NEURAL NETWORK BASED MAXIMUM POWER POINT TRACKING AND CONTROL OF PMSG WIND SYSTEM

BY

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This thesis, written by **M.M. ATIQUR RAHMAN** under the direction of his thesis advisor and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE in ELECTRICAL ENGINEERING**.

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بسم الله الرحمن الرحيم

Dedicated to

My Beloved Mother, Father

My Beloved Brothers and Sisters

And

My respected Teachers

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In the Name of Allah, the Most Beneficent, the Most Merciful.

> Praise belongs to Allah, the Lord of all the worlds (2) The All Merciful, the Very-Merciful. (3) The Master of the Day of Requital. (4) You alone do we worship, and from You alone do we seek help. (5) Take us on the straight path (6) The path of those on whom You have bestowed Your Grace, Not of those who have incurred Your wrath, nor of those who have gone astray. (7)
>
> Al-Fatiha

In the name of Allah, the most Merciful, the most Gracious. All praise is due to Allah; we praise Him, seek His help, and ask for forgiveness. Peace be upon the Prophet Mohammad (Sallala ho Alaihi Wasallam), his family, his companions, and all those who followed him until the Day of Judgment.

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THESIS ABSTRACT (ENGLISH)

Name	M.M. Atiqur Rahman
Title	Neural Network Based Maximum Power Point Tracking and Control of PMSG Wind System
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An artificial neural network (ANN) based maximum power point tracking (MPPT) algorithm has been investigated. The results obtained have been compared with an adaptive neuro-fuzzy inference system (ANFIS). Both ANN-based and ANFIS based MPPT controllers have the ability to estimate wind speed and to track the maximum power point (MPP) and the optimal rotor speed with very low error as compared to the conventional MPPT methods. Moreover, these methods demonstrate remarkable performance under rapidly changing wind conditions in estimating wind speed, tracking MPP accurately and suppressing undesired oscillations around maximum power point. The algorithm is based on two series neural networks, one for wind speed estimation and the other for tracking maximum power point (MPP). The algorithm does not require any mechanical sensor for wind speed measurement. Nonlinear time domain simulations have been carried out to validate the effectiveness of the proposed controllers in terms of wind speed estimation and MPPT under different operating conditions.

The obtained results demonstrate that both the proposed ANN and ANFIS-based MPPT controller has better dynamic and steady state performance than the conventional

methods and the obtained results also demonstrate that ANFIS based controller is better than ANN based controller. Accuracy in wind speed estimation and maximum power point tracking has been used as the performance criterion for evaluating MPPT controllers.

The performance of the ANFIS based MPPT controller is investigated using MATLAB simulation for a grid connected permanent magnet synchronous generator (PMSG) wind system represented through a detailed dynamic model of the generator, the generator turbine, drive train and the converters. Simulation results confirm that the wind turbine system can deliver power to the grid maintaining the optimum value of power coefficient (C_p) for rapidly changing wind conditions.

THESIS ABSTRACT (ARABIC)

ملخص

الأسم : ملا محمد عتيق الرحمن

عنوان الرسالة: تتبع النقطة العظمى للطاقة الكهربائية المبنية على الشبكات العصبية والتحكم بأنظمة طاقة الرياح المعتمدة على المولد المتزامن ذو المغناطيس الدائم

الدرجة العلمية: الماجستير في العلوم

التخصص الرئيسي: الهندسة الكهربائية

التاريخ : سبتمبر، 2014

تم التحقق من خوارزمية تتبع النقطة العظمى للطاقة الكهربائية (MPPT) المبنية على الشبكات العصبية الاصطناعية (ANN) ، ومن ثم تم مقارنة النتائج التي تم الحصول عليها بالأنظمة العصبية الضبابية القابلة للتكيف (ANFIS).

متحكمات (MPPT) المبنية على (ANN) و (ANFIS) لها القدرة على تقدير سرعة الرياح وتتبع النقطة العظمى للطاقة الكهربائية (MPP) والسرعة المثلى للعضو الدوار بواقع خطأ ضئيل جدا بالمقارنة مع أنظمة (MPPT) التقليدية. وعلاوة على ذلك، هذه الأساليب تظهر أداء متميزا في تغير الرياح السريع، تتبع (MPP) بشكل دقيق واخماد التذبذبات غير المرغوب فيها حول نقطة الطاقة العظمى. الخوارزمية مبنية على شبكتين عصبيتين متواليتين، واحدة لتقدير سرعة الرياح والأخرى لتتبع النقطة العظمى للطاقة الكهربائية (MPP). الخوارزمية لا تتطلب أية حساس ميكانيكي لقياس سرعة الرياح. المحاكاة الزمنية غير الخطية تم تنفيذها للتحقق من فعالية المتحكمات المقترحة بالنسبة لسرعة الرياح و نقطة الطاقة العظمى MPP عند ظروف تشغيلية متنوعة.

النتائج التي تم الحصول عليها تظهر أن متحكمات تتبع النقطة العظمى للطاقة الكهربائية (MPPT) المبنية على الشبكات العصبية الاصطناعية (ANN) والأنظمة العصبية الضبابية القابلة للتكيف (ANFIS) لها أداء أفضل من الناحية الديناميكية والحالة المستقرة بالمقارنة مع الطرق التقليدية وأن النتائج التي تم الحصول عليها تظهر أيضا أن المتحكمات المبنية على (ANFIS) أفضل من المتحكمات المبنية على (ANN). كان المعيار في تقييم أداء متحكمات MPPT هو الدقة في تقدير سرعة الرياح وتتبع الطاقة العظمى الكهربائية.

تم التحقق من أداء متحكم MPPT المبني على ANFIS باستخدام برنامج المحاكاة الماتلاب للشبكات المتصلة مع أنظمة الرياح المعتمدة على المولد المتزامن ذو المغناطيس الدائم (PMSG) الممثلة من خلال الموديل الديناميكي التفصيلي للمولد، التوربين، قطار نقل الحركة، المحولات. نتائج المحاكاة تظهر أن نظام التوربين الهوائي يستطيع تزويد الشبكة بالطاقة الكهربائية محافظا على القيمة المثلى لمعامل الطاقة (Cp) خلال التغيرات السريعة لسرعة الرياح.

CHAPTER 1

INTRODUCTION

The demand of electrical energy is anticipated to increase rapidly because of the very fast growth of global population and the development of industry on an extensive scale. This rapid increase in energy demand requires electric utilities to increase their power generation. The net electricity production all over the world was 17.3 trillion kilowatt-hours in 2005 and is expected to increase 24.4 trillion kilowatt-hours (an increase of 41%) in 2015 and 33.3 trillion kilowatt-hours (an increase of 92.5%) in 2030 [1]. A large amount of electricity generated is from fossil fuels, especially from coal. However, the use fossil fuels causes environmental pollution and greenhouse gas (GHG) emissions, those are considered the main reason behind current global warming problem. For example, the emissions of carbon dioxide (CO_2) and mercury are expected to rise by 35% and 8% respectively, by the year 2020 due to the expected increase in power production [2]. Moreover, possible diminution of fossil fuel reserves and unstable cost of oil are two major concerns for industrialized countries.

1.1 WIND ENERGY

To overcome the problems related with production of electricity from fossil fuels, renewable energy sources (RES) can play an important role in the energy mix. Also the deregulation in electricity markets and the growth of the distributed generation (DG) systems are advancing the use of RES in power production [3]. Among the renewable energy sources (RES), wind energy is the most promising and wind turbine system provides the most direct method to convert wind energy into electrical energy without any environmental pollution [4]-[5]. Wind energy systems require very little capital cost, replacement cost, operation and maintenance cost as compared to other RES like solar energy. Also considering the energy conversion efficiency wind energy system is better than the solar energy system. In spite of the intermittency of wind speed, numerous wind energy systems have been developed in many countries all over the world because of their long term gains and other schemes offered by governments to encourage the use of renewable energy sources (RES). The first wind turbine system for electricity generation started on July, 1887 in Scotland was a battery charging machine and currently updated technology related to wind energy conversion system is growing rapidly worldwide. In fact, many organizations expect a bright future for these systems because it is clean energy, abundant, ubiquitous, sustainable, environmental friendly and wind is free of cost. The total installed capacity of wind energy systems all over the world was 273TWh in year 2009. In 2020, IEA's expects globally the wind generated electricity will be around 1282TWh annually, which is 369% increase from 2009. It is anticipated that by

2020 around 12% of the world's electricity will be generated from wind energy. By 2030 that figure will be 2182TWh [6],[7]. Rapidly growing wind energy deployment has led the researchers to work on the different issues related to wind system: modeling of the wind turbine, maximum power point tracking algorithms, power electronic converters used to integrate wind turbine with grid and its impact on power system.

Wind turbines are usually used in roof top and stand-alone micro-grid systems to serve remote or hilly areas that are not connected to the electric grid [8]. Grid-connected wind systems designed for supplying energy to local loads as well as to the electric grids, are currently dominating the electricity market and can be installed on the onshore, offshore, beside the highway and on the open field where wind speed has good potential to generate electricity.

Large penetration of wind power into the electricity grid would have adverse effects on the transmission/distribution network and also on the other connected generators due to the intermittency of the wind speed. It may cause security and stability issues of power system especially in the case of disturbances. An accurate wind turbine model is required that can simulate its output characteristics with the change in wind conditions, i.e. wind velocity, to study and analyze the impact of wind generation on the utility power grid.

1.2 MAXIMUM POWER POINT TRACKING (MPPT)

The efficiency of wind system depends on turbine efficiency, efficiency of the converters and efficiency of the MPPT algorithm. Increasing the efficiency of wind turbine and the converters is not an easy task, because it depends on available technology. Updated components may increase the efficiency but it increase the installation cost extremely. Improving efficiency, using MPPT algorithm is easier and inexpensive and can be done in a wind system which is already in operation.

