution will be introduced. Figure 6.3 below shows the wind profile applied for the optimization study.

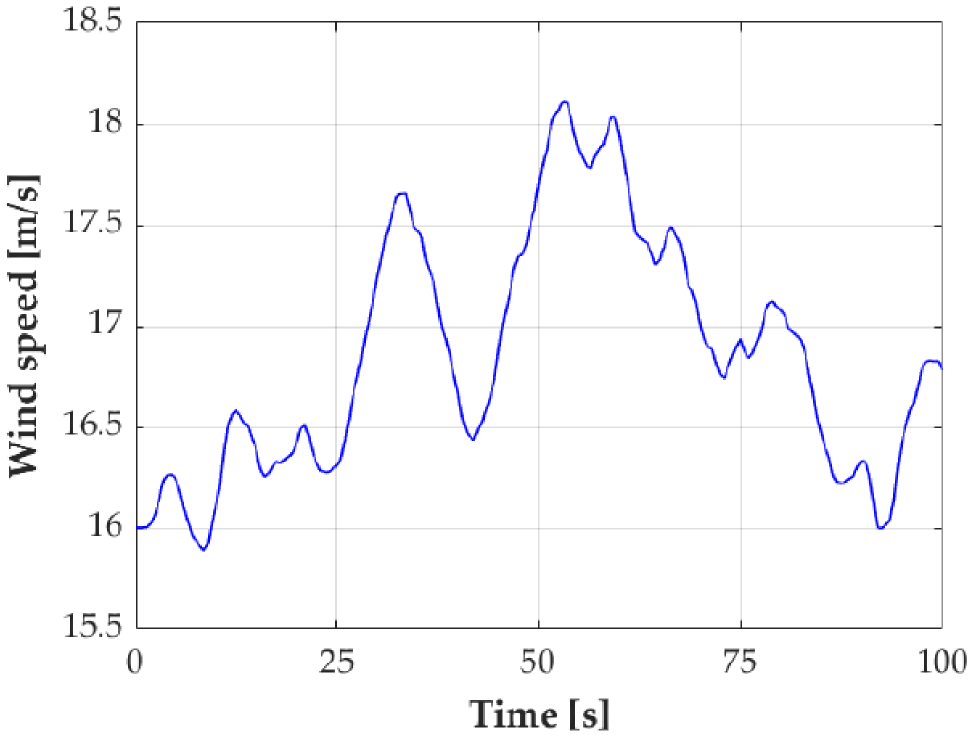

FIGURE 6.3: Wind speed profile

As shown in the figure 6.3, a highly fluctuating manner of wind profile is applied throughout the optimization process for the PID controller coefficients. This wind profile has a mean value of 17m/s that is specially applied to examine the effects of the controller under high-speed zone. Figure 6.4 below shows the results of the PID controller with the lower boundary coefficients.