The maximum power point tracking (MPPT) controller plays an important role to improve the efficiency of the wind energy conversion system. The MPPT algorithms can be classified into three main control methods, known as tip speed ratio (TSR) control, hill-climbing search or perturb and observe (P & O) method and power signal feedback (PSF) control. To extract maximum possible power from wind both TSR and PSF control methods required accurate measurement of wind speed and rotor speed using mechanical sensors. HCS control algorithm has the ability to overcome the drawbacks associated with TSR and PSF, but the trade-off characteristics between tracking speed and oscillation makes this algorithm less effective [9]. Current research focuses on new MPPT methods such as fuzzy logic (FL), artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). Recent investigations represent better performance of ANN and ANFIS based MPPT over conventional methods.

MPPT algorithm is applicable for variable speed wind turbine configuration due to its property of controllable rotor speed, which leads the system to operate persistently near the optimum value of tip-speed ratio to extract maximum power.

1.3 MOTIVATION AND PROBLEM DESCRIPTION

The major concerns of variable speed wind generation systems are maximization of the wind energy conversion efficiency, system stability and power quality. The energy production using wind turbine system can be increased in two ways; one is to build a higher generation wind turbine system and the other one is to achieve higher efficiency in converting kinetic energy of wind into energy electrical energy. Building higher generation wind energy systems is very expensive because it required replacement of existing system with a higher generation system. The high efficiency of wind generation system depends upon factors such as wind speed, wind turbine technology, converter efficiency and MPPT controller. Wind speed depends on natural condition and it is not controllable. On the other hand wind turbine and converter efficiency is technology dependent. So the easiest and feasible way to improve the efficiency of the wind energy system is to use MPPT controller. By extracting the maximum possible power for a particular set of operating conditions, the total cost of the wind generation system can be reduced.

The MPPT is a complete electronic system that changes the electrical operating point of the wind turbine system as a result the system is able to deliver maximum possible power at any wind speed. In a grid connected wind energy system, the main goal is to extract maximum possible power from wind system over the entire time of operation. Therefore, wind turbine systems required an MPPT controller, which enables the system to operate at maximum power point.

Over the last decades many MPPT algorithms have been developed to find out the maximum power point (MPP). These algorithms differ in many aspects such as required mechanical sensors, convergence speed, effectiveness, cost, complexity, tracking accuracy during rapid change in wind speed and hardware required for implementation. The commonly used MPPT algorithms are tip speed ratio (TSR) control, hill-climbing search also known as perturb and observe (P & O) method, power signal feedback (PSF) control and functional relation based techniques. To track the maximum power point both TSR and PSF control methods required accurate measurement of wind speed and rotor speed. Anemometer is used as mechanical sensor to measure the wind speed, which is very costly. The main advantages of both methods are simplicity and ease of implementation but performance and accuracy are degraded due the rapid change in wind speed. HCS control algorithm has the ability to overcome the drawbacks associated with TSR and PSF, but its tracking is slow when step size is small and causes oscillations around the maximum power point if the step size is large. The main drawbacks of HCS technique is lose tracking the MPP during the rapidly changing wind conditions [9]. At present fuzzy logic (FL), artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) is becoming popular because these techniques has the ability to deal with imprecise inputs, fast convergence, great ability in handling nonlinearity and accuracy in tracking MPP (negligible oscillation around MPP) even when the wind speed changes rapidly. The researchers already found that for wind speed estimation and MPPT the performance of ANN and ANFIS is better than any other conventional methods.

The characteristics of turbine power and rotor speed for different wind velocity is shown in Figure 1.1 The turbine power vs rotor speed characteristic of wind system is non-linear because turbine power is the cubic function of rotor speed. Turbine power output varies as the rotor speed and wind velocity changes. For a particular wind speed there is only one maximum power point (MPP) and that point is vulnerable due to any change in the wind velocity. In Figure 1.1 circular points on curves shows the MPP's for different wind speed, whose represents that to extract maximum possible power the turbine need to be operated at those point. MPP is the point where the wind turbine is most efficient in converting the wind energy into electrical energy. Therefore maximum power point tracking (MPPT) controller plays an important role to extract maximum possible power and forces the system to operate at its maximum efficiency.

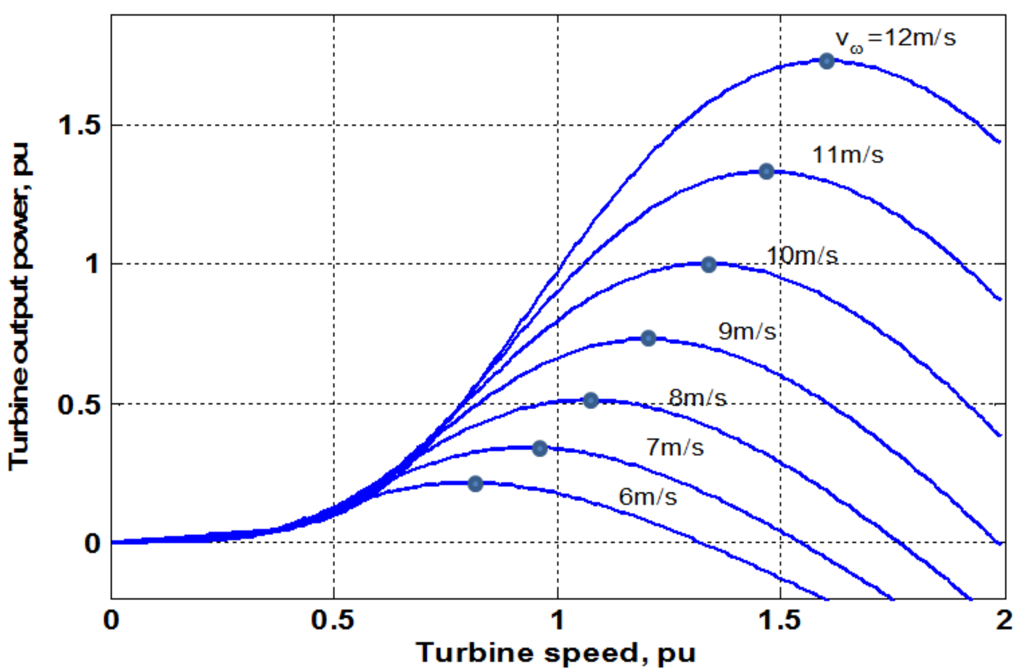

Figure 1.1: Turbine power vs rotor speed showing key points.

Overall efficiency of the wind system depends upon the efficiencies of wind turbine, power electronics converters and maximum power point tracking (MPPT) controller. Wind turbine systems have maximum efficiency around 30% only, converters have efficiency about 95-98% and MPPT controller has more than 98%. The efficiencies of electronic converters and wind turbines are technology dependent but MPPT efficiency can be increased by improving its tracking techniques.

1.4 THESIS OBJECTIVES

The wind turbine output power is the cubic function of wind speed. For a particular wind speed there is only one maximum power point (MPP) and the MPP point is vulnerable due to any change in the wind speed. It is always efficient to obtain maximum power at particular wind speed. To extract maximum power from wind, wind turbine must be operated at the peak point of its power-rotor speed characteristics curve for a certain wind speed.

Following are the major objectives that are focused in this thesis:

1. To develop an adaptive control algorithm using ANN for sensor-less wind speed measurement and to design a controller to track the wind speed efficiently and accurately.
2. To present a new adaptive control algorithm based on ANN for maximum power point tracking (MPPT) in wind energy system and to design a controller for

maximum power point tracking (MPPT) accurately for any change in the wind velocity.

3. To develop an adaptive control algorithm using ANFIS for sensor less wind speed measurement and to design a fuzzy controller to track the wind speed efficiently and accurately.
4. To presents an ANFIS based new adaptive control algorithm for maximum power point tracking (MPPT) in wind energy system and to design a controller for maximum power point tracking (MPPT) accurately for any change in the wind velocity.
5. To test and compare the performance of both the ANN and ANFIS based MPPT controllers for different wind speed.
6. To evaluate the performance of the MPPT algorithm for a grid connected PMSG wind system.

1.5 PROPOSED WORK

The methodology that is used to fulfill the objectives is comprised of two major phases:

1) Design and implementation of MPPT controller

2) Testing the proposed MPPT controller on a PMSG wind system

1.5.1 Design and implementation of MPPT controller

1) Two series artificial neural network (ANN) is used in the proposed MPPT algorithm; one for wind speed estimation and the other for maximum power point tracking. The algorithm does not require any anemometer or look-up table.
2) Two series adaptive neuro-fuzzy inference system (ANFIS) controller is used in the proposed MPPT algorithm; one for wind speed estimation and the other for maximum power point tracking. The algorithm is able to track MPP without using any anemometer or look-up table.
3) Time domain MATLAB/ Simulink simulations of a wind system are carried out to verify the robustness and accuracy of the proposed controller under different operating conditions.
4) The dynamic performance of the proposed MPPT controller is tested under random variation in wind conditions.

1.5.2 Testing the proposed MPPT on a PMSG system

1) Among the proposed ANN and ANFIS based MPPT algorithms, the most efficient one will be tested on a 2.5 MW permanent magnet synchronous generator tied to the grid.
2) The detailed dynamic model of the generator, the generator turbine, drive train and the converter system will be considered for testing.

3) The testing is based on how well the wind turbine can deliver power to the grid maintaining the optimum power coefficient for randomly varying wind conditions.

1.6 THESIS ORGANIZATION

This thesis is organized as follows:

Chapter 2 contains the brief description of wind turbine technology and extensive literature review on wind turbine modeling and maximum power point tracking (MPPT) techniques.

In Chapter 3 an adaptive artificial neural network (ANN) based MPPT controller has been presented and its effectiveness and accuracy is investigated in the MATLAB/Simulink environment.