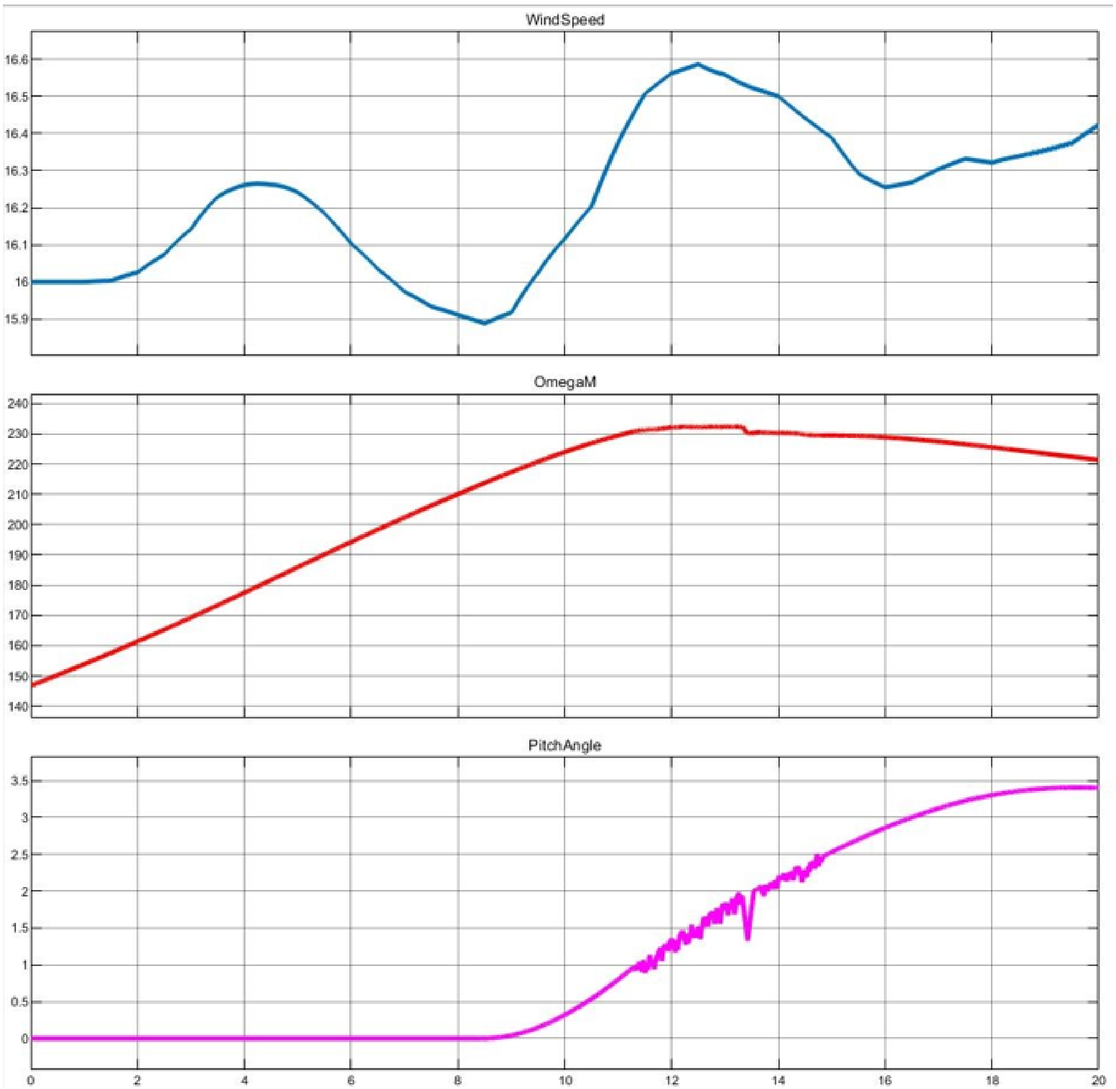

FIGURE 6.4: Results before GA optimization

As shown in figure 6.4, the generator speed of the wind turbine with initial coefficients has a very high overshoot value and longer steady state settling time. This affects power production negatively. Moreover, pitch angle response has also a chattering effect due to the lack of a controller effect. Unless the turbine controls the blades well with proper pitch angle output with correct timing, the performance of power does not reach optimum values.

As has been illustrated in figure 6.5, generator power reaches the reference value with lower overshoot and with fewer fluctuations. Because of the smooth effect of the pitch angle output, the generator speed converges to the reference value faster. This leads to the maximization of annual energy production.

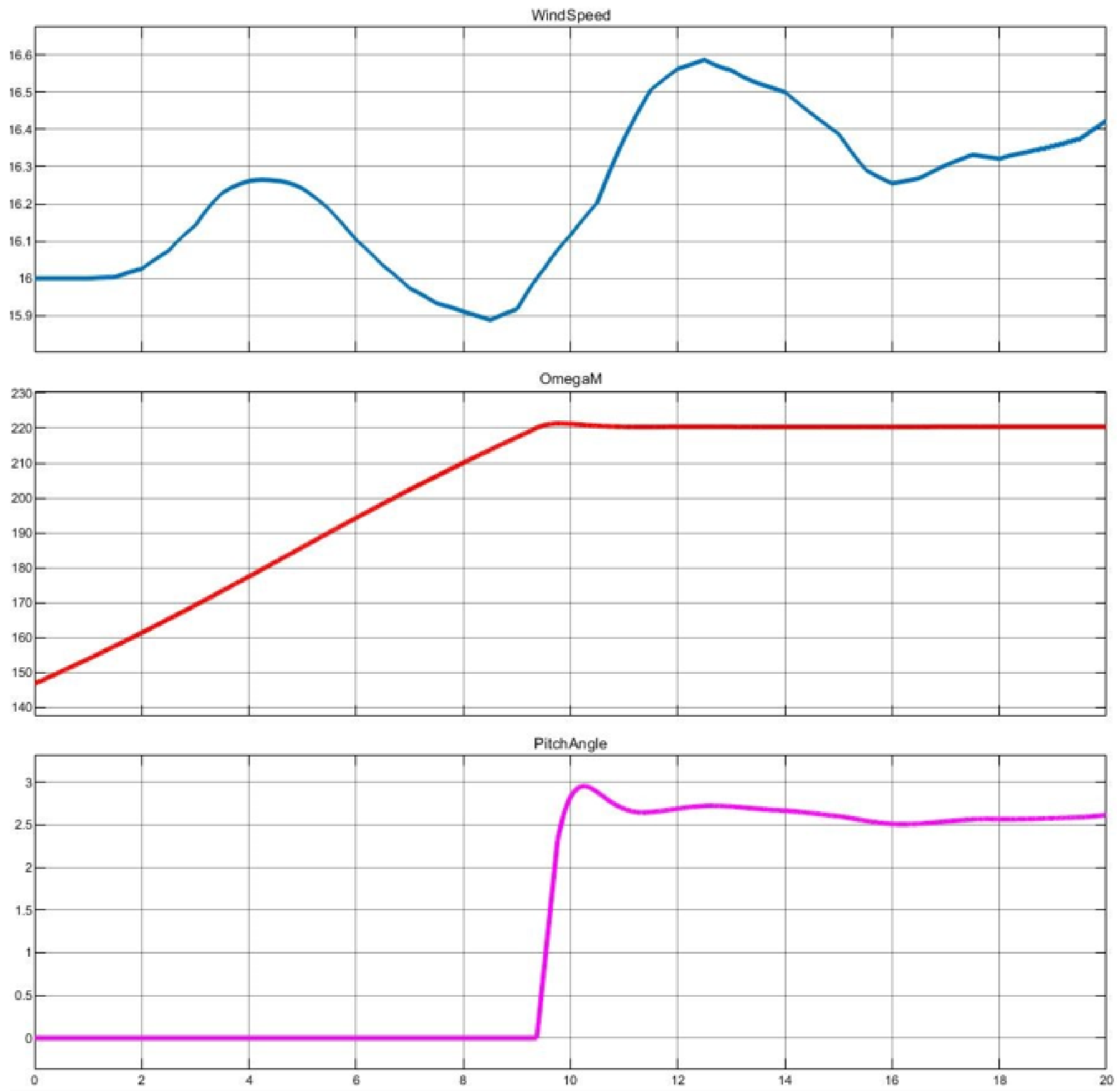

FIGURE 6.5: Results after GA optimization

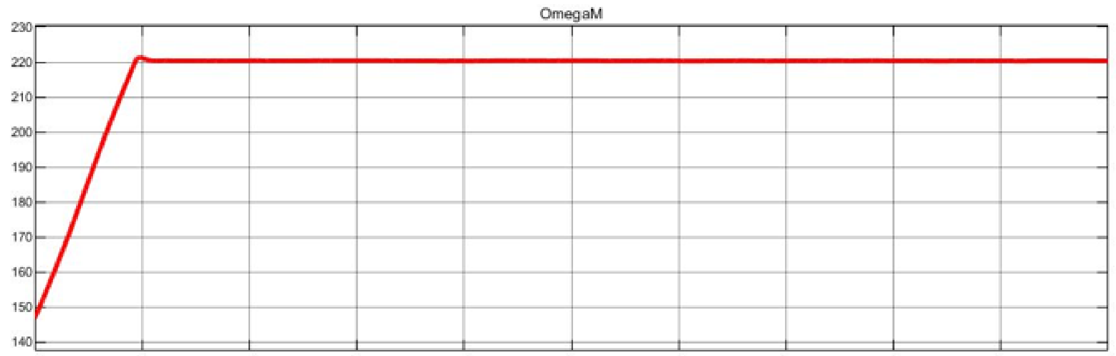

FIGURE 6.6: Generator speed after GA optimization

Figure 6.6 indicates that the generator speed value reaches to reference value which is 220 rad/s with a very smooth path. There exists almost no overshoot nor undershoot and steady state is reached much faster. As mentioned previously, due