In chapter 4 an Adaptive neuro-fuzzy inference system (ANFIS) based MPPT controller has been presented and its effectiveness and accuracy is investigated in the MATLAB/Simulink environment. In addition, a comparison between the overall performance of ANN based MPPT controller and the ANFIS based MPPT controller is made.

Chapter 5 investigates the performance of the proposed most accurate maximum power point tracking (MPPT) controller tested on a grid connected PMSG system.

Chapter 6 presents the conclusions drawn from this research work and states directions for the possible future work.

CHAPTER 2

LITERATURE SURVEY

Wind turbine (WT) system is one of the best promising renewable energy sources (RES) that can generate clean energy to the power grid and remote loads connected through the power electronic devices. This chapter presents a detailed literature review on the WT modeling and maximum power point tracking (MPPT) techniques.

2.1 RENEWABLE ENERGY FOR POWER PRODUCTION

Over the past few decades, it is evident that there is a significant increase in global demand for electricity. Recent studies predict that the electricity generation is expected to rise from 17.3 trillion kilowatt-hours in 2005 to 24.4 trillion kilowatt-hours (an increase of 41%) in 2015 and 33.3 trillion kilowatt-hours (an increase of 92.5%) in 2030 [10]. Many traditional and conventional methods are applied for generation of electrical energy, but when it comes to environmental safety they have adverse effects on environment. For example, the emission of carbon dioxide and mercury are expected to increase by 35% and 8%, respectively, by the year 2020 due to the increase in electricity generation [11]. Though the environmental concern increases and the natural resources like fossil fuels are going to be depleted; now researchers are focusing to obtain new environmentally friendly sources of power. To overcome the problems associated with generation of electricity from fossil fuels, Renewable Energy Sources (RES) can be used in the energy mix. Also the deregulation in electricity markets and the development of the distributed generation (DG) technologies are promoting the use of RES in power generation [12]. Because of this environmental concern with fossil fuel, it is desirable to search for clean energy. Renewable energy (RE) is one of the best sources of clean energy that have a very low environmental affect compared to the conventional energy sources. Among the all RE sources, Wind energy is a pollution-free and inexhaustible source. Therefore, a wind energy generation system could be one of the potential sources of alternative energy for the future [13],[14]. As a result, the focus on production of energy using RE sources is increased to reduce greenhouse gas emission. Wind, solar, tidal, wave, geothermal and bio-fuels are considered as renewable energy sources.

One of the best renewable sources to serve this purpose is Wind energy. One can rely on wind as it is mostly available at all time, but primary focus would be given to the installation of plants on a region where the wind blows at a sufficient speed. At present wind generators have been widely used in both grid-connected applications and stand-alone hybrid power systems in remote areas. Compared to the photovoltaic systems, wind generators (WGs) have lower installation cost. Moreover, the overall system cost can be further reduced by using more-efficient power converters and by controlling such a way so that the maximum power is acquired according to the current atmospheric conditions.

2.2 WIND ENERGY CONVERSION PRINCIPLES

The power in wind energy can be calculated on the basis of kinetic energy. The wind turbine converts the kinetic energy of wind to mechanical energy. The kinetic energy of wind is shown in (2.1).

$$\text{Kinetic energy} = \frac{1}{2}\rho A V_w^3 \quad watts \tag{2.1}$$

Where, ρ is the air density and A is the swept area by the turbine blades and V_w is the velocity of wind.

Kinetic energy equation shows that the wind energy is directly proportional to the swept area. As the swept area increases the energy also increases. As a result, the machines with higher swept area produced more energy comparing to the lower one. The characteristics of wind power are related to the cubic function of wind velocity, which is shown in Figure 1.1.

2.3 WIND TURBINE MODELING

The wind power captured by wind turbine depends on its power co-efficient (C_p), which is proportional to the power extracted from the wind hitting the blades of the turbine. C_p can be expressed by (2.2).

$$C_p(\lambda,\beta) = 0.5176\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{\frac{-21}{\lambda_i}} + 0.0068\lambda \tag{2.2}$$

The value of C_p is related to tip speed ratio (λ). The λ is defined in (2.3). Here β is the blade pitch angle.

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \tag{2.3}$$

There is a strong relation between the turbine output power and power coefficient (C_p). The wind turbine power output is limited by power coefficient that is a function of tip speed ratio (λ). The power coefficient versus tip speed ratio is turbine specific and depends particularly on the turbine blade design which is shown in Figure 2.1. It can be noticed that the maximum value of power coefficient is about 0.48 when the value of tip speed ratio is around 8.

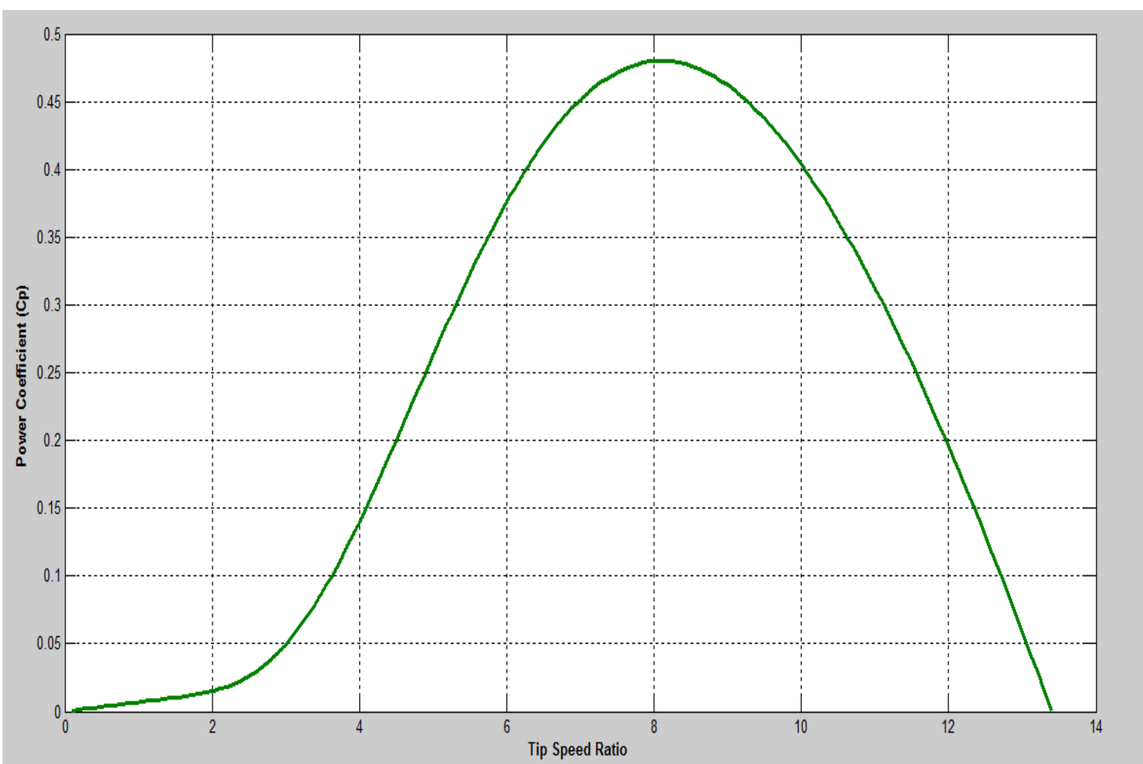

Figure 2.1: Tip speed ratio vs power coefficient curve.

The value of λ can be calculated using (2.4).

$$\lambda = \omega_r . R / V_w \tag{2.4}$$

The wind turbine mechanical output is related to the wind speed V_w and can be expressed by (2.5).

$$P_m = \frac{1}{2}\rho A C_p V_w^3 \tag{2.5}$$

Here ρ is the air density and A is the swept area of the wind turbine blade. When the TSR is adjusted to its optimum value λ_{opt} then the power coefficient C_p will be its maximum value C_{pmax} and the maximum power extraction will be achieved.

Rearranging the equation (2.4) and (2.5), the relation between turbine power (P_m) and rotor speed (ω_r) ca be related as in (2.6).

$$Pm = \frac{1}{2}\rho A C_{p_{opt}} \left(\frac{\omega_r R}{\lambda_{opt}}\right)^3 \tag{2.6}$$

From (2.6), it is clear that the maximum power generated is proportional to the cube of the rotational speed as shown in (2.7).

$$P_m \propto \omega_r{}^3 \tag{2.7}$$

2.4 WIND TURBINE SYSTEMS

Generally, wind energy conversion systems can be categorized in two groups. The first group operates at almost constant speed (variation is limited to around ±1%) and termed as “Danish Concept” [15]. In this type the generator directly coupled the grid with the drive the drive train. This type of configuration allows very little changes in rotor shaft speed; as a result small turbulence in wind speed and load variation creates mechanical stress and decrease the life time of the wind turbine [15]-[18]. The big disadvantages of this type are, the optimum tip speed ratio occurs only at one wind speed and unable to extract maximum possible power with the change in wind speed [16]-[18]. On the other hand, variable speed configuration allows the control of rotor speed, which leads the wind turbine to operate constantly near the optimum value of tip-speed ratio and MPPT is applicable. There are many advantages of variable speed configuration over fixed speed, such as-

- Annually up to 10% more energy collection is possible based on wind regime and turbine aerodynamics [16].
- Less mechanical stress and torque pulsations due to the turbulences as a result machine life time increases [15],[19].
- When wind gust occurs, by increasing rotor speed the inertia of mechanical system absorbs the extra energy.
- Power injection to the grid increases due to the improved power quality. The reduction in power pulsations, increases the power quality and limit the voltage deviation [15],[19][19].
- The pitch control time constant is longer in variable speed configuration, which minimizes the pitch control complexity. These types of configuration also produce less acoustic noise [15].

Most modern variable speed generators are based on DFIG (which is round rotor machine) and PMSG (permanent magnet synchronous generator). The energy conversion efficiency of the variable speed wind turbine system can be improved by using MPPT algorithm.

2.5 MAXIMUM POWER EXTRACTION

The wind energy conversion technique is although a straightforward process, but the maximum power extraction process is very complicated and incorporates different highly correlated parameters like power coefficient, tip speed ratio, wind speed, rotor speed and so on. From the speed-power curve for wind turbine shown in Figure 1.1, it is obvious that there is different operating rotor speed corresponding to each wind speed at which maximum power extraction can be obtained. Due to the aerodynamic nature of the wind turbine, for a very small change in rotor speed will change the amount of power significantly extracted from the wind energy. The rotor speed depends on the wind velocity fluctuation as well as the generator loading. As a result, the wind turbines may not operate at optimum rotor speed for a particular wind velocity, which causes a waste of significant amount of wind energy. The cost effectiveness of wind energy depends on the percentage of energy extraction. The more energy we can extract, the more cost effective the wind system. So the initial challenge is to extract more with in the shortest possible time. As the modern advancement of electronic devices, it can be done by using various converter topologies and using maximum power point tracking (MPPT) algorithms.

For electricity generation, the capital cost for wind turbine system is very competitive with the other renewable energy sources. The most important application of wind turbine system is to supply electricity to the remote or hilly areas, those are far away from the power grid connection and from the economic point of view the grid connection is not feasible. Another big advantage of wind turbine system is, it requires very little or no maintenance cost. Using maximum power point tracking technique, it is possible to achieve the optimum wind energy utilization as well as maximum aerodynamic efficiency. So MPPT is a very popular technique that is especially beneficial for small wind system [20]-[36]. However, there will be only one rotor speed for every wind velocity, which will provide maximum power available, is termed as MPPT [37]. In order to implement maximum power extraction, variable-frequency mode operation is required for wind turbine generator. In recent years, variable speed wind turbine systems are becoming popular than the fixed speed system, because the energy capture ability in the later one is poor. Moreover, fixed speed system suffers from poor power quality and causes higher stress in mechanical parts. On the other hand variable speed wind turbine systems support MPPT algorithm and able to operate at its maximum power coefficient over a wide range of wind velocity by reducing the drawbacks discussed for fixed speed systems [38]-[41].

By using MPPT techniques the efficiency of the wind turbine system will be increased at any wind speed of the environment. Therefore an effective and low implementation cost MPPT algorithm is essential to enhance the efficiency and economics of wind energy conversion systems (WECS). As a result, the maximum power extraction technique becoming the interesting research topic during the past twenty years. To track the MPP, there are various algorithms in the literature based one tip speed ratio (TSR) control [20]-[22], power signal feedback (PSF) control [23]-[25] and hill-climb search (HCS) control [26],[27]. A revision of the Hill climb searching technique in MPPT was introduced in [42] for wind turbine generator system. This was done by developing a peak detection method that is capable of maintaining accurate result despite the rapid weather changes. The control method was based on referring to the optimal power curve. Such reference will dictate the required perturbation step size [42]. Perturbation and observation technique often used for the MPPT problem but the tracking performance is very slow and continuous oscillation occurs around the maximum power point [28],[29]. Anemometer is generally used in most of the wind turbine systems [23],[24],[43][43] for wind speed measurement to implement MPPT algorithm, but due to the inaccuracies in wind speed measurement, the reliability of the wind energy conversion system decreases [14]-[76].

Different MPPT control techniques to estimate wind velocity were reported in [20]-[22],[44]; however those techniques needed the knowledge of air density and some mechanical parameters of the wind turbine system. Neural networks with multilayer neurons were widely used to approximate an arbitrary input-output mapping of an uncertain system so as to have a faster convergence property [43],[45]. Based on the ratio of mechanical power versus turbine rotation speed to eliminate uncertain parameters and avoid oscillation, neural networks can be used for MPPT problem [30]. A neural network based control can be used to track MPP for both the dynamic and steady states and to estimate wind velocity quickly and accurately without using anemometers [31]. TSR control directly regulates the turbine speed to keep the TSR at an optimal value by measuring wind speed and turbine speed [46],[47]. In such systems, a fuzzy logic controller is used instead of using a regular PID controller to manipulate the optimum rotor speed [46]. No detailed mathematical model or linearization about an operating point is needed and it is insensitive to system parameter variation. As the measured wind speed changes, the turbine pitch also gets regulated. Fuzzy logic and neural network based controller can be used to get better performance [48]. The value of the optimum TSR may change with the aging of the wind turbine and other system parameters. So an adaptive algorithm can be used to increase the system stability as well as the system performance [10], [49].

Finally, we can conclude that TSR control has better efficiency and good performance with fast response, but it requires a very accurate anemometer which is very expensive and requires extra cost for the wind turbine system. HCS and fuzzy logic can be used to track the maximum power point of a grid connected PMSG wind turbine system. The fuzzy-control-based MPPT scheme is good, but complex to implement [50]. However, the adaptive fuzzy controller for MPPT control can implement sensor-less peak power tracking and overcome some disadvantages of classical methods. The maximum power can be estimated through a Takagi-Sugeno-Kang (TSK) fuzzy controller by measuring the rotor speed and power generated by the generator without measuring wind speed and wind turbine parameters. The advantages of fuzzy logic over HCS are variable step size and fuzzy is capable to remove all output power oscillations that appears in HCS [51]. In [52], a data-driven design methodology has been proposed which is able to generate a Takagi–Sugeno–Kang (TSK) fuzzy model for maximum energy extraction from variable speed wind turbines. In this model turbine power and rotor speed is used as input and corresponding maximum power is the output for training process. As a result maximum power can be tracked without getting any information about the wind velocity.

Recently, various techniques have been developed to track the MPP for any change in the wind speed without using the mechanical sensor to estimate the wind speed [20],[21], [25],[26]. Polynomial can be used to determine the wind power co-efficient; then the wind speed is estimated online by calculating the roots of the polynomial using an iterative algorithm (e.g., Newton's method or bisection method). However, real-time calculation of the polynomial roots is very complex and time-consuming process. As a result the system performance will be reduced. Neural network based wind speed estimation had in [53], which used manual calculation based on optimum tip speed ratio to determine the maximum power point corresponding to the estimated wind speed. But, optimal tip speed ratio changes with the aging of the wind system that will give erroneous result. MPPT algorithms have been developed depending on optimum relations among quantities like wind speed, turbine output power, DC voltage, current and power of the converter. Functional relationship based control is a variant of perturb and observe (P & O) method. The advantages of this method are sensor-less wind speed measurement and no need for look up table [11]-[12]. The wind speed can be estimated using the theory of support vector regression (SVR) in a wind energy system. By using turbine power and rotor speed as input to the SVR estimator, the wind speed can be estimated with high accuracy and fast transient performance is achievable [22]. Wind speed can be estimated using ANN by giving turbine power and rotor speed as input. Then MPPT can be obtained by identifying the optimal rotor speed using, λopt =K*r_m and $\omega_r =$ (λopt*V_w)/R [53]. In [13], ANN and PSO is used together to estimate the wind speed and to track the maximum power point. The methodology of RBFNN and PSO can efficiently improve power output of a small wind power generator in the conditions of wind speed and load impedance variations. Optimization based MPPT has been proposed in [54], where two series neural network is used to estimate the wind speed and optimal power then PSO is used to determine the optimal rotor speed. Furthermore, considering the condition of wind speed and load variation, the maximum output power can be tracked. For MPPT using pitch angle, various intelligent control technique can be used such as fuzzy, neuro-fuzzy, and genetic algorithm based fuzzy controllers can be used for DFIG based wind generation system. According to the simulation results found in [55], the performance of intelligent controllers are better than the PID controllers and among the intelligent controllers, GA based fuzzy controller is the best. MPPT algorithms have been developed which depend on optimum relationship among quantities like wind speed, turbine power output, converter DC voltage, current, power etc. A sensor-less MPPT technique by controlling duty cycle of the DC-DC boost converter switch and measuring DC voltage and current was reported in [56]. There is a liner relation between the DC voltage and the rotor speed of the PMSG. So the operating point can be shifted from one curve to another with changing wind speed by changing the duty cycle of DC-DC boost converter. Based on the optimal relationship between maximum converter power and DC voltage an MPPT algorithm has been developed for permanent magnet synchronous wind generator. This algorithm does not require the measurement of wind conditions or turbine parameters [57].

Maximum power point tracking (MPPT) controller is a crucial part of the wind system. It tracks and extracts the maximum possible power from the wind turbine under different operating conditions and improves the overall efficiency of wind system. The idea of MPPT is not new; many MPPT methods had been reported by researchers that discussed in the literature review. Comparing to the others conventional techniques, researchers already proved that ANN and ANFIS based MPPT controller are much more accurate and efficient. The performance of trained ANN is good, but it will not provide the details about the system performance for a particular output, it act as a black box. ANFIS combines the advantages of both ANN and FIS, which makes ANFIS a very powerful intelligent technique [58]-[59]. To use ANFIS based MPPT technique, a large number of training data is required. In [60], the authors used practical data for training process and proved that its performance is better than the conventional MPPT technique. Researchers already used neural network (NN) and Fuzzy logic (FL) for MPPT. Sometimes NN/ANFIS are used for wind speed estimation and look up table for MPPT. In some other works, they used Anemometer for wind speed estimation and NN/ANFIS based controller for MPPT. The use of anemometer and look-up table is the main drawbacks for the previously reported ANN/ANFIS based MPPT controller systems.

The main objective of this research is to use neural networks (NN) principles and adaptive neuro-fuzzy inference system (ANFIS) both for wind speed estimation and to track both MPPT and optimum rotor speed for any change in wind velocity.