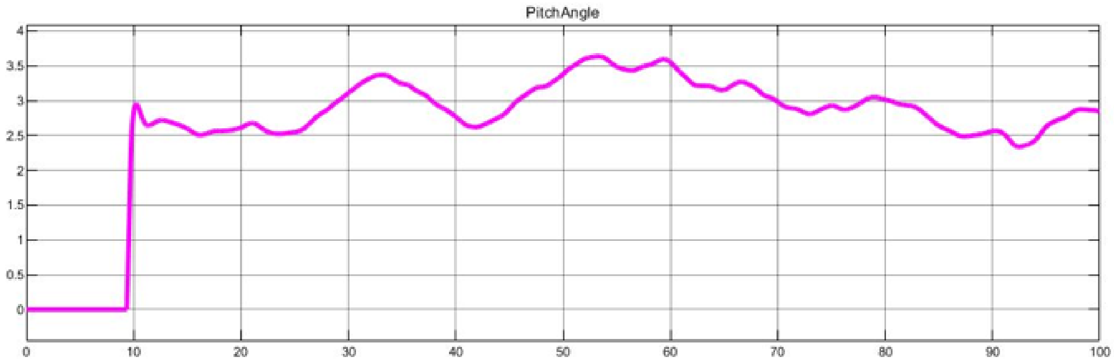

FIGURE 6.7: Pitch angle output after GA optimization

to the optimum coefficients of the PID controller, power production maximization is achieved. Due to the help of steady-state error minimization, the overshoot value is lowered to reach steady-state conditions faster.

6.3 Discussion

In this chapter of the study, the genetic algorithm process was intended to be described. PID controller is one of the main industrial and commercial applications for wind turbines' pitch angle controllers. Therefore, observing the PID performance for our proposed plant has always been important. The PID controller algorithm was designed and implemented for the 2MW wind turbine power plant. Integral time absolute error methodology is used to optimize the error of the controller. The method was applied to the Simulink model of the wind turbine. The coefficients for the PID controller of K_p, K_i and K_d are optimized to minimize the steady-state error.

The lower boundary for the coefficients are set to [10 10 10] respectively. The upper boundaries for the coefficients are selected as [1000 1000 1000]. The optimization study was conducted with 2500 iterations. Unlike chapter 4, simulations were conducted for 20 seconds, whereas in chapter 4 the simulations were in 100 seconds. After the simulation runs of 2500 iterations [384,256,24] were reached for K_p, K_i and K_d respectively. The PID controller performs better in terms of power maximization. As the steady-state error minimizes, power production gets bigger and bigger. When the converged PID coefficients are applied the production of power increases %2.5 than the PID controller proposed in chapter 4.

Chapter 7

Fuzzy Logic Controller Design for a Pitch Angle Controller with Genetic Algorithm Optimization Methodology

In this chapter of the dissertation study, the extension of the performance in chapter 5 will be presented. The proposed fuzzy logic controller for the 2MW wind turbine plant was described in detail in chapter 5. As mentioned previously, genetic algorithm optimization methodology has been applied in several disciplines of wind turbine technology. Aerodynamic design, blade shape optimization and pitch angle controller design can be given as examples of the implementation of genetic algorithm optimization for wind turbines. In the following parts of this chapter, the methodology for genetic algorithm about the implementation on fuzzy logic controller, simulation results and discussion part will be discussed.

7.1 Methodology

In the genetic algorithm for fuzzy logic blade angle controller, a population-based algorithm is used. Every member of the population has a fitness value, which reflects the relative importance of the objective function. The greater the fitness value of a member, the more likely it will become a next-generation parent. Various methods, such as a roulette wheel, tournament and ranking, are utilized to choose the proper individuals from the formed population. The tournament approach is used as a selection method in this study. Compared to other selection methods for genetic algorithms, tournament selection provides a number of advantages. Coding is doable and it operates on parallel architectures [147].

The crossover technique creates new population members from two existing ones. The number of population members who will be crossed is determined by the crossover rate. This ratio fluctuates based on the work at hand and the design process. In this investigation, the crossover ratio is set at 80%.

The fitness function represents how close each member of the population is to the solution. The function tolerance value is selected as 1e-6 as convergence criteria for the objective function, and the fitness function is selected as integral time absolute error (ITAE), defined as follows.

$$ITAE = \sum_{l=0}^{k} |e(l)| \tag{7.1}$$

Here, $e[t]$ is power error and t is time. The genetic algorithm optimization is utilized to compute optimum membership function values for fuzzy logic control. The optimized variables can be seen in figures 7.1,7.2 and 7.3 below respectively. These variables are E_1,E_2,E_3,E_4 and E_5 for membership functions of power error, C_1,C_2,C_3,C_4 and C_5 for membership functions of change in power error, S_1,S_2,S_3 for membership functions of generator speed and scaling factor K_p.

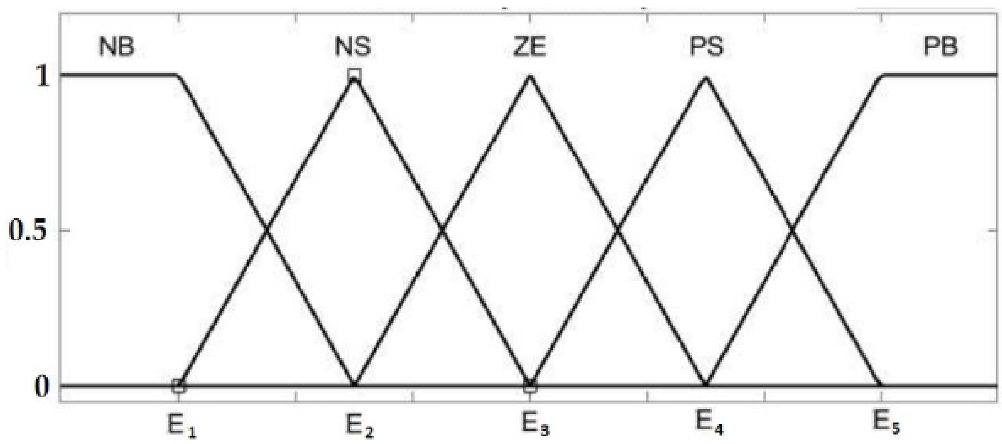

FIGURE 7.1: Fuzzy control membership functions for generator power error

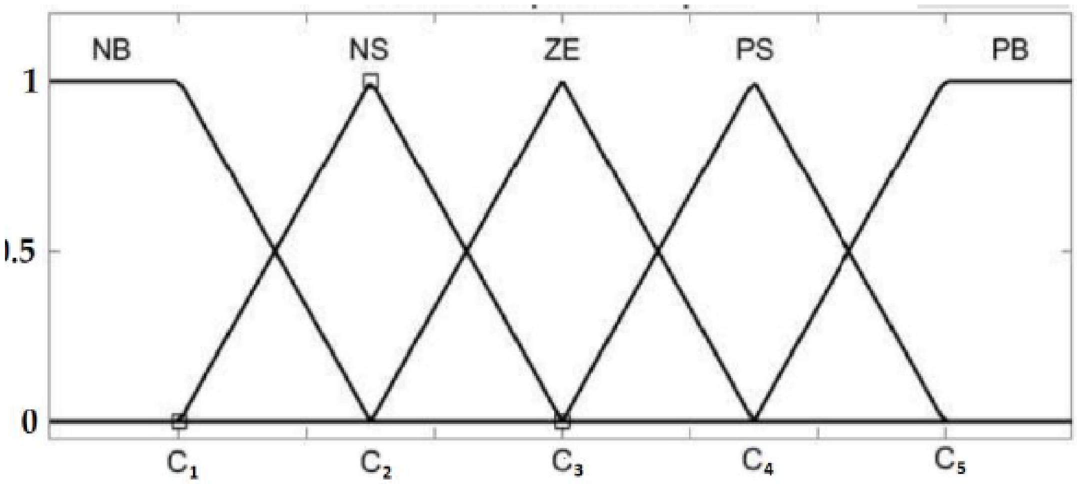

FIGURE 7.2: Fuzzy control membership functions for change in generator power error

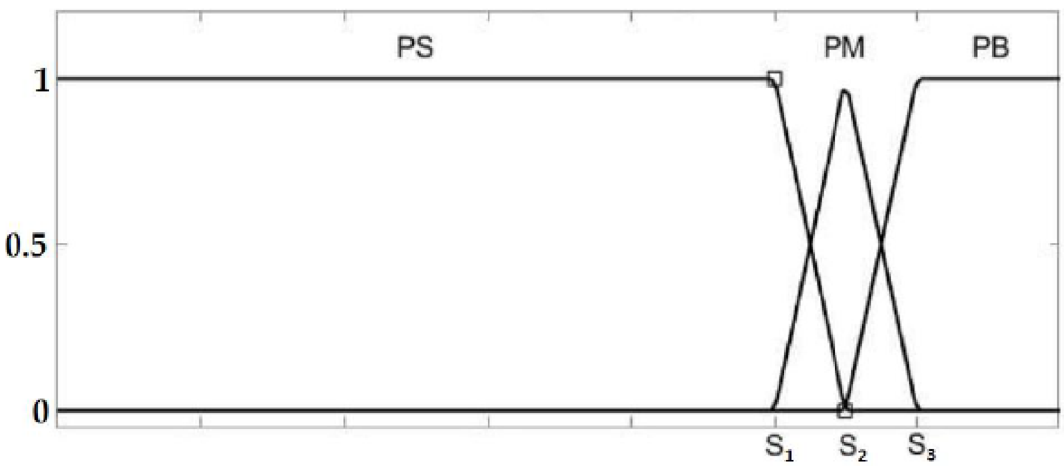

FIGURE 7.3: Fuzzy control membership functions for change in generator speed

Table 7.1 presents optimization results for these parameters and allowed intervals. These intervals are found with a trial-and-error method in order to find approximate regions in which the controller performs adequately.

TABLE 7.1: Fuzzy logic control parameters optimized by GA

Variable	**Interval**	**Value**	**Variable**	**Interval**	**Value**
E_1	[-4.2,-1.3]	-3.076	C_3	[0,0]	0
E_2	[-3.6,-1.15]	-2.746	C_4	[0.00003,0.00033]	0.00003
E_3	[-3,-1]	-2.416	C_5	[0.00006,0.00066]	0.00006
E_4	[-2.85,-0.4]	-2.085	S_1	[-0.111,0]	-0.013
E_5	[-2.7,0.2]	-1.755	S_2	[-0.088,0.022]	0.002
C_1	[-0.000066,-0.0006]	-0.00006	S_3	[-0.066,0.044]	0.018
C_2	[-0.000033,-0.0003]	-0.00003	K_p	[19,21]	19.997

The controller for the pitch angle system with fuzzy logic advances in terms of performance results than the commercial PID controllers. When the fuzzy logic is optimized with genetic algorithm methodology, maximized results are reached in terms of power production.

7.2 Simulation Results

The controller is simulated with significantly fluctuating wind data obtained from a wind field for 100 seconds. However, optimization studies were conducted for 20 seconds. Since the simulation converges to steady state after 10 seconds, simulations for 20 seconds were enough for the performance of optimization. The controller reaction is detected when the wind speed in region three is simulated to be 5 m/s over the nominal speed, as illustrated in Figure 7.4. The controller's ability to produce the necessary power output in the least amount of time and for the longest period is another goal.