2.6 MAXIMUM POWER POINT TRACKING (MPPT) STRATEGY

The maximum power point tracking concept with the change in wind velocity is illustrated clearly in Figure 2.2. As wind speed changes, the turbine power curve also changes. Let us consider that the wind speed known and the turbine is operating at point A, so we can easily determine the maximum power point for that wind speed is B and the corresponding rotor speed is ω_r*. Then the rotor speed of the generator will be controlled until it reaches to ω_r*, where the turbine power is maximum.

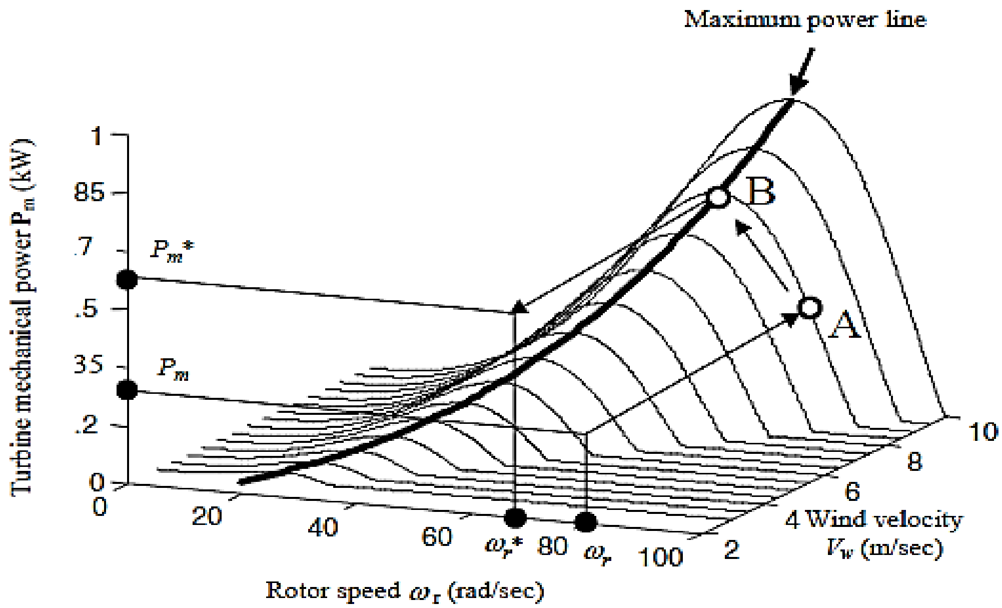

Figure 2.2: Three dimensional turbine speed vs power curves

So first we have to estimate the wind velocity by using the operating condition. It can be easily done by using anemometer, which is very costly. So the sensor-less wind speed measurement technique will be most cost effective one. Artificial Neural Network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) can be used to do this job. With the change in wind velocity, the operating turbine power and rotor speed will be changed; though the measurement of power and rotor speed can be done precisely, those will be used as input to the ANN/ ANFIS network. Based on the given input ANN/ANFIS will identify the wind speed as well as the maximum power corresponding to the estimated wind velocity and will also specify the turbine optimum rotor speed for which we will get maximum power. Though the relation between turbine power and rotor speed is nonlinear regarding to the wind speed change and ANN and ANFIS have great ability to deal with the nonlinear objective function; so we can do wind speed estimation and MPPT tracking using ANN and ANFIS.

CHAPTER 3

ANN-BASED MPPT CONTROLLER DESIGN

3.1 INTRODUCTION

Wind turbine converts the kinetic energy of wind into electrical power. The generated power of turbine is the cubic function of wind speed. Figure 1.1 demonstrates that the characteristics of turbine versus rotor speed are non-linear in nature. For a particular wind speed there is a particular curve and each curve has one optimum point called Maximum Power Point (MPP) as discussed in previous chapters. This maximum power point varies with the wind speed as well as the operating speed of the rotor. As wind speed is intermittent and time to time it changes, that also keeps varying the maximum power point (MPP). Therefore, the maximum power point tracking (MPPT) controller is essential to extract maximum possible power from any wind speed.

Already researcher's reported some ANN based MPPT techniques in literature. Among all the previously proposed ANN based MPPT technique, they used single neural network for wind speed estimation or to track maximum power point. When neural network is used to estimate wind speed then look-up table or manual calculation or PSO is used to track maximum power point. In other literature, anemometer is used to measure the wind speed then measured wind speed is used as input to neural network to track the maximum power point. The researcher's already proved that the performance of all the proposed ANN based MPPT controller is better than the conventional methods (TSR control, PSF control, HCS and P & O control) in terms of accuracy, fast convergence and able to track MPP correctly in rapidly changing wind speed conditions. Both anemometer and look-up table are considered as the drawback of the ANN based MPPT techniques. The anemometer is costly and required numbers of anemometer in different locations for accurate measurement of wind speed. On the other hand look-up table required memory space and billions of data has to be stored for getting accurate result, therefore MPPT accuracy depends on the available system memory.

In this chapter, the new intelligent MPPT controller based on the artificial neural network (ANN) is proposed and developed for wind speed estimation and MPPT. Two series neural network will be used, one for wind speed estimation and the other to track maximum power point. In the proposed algorithm there is no need of anemometer or look-up table.

3.2 ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network (ANN) is a computational tool that follows the activities of human brain. The basic processing unit of ANN is neuron [61], introduced by Cajal in 1911 [62]. The function of ANN's neuron is similar to the biological neuron. Artificial neural network (ANN) has been successfully employed over the past decades to solve for various complex problems. Recently, ANN is used in various engineering problems as an estimation method due to its great pattern identification ability. The application of neural networks supports the following useful attributes and capabilities includes nonlinearity, adaptively, massive parallelism, uniformity of analysis and design, learning ability, generalization ability, input-output mapping, fault tolerance, evidential response, VLSI implement ability, distributed representation and computation and neurobiological analogy. An artificial neuron generally consists of a computing element that performs the weighted sum of the input signals and the associating weights. The weighted sum is added with the bias value called threshold and the resultant signal is passed through a non-linear activation function. The commonly used activation functions are either sigmoid or hyperbolic tangent. Each neuron is interconnected with three parameters whose learning can be adjusted. These are the connecting weights, the bias value and the slope of the nonlinear activation function. For the structural point of view a NN may be single layer or it may be multilayer.

ANN is so configured that any set of inputs produces a desired output. Two basic classes of Neural network namely

1. Feed-forward back-propagation network (FFBP)

2. Radial basis function network (RBFN)

3.2.1 Feed forward back-propagation neural networks

In feed forward neural network, the information enters at the inputs and passes through the network layer by layer, until it arrives at the outputs. During normal operation data moves only in forward direction, there is no feedback. There are three layers in a feed forward network termed as input layer, hidden layer and output layer. A set of inputs is provided to a hidden layer by different strength of connections or weight function, and then finally passed to the output layer as shown in Figure 3.1. Every node in a layer is linked with all the nodes in the previous layer. These links are not all same; each link may have a different strength or *weight*. The weights on these connections encode the knowledge of a network. In order to obtain desired output, the weights shall be updated.

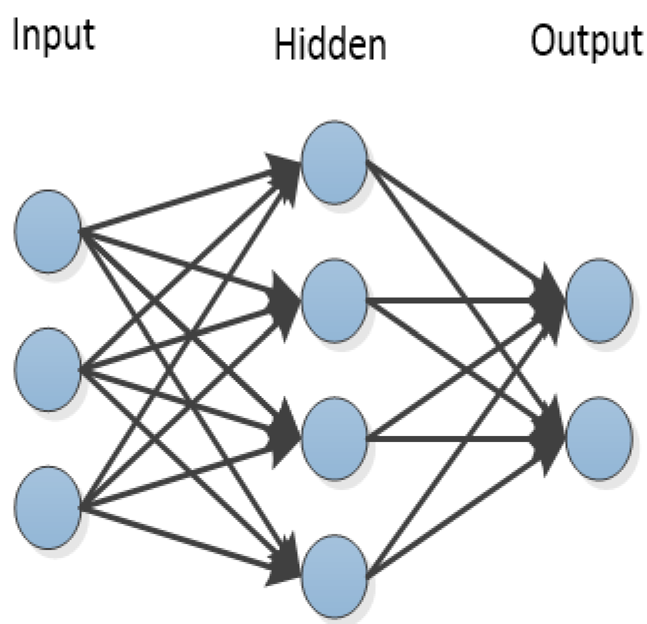

Figure 3.1: Feed forward ANN

The learning process of feed-forward network (FFN) cannot assure you the global optimum, sometimes it struck into the local optimum. By using back propagation (BP) algorithm along with the FF algorithm, the learning process of FFN can be improved. BP is widely used technique due to its simplicity [63]. There are three layers in a feed forward back propagation network termed as input layer, hidden layer and output layer as shown in Figure 3.2. BP learning algorithm is proposed in [64] and become one of the best learning algorithms among ANNs. During learning process, BP network use gradient-decent search technique to adjust link weights between nodes to minimize the error of ANNs. Back propagation algorithm is very popular and used successfully in many applications like pattern recognition, location selection, performance evaluations and so on. Since error propagates from output layer through hidden layer to the input layer (propagates in backward direction), this method is termed as back propagation.