Criteria such as settling time, overshoot, rising time, and steady-state error are used to gauge the performance of the controller. As seen in Figure 7.5, the system enters its steady state with the highest power output around the 10th second.

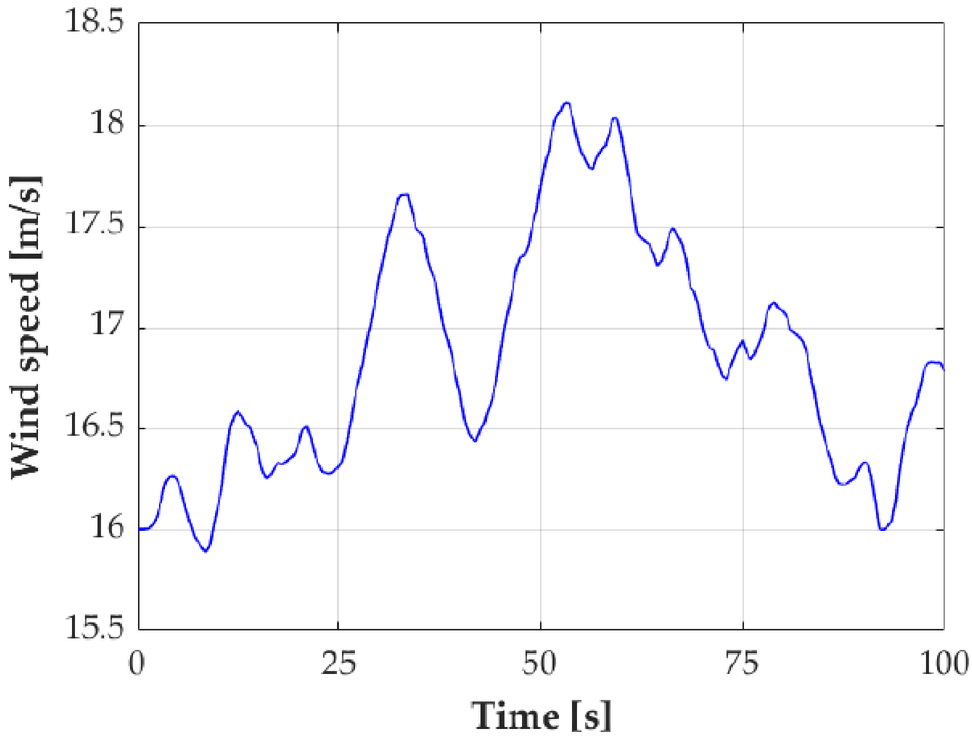

FIGURE 7.4: Wind speed profile

Without genetic adjustment, the power oscillations have a magnitude of 0.015 MW. This magnitude is reduced through the genetic adjustment to 0.005 MW. With wind speeds above 50% higher than the nominal wind speed, similar earlier experiments were not carried out in area three [123], [138]. But this is the case with the work that is being presented. In contrast to earlier studies [123], [138] that had more stable profiles, the controller in this research operates in conditions with considerable wind speed variability.

In Figure 7.6, the maximum power is reached when the transient phase is finished and the evolutionary algorithm has reduced the change in power error by around 50%. There are large faults in power and the power error rate of change in study [138], which uses fuzzy logic control without genetic algorithm optimization.

Because the controller's response time is prolonged, it begins to act once the generator's rotational speed hits 220 rpm, at which point the pitch angle begins to change from zero. Following the initial step reaction of the pitch angle, the controller smoothly changes the pitch angle to control the generator's 220 rpm

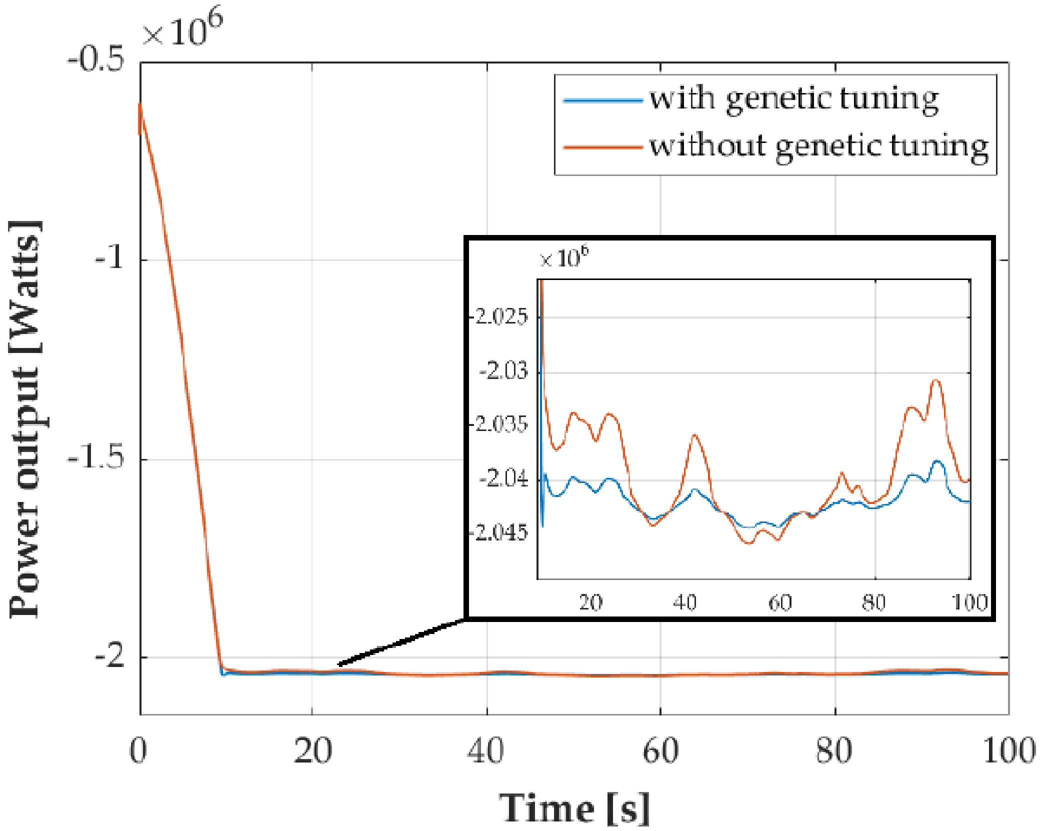

FIGURE 7.5: Power output with(blue line) and without (red line) using genetic algorithm

rotational speed. The pitch angles of the blades alter in response to significant changes in wind speed. The output pitch angle regime of the controller with and without genetic tuning is shown in Figure 7.7.