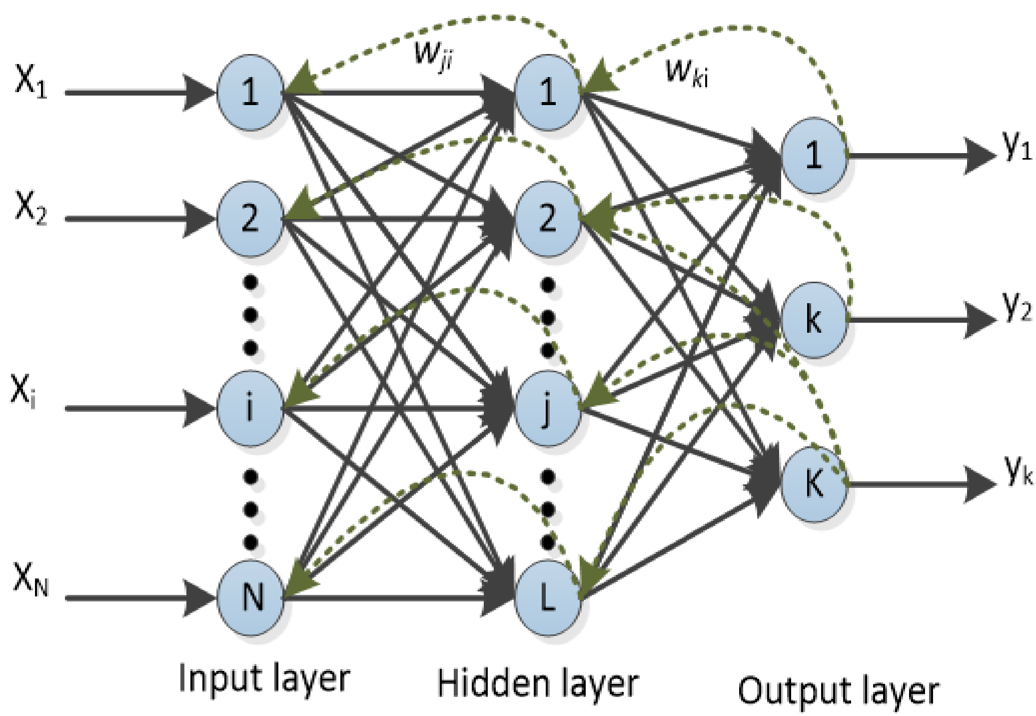

Figure 3.2: Back-propagation ANN

If the dimension of input is j there would be j weights, as a result the net signal available to the neuron would be given by u_j in Equation (3.1), where x_i is the i_{th} input, w_{ji} is the weight connecting neuron j and neuron i and b_j is the bias of neuron j. The output for neuron V_k is best expressed as sigmoidal function as in Equation (3.2), the amplitude of the output ranges from 0 to 1. The final actual output is given by Equation (3.3)

$$u_j = \sum_{j=1}^{n} x_i w_{ji} + b_j \qquad (3.1)$$

$$V_k = \frac{1}{1 + e^{(-u_i)}} \qquad (3.2)$$

$$Y_i = \frac{1}{1+e^{(-s_i)}} \qquad (3.3)$$

The sum of squared error or cost function (E) is given as square of difference of target output t_i and estimated output y_i best describes by Equation (3.4)

$$E = \frac{1}{2}\sum_{m=1}^{M} E_m = \frac{1}{2}\sum_{m=1}^{M}\sum_{i=1}^{I}(t_i^m - y_i^m)^2 \qquad (3.4)$$

Here, m represents all training pattern, E_m is the total error over all training pattern and i represents all output nodes for a given pattern.

The weights are altered to minimize the cost function to a value by gradient descent method. In back-propagation networks the initial weights and biases are selected randomly by deploying maximum and minimum value of input. These weights are continuously updated, for i^{th} neuron the j^{th} weight. The equation used to update weight is shown in (3.5).

$$w_{ij}(t+1) = w_{ij}(t) + \eta\left(\frac{\partial E_m}{\partial w_{ij}(t)}\right) \tag{3.5}$$

Where learning rate is denoted by η, $w_{ij}(t)$ is the old weight, $w_{ij}(t+1)$ is the new weight.

3.2.2 Radial basis function (RBF) network

The radial basis function network has similar type of structure like feed forward back propagation network as shown in Figure 3.3 .

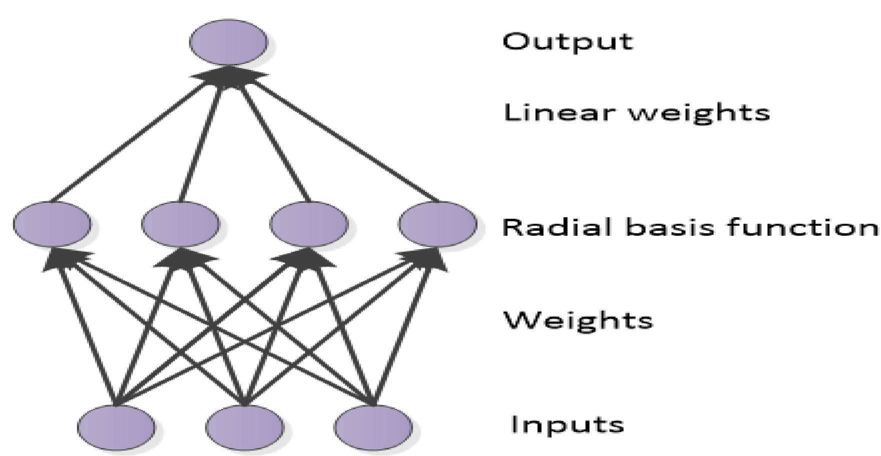

Figure 3.3: Radial basis Function network

The transfer function for a radial basis neuron is

$$radbas(n) = e^{-n^2} \tag{3.6}$$

RBF network can be trained by two step algorithm. Firstly, in the hidden layer the center vectors C_i are chosen for RBF function. This can be done in many ways; one is to sample randomly from set of examples or by using K-means clustering. Then use back-propagation to determine all network parameters of RBF. Secondly, a linear model is fit with coefficient W_i to output hidden layer with respect to least square objective function.

The artificial neural network which employs an activation function as radial basis function is called RBF network. Like feed forward networks, the RBF networks also have three layers, but the only difference is the hidden layer has nonlinear radial basis activation function. Input layer consists of m_a source nodes, m_a is the dimension of input vector. The hidden layer consists of equal number of computation nodes as the size of training sample. Each node is mathematically described by a radial basis function as shown in (3.7).

$$\varphi_a(X) = \varphi(\|X - X_a\|) \tag{3.7}$$

Here, a=1,2,……..,N. N is the training sample size, X is the applied signal to the input and Xa defines the center of the radial basis function of a-th input data point. In Figure 3.3, output layer consists of single computational nodes, but there is no restriction on the size of the output layer, typically size of the output layer is much smaller than hidden layer.

The input units are directly connected to the hidden layer and the hidden layer is fully connected to the output layer via output weights [65]. In general radial basis function neural network (RBFNN) is a feed forward 3-layers network based on radial basis functions like Gaussian function is chosen as their activation function [66]. In RBFNN Gaussian function is used as basis function, which depends on two parameters σ_a and μ_a as shown in (3.8).

$$\varphi(\|X-\mu_a\|,\sigma) = \exp\left(\frac{-\|X-\mu_a\|}{\sigma_a^2}\right) \tag{3.8}$$

Here, X is the input vector, σ_a is the shaping parameter and μ_a is the a-th center.

The hidden layer of RBF network takes p-dimensional input vector (Xp) with unit connection strengths and determines the Euclidean distance between input and center. The calculated result passes to the activation function. The hidden layer maps the input space onto a new space by performing the fixed nonlinear transformation. The output layer performs the linear combination onto this new space by adjusting the weight matrix [67]. The output of RBFNN network is defined as the weighted sum of the hidden layer outputs as shown in (3.9).

$$O(i) = W_{oi} + \sum_{a=1}^{h} W_{ai}\varphi(\|X-\mu_a\|,\sigma_a) \tag{3.9}$$

Here, i=1,2,3,…….,m and a=1,2,3,…,h. h represents hidden nodes and $\|X-\mu_a\|$ represents the Euclidean distance between inputs and the a-th center. The weight value between i-th center and a-th output node is denoted by W_{ai}.

In radial basis neural network, every hidden unit calculates a nonlinear function by evaluating the distance between the input and the unit weight vector. The unit vector is generally called the center of the unit and the distance is called Euclidean distance. The a_{th} hidden node Euclidean net function for p_{th} training pattern can be calculated by (3.10).

$$Ed_p(n) = \sum_{n=1}^{N} \left(X_p(n) - \mu_a(n)\right)^2 \tag{3.10}$$

Here, $C_a(n)$ is the n-th element of C_a corresponding to n-th input node. The training mean square error (MSE) for each pattern can be calculated according to (3.11).

$$E_{MSE} = \sum_{j=1}^{m} [y_d(j) - O(j)]^2 \tag{3.11}$$

Here, y_d is the desired output and O is the output calculated by RBFNN and both are the column vectors.

First step of the training is to prepare input and target data set and spread constant. Then set the error goal, after calculating Euclidean distance in each iteration one more neuron will be added and the MSE of the new network will be checked. This procedure will be continued untill MSE falls down the error goal or maximum number of neuron have reached. The flow chart of radial basis function neural network algorithm is shown in Figure 3.4.