The generator's reaction to the described wind regime is shown in Figure 7.8. Rotor speed fluctuations in the FLC with the GA optimization are about 0.3 rad/s, while those in the FLC without the optimization are about 0.6 rad/s. This indicates that the fluctuation problem is effectively solved by the genetic algorithm. A controller with a better settling time performance in comparison to other research is also produced by using GA optimization to the proposed fuzzy logic controller [138]. The annual energy production will rise as the settling time decreases.

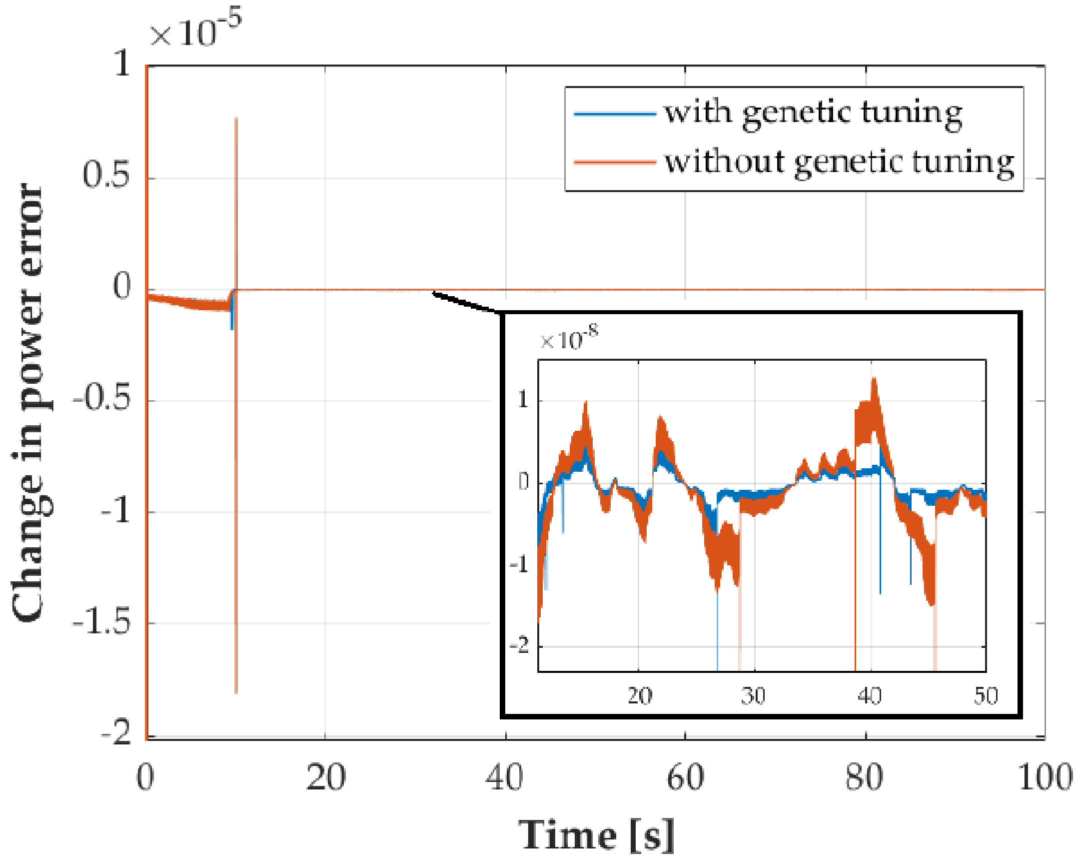

FIGURE 7.6: Change in power error with (blue line) and without (red line)using genetic algorithm

7.3 Discussion

In this section, simulation results are presented with and without the tuning of the fuzzy control parameters by a conventional (without optimization parameters update between population iterations) GA system. Our motivation in using a straightforward (conventional) GA parameter tuning approach in this study is as follows. A number of metaheuristic optimization techniques could be applied as alternatives to the conventional GA approach employed in this dissertation. Examples of these approaches are MPA (Marine Predator Algorithm), PSO (Particle Swarm Optimization), GSA (Gravitational Search Algorithm), CS (Cuckoo Search), FA (Firefly Algorithm), CMA-ES (Covariance Matrix Adaptation Evolution Strategy), BO (Bonobo Optimization), BA (Bat Algorithm), BSO (Brain Storming Optimization), and TLBO (Teaching Learning Based Optimization). These approaches, as standard or with modifications, are capable of introducing