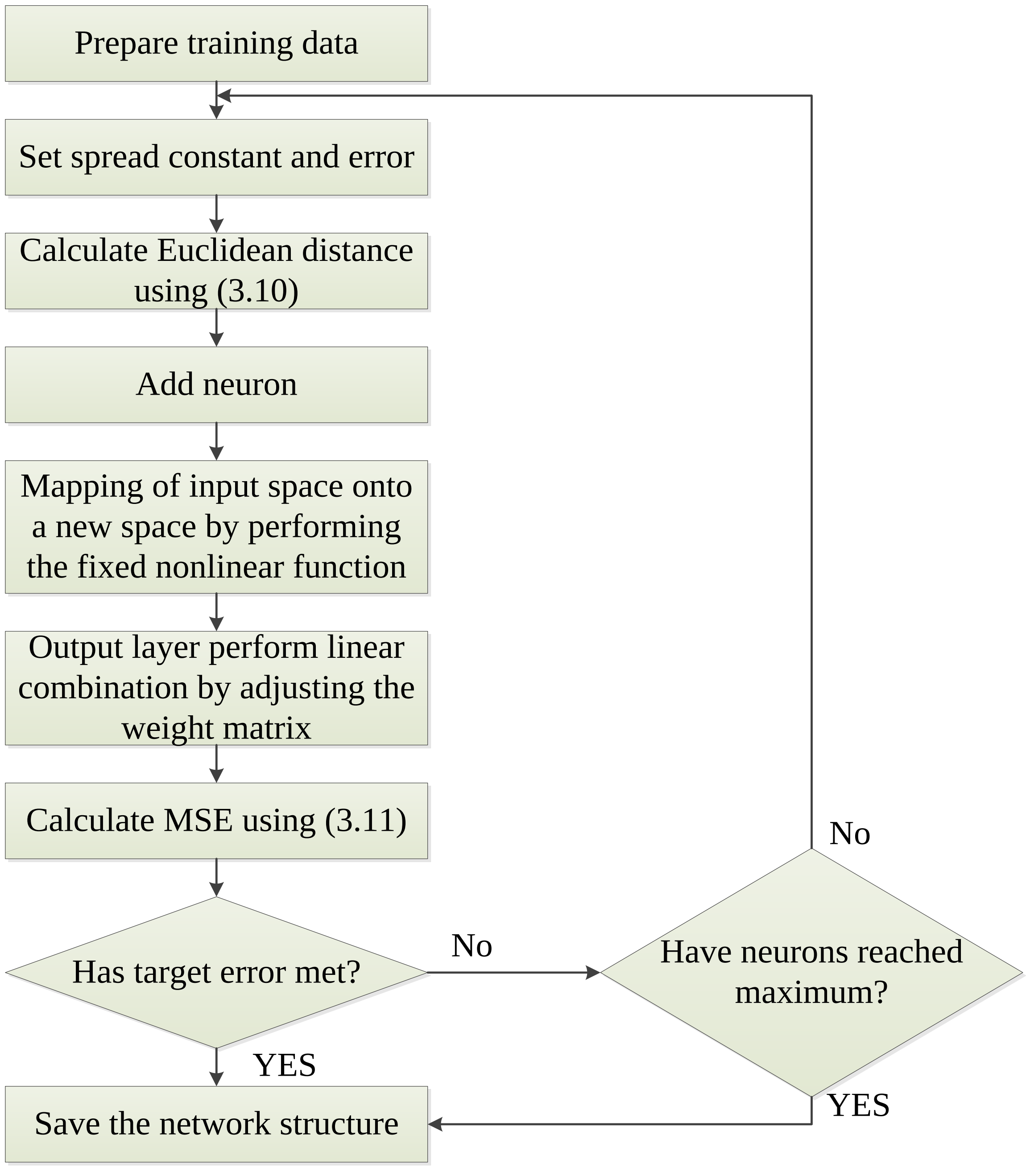

Figure 3.4: RBFNN learning algorithm flow chart

3.3 IMPLEMENTATION OF ANN ALGORITHMS

A superviesd ANN algorithm is used for wind speed estimation and maximum power point tracking (MPPT). Training of neural network is done by using both feed-forward back-propagation (FFBP) and Radial basis function networks (RBFN). FFBP algorithm is used for wind speed estimation. On the other hand, both FFBP and RBFN algorithm are used to track the maximum power point. There are numbers of learning algorithms (forward propagation, back propagation, radial basis function and Hopfield algotithm) reported in literature to determine the accurate strengths of ANN, among the proposed algorithm FFBP and RBFN are widely used for wind speed estimation and MPPT.

Two series neural network is used for maximum power point tracking (MPPT). One network for wind speed estimation and the other to track maximum power point and optimal rotor speed. This method does not required any mechanical sensor for wind speed measurement or any pre-system memory.

3.3.1 Wind Speed estimation using ANN

The initial capital cost of the wind energy conversion chain can be reduced by removing the need of the wind velocity sensor. For this, an ANN is used to estimate the wind velocity. The proposed training scheme of neural network to estimate wind velocity is shown in the following Figure 3.5.

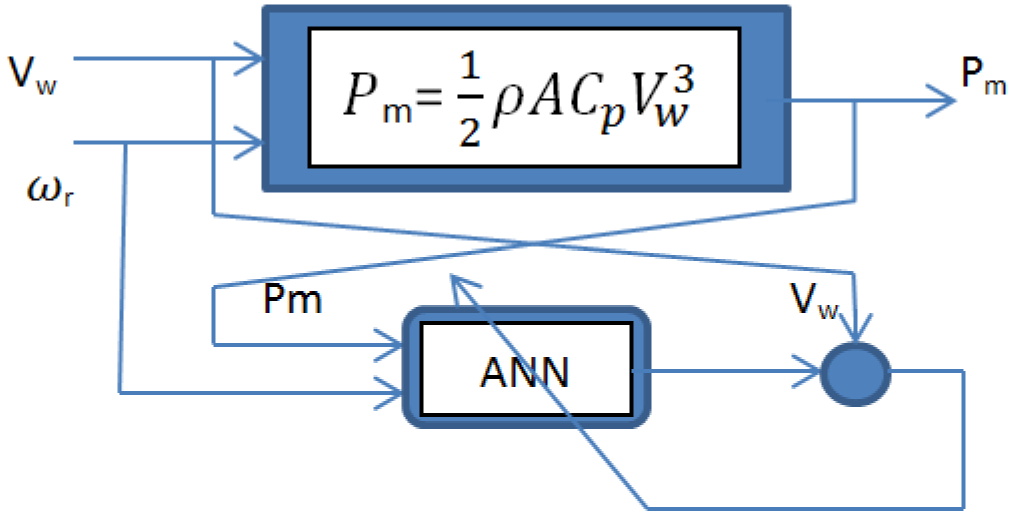

Figure 3.5: The proposed training scheme for ANN based wind speed estimation

Wind speed estimation is done in following steps:

1. The turbine power data (Pm) is generated from the turbine power equation for the preselected rotor speed (ω_r) and the wind velocity samples (V_w).

2. The rotor speed and turbine power are recombined as data pairs {ω_r, Pm}, which are employed as input matrix of the neural networks. On the other hand, the samples of wind speed (V_w) are set as target for the training process.

3. Training starts with the random values of the weights and proceeds iteratively. During the training process (learning stage), the estimated wind speed is compared with the actual wind speed to calculate the estimation error.

4. Back propagation algorithm propagates that calculated error in backward direction to adjust link weights between nodes to minimize the error of ANNs.

In this training scheme, the first step is to generate data set for training process. The typical operating range for wind is specified between 3~19.5 m/sec. Wind speed will be estimated based on the turbine power and the rotor speed. 140 samples of wind speed has been taken between 3~19.5 m/sec. The blade pitch angle β is set constant, selecting the tip speed ratio λ between the range of 0.1~14 to obtain 140 averagely sampled tip speed ratio. Based on this sample data, 19,600 data pair of $\{V_w(i), \lambda(j) |\ \mathrm{i} = 1, \dots \dots 140, \mathrm{j} = 1, \dots \dots .140\}$ are generated. With this obtained data pairs $\{V_w(i), \lambda(j)\}$, 19,600 data set of mechanical Power $\{P_m(i,j) |\ i = 1, \dots \dots \dots .140, j = 1, \dots \dots \dots 140\}$ and 19,600 data set of rotor speed $\{\omega_r(i,j) |\ i = 1, \dots \dots ..140, j = 1, \dots \dots .140\}$ are assembled. Finally, for preselected rotor speed and wind speed samples (6~19.5 m/s), 797 data pairs $\{P_m, \omega_r\}$ is generated and used as input to the ANN and equal number of wind speed samples are used as output for training.

A three layer network is used for training, which configured with two linear neurons in the input layer, ten tan-sigmoid neurons in the hidden layer and one linear neuron in the output layer; wind speed V_w is used as target shown in Figure 3.6. W1 and B1 denotes the input weights and bias, on the other hand W2 and B2 denotes the linear weights and bias for the output.

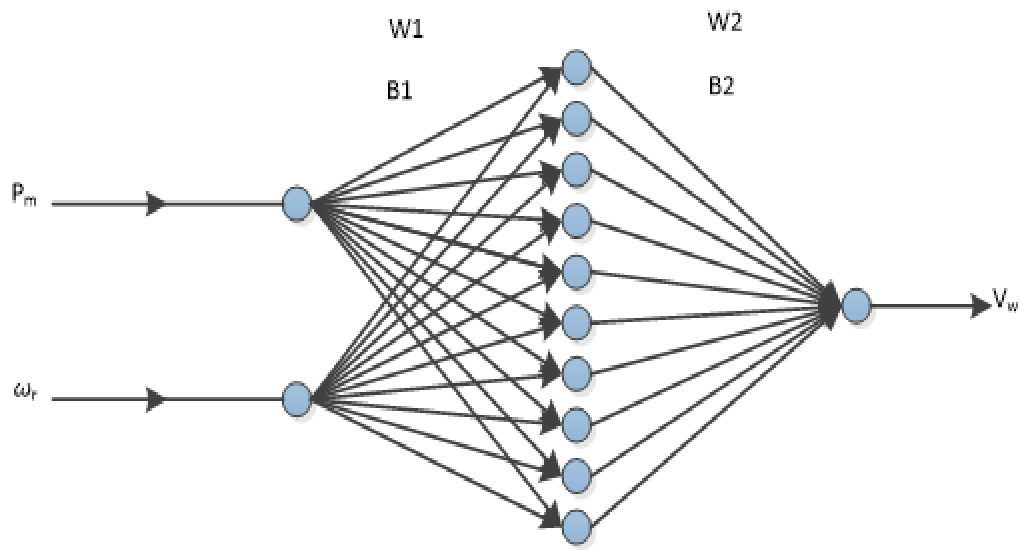

Figure 3.6: Wind velocity estimation ANN with ten tan-sigmoid neurons and one linear neuron

3.3.2 Testing of trained ANN

The ANN based wind speed estimation is developed in MATALB/Simulink using feed-forward back-propagation. Figure 3.7 plots the training errors, validation errors and test errors with respect to the number of epochs (iterations). In learning stage, the input and target data sets are divided into three types: 60% for training, 20% for validation and the remaining 20% for testing. Figure 3.7 demonstrates that the validation stop at epochs 37, when the validation curve touches the best error (targeted error) curve; means validation performance reached at minimum without any over fitting. Validation is needed to stop training before over fitting, because over fitting just memorize the input and output data sets.