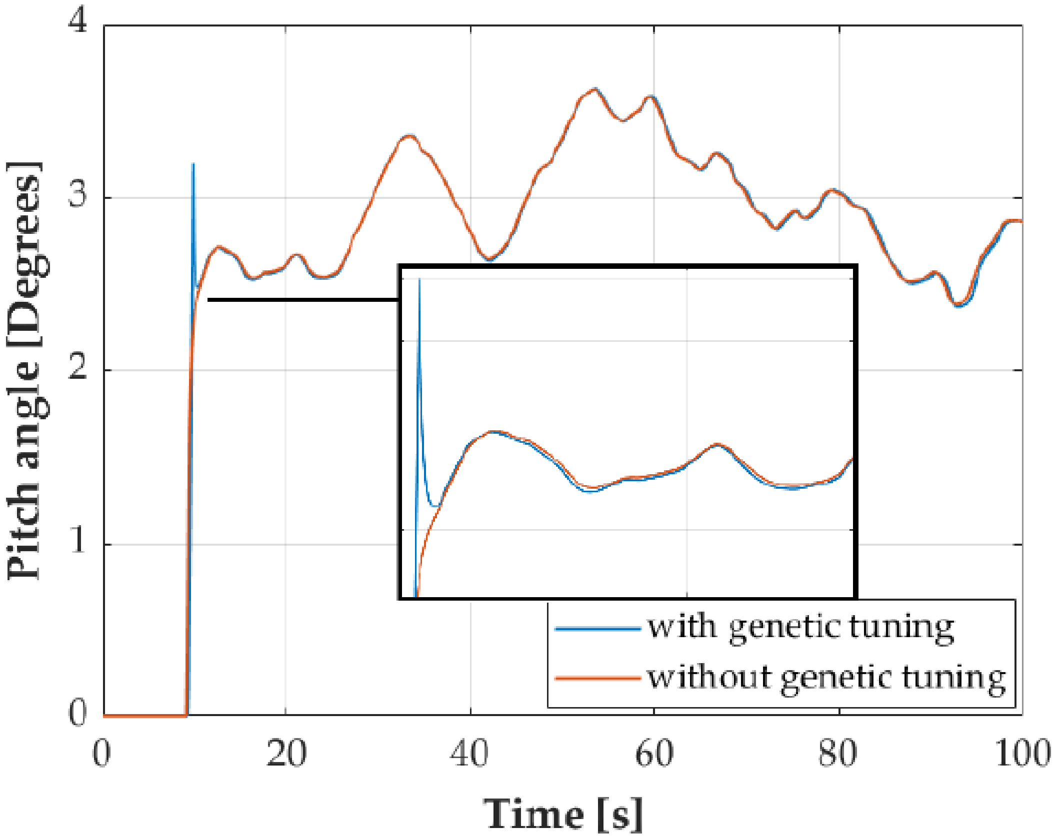

FIGURE 7.7: Pitch angle with (blue line) and without (red line) using genetic algorithm

online (between optimization iterations) optimization parameter updates. These updates can achieve superior convergence properties, for example, by increasing the reached fitness or by reducing the number of necessary iterations, and hence the computation time. BO algorithm can be employed to regulate the yaw angle in the context of horizontal axis wind turbines. Other techniques, based on machine learning could also be applied. Gain adjustment can be studied in the framework of reinforcement learning, too. The alternative optimization technique and GA with online optimization parameter updates do have the potential of outperforming the conventional GA (GA without parameter updates). However, there are a number of fuzzy control systems reported in the wind turbine control literature, many of which are tuned by conventional GA systems. Our work aims at creating another example in this category to be compared with such work. It is yet to be mentioned that the genetic tuning of a three-dimensional fuzzy control rule base contrasts the literature by adding one more complication level to the tuning task

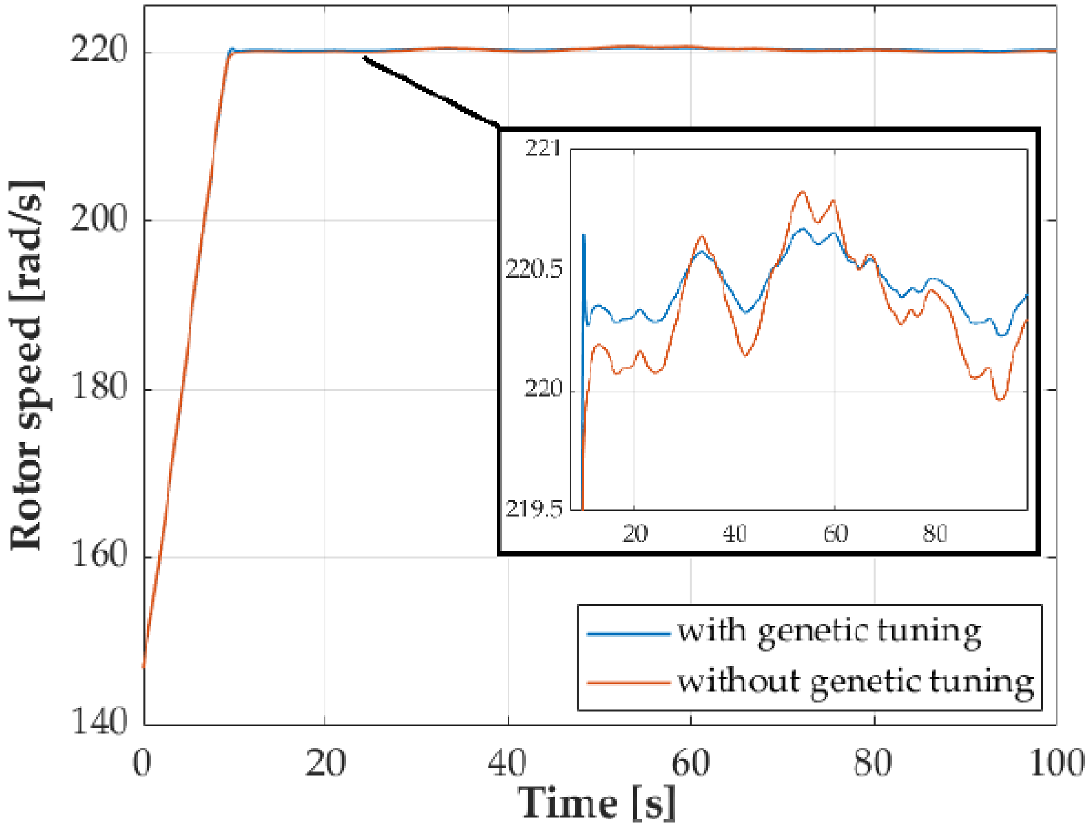

Figure 7.8: Rotor speed with (blue line) and without (red line) using genetic algorithm

at hand. Reported in the wind energy field previously are two-dimensional fuzzy control rule bases adjusted via GA. It may also be argued that the straightforward implementation of the classical GA can be considered as a merit when compared with more complicated optimization systems.

Table 7.2 compares energy production of five controllers tested in this thesis.

Table 7.2: Comparison of energy production with the simulated controllers

Controller Type	**Power Production**
PI Energy	202.00 MWs
PID Energy	203.50 MWs
PID GA Optimized Energy	203.90 MWs
FLC Energy	204.25 MWs
FLC GA Optimized Energy	204.40 MWs

As can be seen in table 7.2, the GA-tuned fuzzy logic controller proposed improves the production by 1.1 % over the conventional PI technique. It also displays improvements over PID and genetically tuned PID controllers. GA tuning on the FLC system provides an automatic gain adjustment system and improves energy production.

In this study, FLC algorithms and genetic tuning are used to execute controller design on a 2MW wind turbine model with a DFIG architecture. Three inputs are used to create a new control system that employs fuzzy logic. Inputs include generator speed, power error and power error rate. Control settings for fuzzy logic are modified by a genetic algorithm. Multiple simulations conducted in MATLAB/SIMULINK show optimized fuzzy logic control performance. For the annual energy production to be maximized, controller performance is essential. An ideal set of fuzzy logic control parameters is produced by genetic algorithm adjustment. With a quicker settling time and less power fluctuation, optimized FLC outperformed hand-tuned and existing conventional FLC approaches.

Chapter 8

Conclusion and Future Work

This dissertation describes a novel fuzzy pitch angle controller design with parameter optimization via evolutionary computing. The controller is tested in dynamic simulations with the model of a 2MW DFIG type wind turbine. The double fed structure is one of the mostly applied mechanism in the wind technology. The considered power rating, being quite commonly employed, is also representative for the wind industry.

Controller performance is an essential factor in annual energy production. The main target set for the control in this work is performance in the third region of wind speed and under abrupt wind speed changes. A variety of conventional controller structures are implemented, tested and compared. As an alternative to conventional techniques, fuzzy logic based approach is concentrated on, due to its flexibility. A novel fuzzy control system which uses generator power error, power error rate of change and generator speed as inputs is developed. These three inputs have the potential of improving controller performance when utilized with a three-dimensional fuzzy rule base and appropriate fuzzy inference rules. The three-dimensional rule base, however, has more parameters to be tuned when compared with two-dimensional fuzzy rule bases reported in the literature. This is where evolutionary optimization techniques can be resorted to. Genetic tuning of parameters is applied in order to optimize performance this fuzzy controller. Integral power error is employed as the fitness function. Genetic tuning is also applied on PI and PID controllers to contrast their performance to that of the genetic-algorithm-tuned novel fuzzy controller.

The fuzzy logic controller with genetic parameter adjustment outperforms the PI and PID based pitch angle controller designs which are also tuned via genetic algorithms. Whereas the PID controller performs marginally better than the PI technique in terms of power production, the fuzzy logic controller surpasses both of these conventional techniques by a significant improvement.

The genetic-algorithm-optimized fuzzy controller exhibits virtues in terms of quicker settling time and less power fluctuations, and performs better than the the standard fuzzy logic controller. Under the fuzzy logic controller with genetic algorithm optimization the rotor speed exhibits fluctuations around 0.3 rad/s, whereas the fluctuations with the fuzzy logic controller without optimization are in the order of 0.6 rad/s. The genetic algorithm parameter adjustment reduces the rotor speed fluctuations significantly. Decreasing rotation speed fluctuations improves reliability of the wind turbine. Shorter settling time is achieved when compared with the existing previous studies in the literature, including other fuzzy controller designs. The generated power is higher when compared with these investigations as well. The proposed technique has advantages in enhancing the annual energy production of a wind turbine.

Last but not the least are frequency stability benefits of the proposed controller to be mentioned. Since the controller uses the generator rotation speed as one of its inputs and takes rule-based actions for its regulation, this speed is kept very close to its rated value under challenging wind conditions. This results in a stable frequency of the generator output voltage connected to the power grid.

As a future study, gust wind speed profiles can be targeted in addition to the controller performance in the third region. Larger scale wind turbines can be studied. Controller designs for direct drive turbine mechanisms also make an interesting future research direction. This thesis presents a parameter tuning approach which is facilitated with offline dynamics simulations. The use of online tuning via machine learning techniques for the same purpose is also an appealing research problem.

Appendix A

List of Publications

- A. S. Pehlivan, K. Erbatur, “Performance Comparison of Pitch Angle Controllers for 2MW Wind Turbine ,” *International Conference on Sustainable Energy and Energy Calculations* (ICSEEC 2020), Istanbul, Turkey, 2020.

- A. S. Pehlivan, K. Erbatur, “Genetic Algorithm Optimization of PID Pitch Angle Controller for a 2MW Wind Turbine, ” *International Conference on Sustainable Energy and Energy Calculations* (ICSEEC 2020), Istanbul, Turkey, 2020.

- A. S. Pehlivan, B. Bahçeci, K. Erbatur, “2MW Rüzgar Türbini için Kanat Açısı Kontrolörleri P, PI, PID ve Optimize Edilmiş PID’nin Performans Karşılaştırması,” *Otomatik Kontrol Türk Milli Komitesi Ulusal Kongresi* (TOK 2021), Van, Turkey, 2021 (in Turkish).

- A. S. Pehlivan, B. Bahçeci, K. Erbatur, “Performance Analysis of a Pitch Angle Controller for 2MW Wind Turbine under Abrupt Wind Speed Conditions,” *2021 International Conference on Electrical, Computer and Energy Technologies* (ICECET), Cape Town, South Africa, 2021, pp. 1-5.

- A. S. Pehlivan, D. Kraljevic, I. Triplat, B. Bahçeci, “Critical Speed Calculation of a Refurbishment of 11MW Hydro Power Plant Unit, ”Turkish Journal of Electrical Engineering & Computer Sciences, 2021

- A. S. Pehlivan, M. F. Aksit, K. Erbatur, "Fatigue analysis design approach, manufacturing and imple-mentation of a 500kW wind turbine main load frame," Energies, 2021

- A. S. Pehlivan, B. Bahceci, K. Erbatur "Genetically Optimized Pitch Angle Controller of a Wind Turbine with Fuzzy Logic Design Approach," Energies, 2022

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