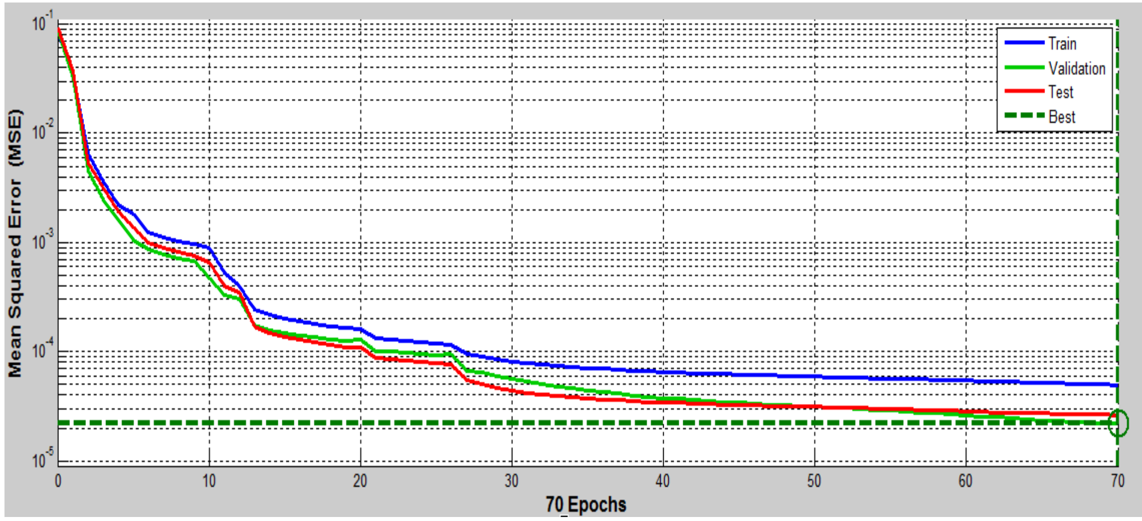

Figure 3.7: Training, validation and testing errors versus epochs for the ANN

The final Mean Squared Error (MSE) is very small and the test and validation set errors have similar characteristics. The best validation occurs after 70 epochs as shown in Figure 3.7. The error comes to a value of $2.6507\text{x}10^{-5}$ in epochs 70.

Linear regression between network outputs and corresponding targets analyze the performance of the trained network. In Figure 3.8, the dashed line in each plots indicates the perfect result (outputs=targets) and the solid line represents the best fit linear regression line among the outputs and targets. If the value of R=1, then there is an exact linear relationship exists between outputs and target. Figure 3.8 demonstrates that the ANN is so trained that the training data (small circular points) indicates a good fit and the outputs tracks the targets accurately for training, testing and validation , because the R value is close to 1.

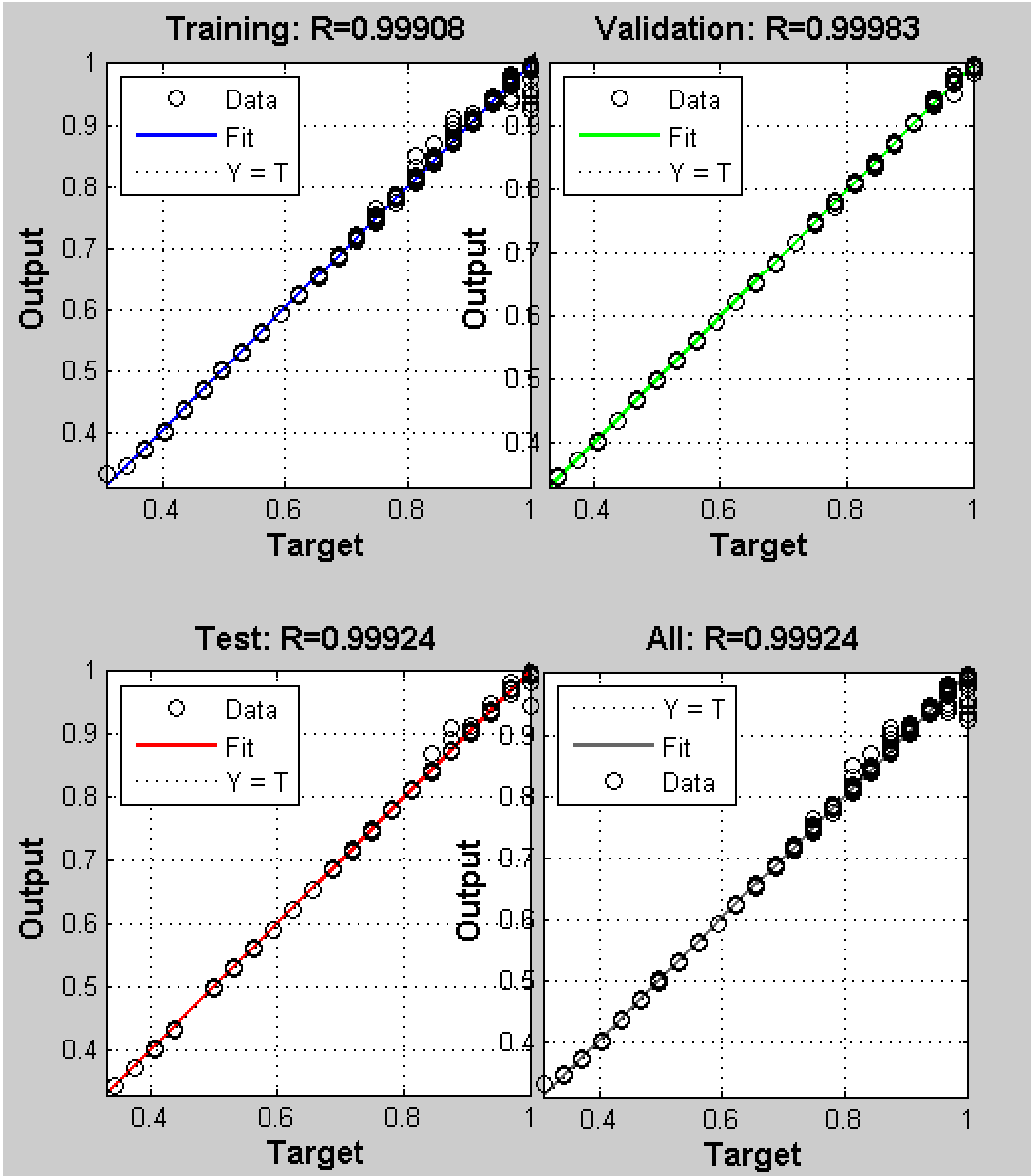

Figure 3.8: Linear regression between network outputs and corresponding targets

3.3.3 Maximum power point tracking (MPPT) using ANN

For a particular wind speed, there are different turbine power and rotor speed, but there will be only one power point, at which the power will be maximum (P_{max}). The rotor speed corresponding to that maximum power point is termed as optimum rotor speed (ω_{opt}). To extract maximum possible power from a particular wind speed, the rotor must be rotates at the optimum rotor speed. The proposed training scheme of neural network to track maximum power point and optimum rotor speed is shown in the following Figure 3.9.

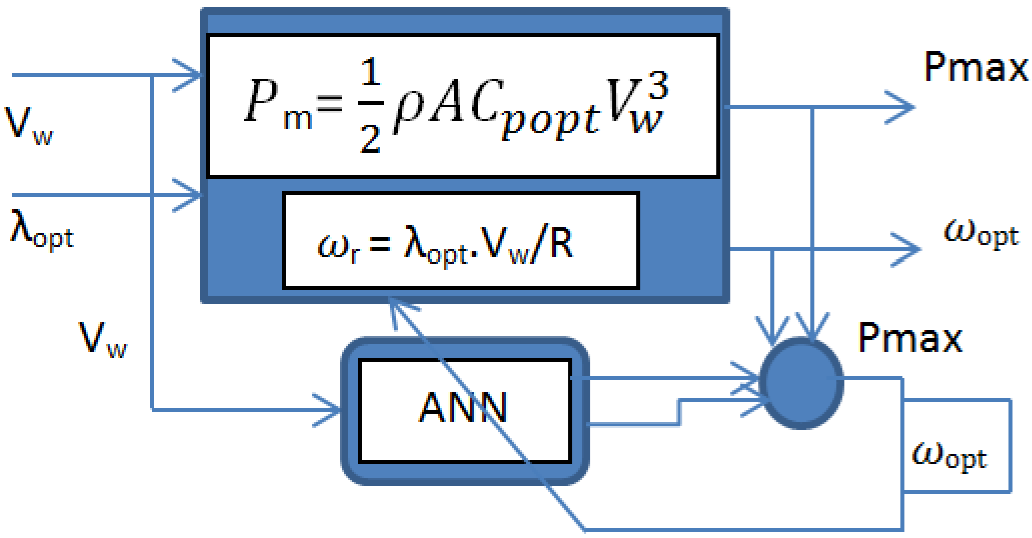

Figure 3.9: The proposed training scheme for ANN based MPPT

Maximum power point tracking is done in following steps:

1. the turbine maximum power data (P_{max}) is generated from the turbine power equation for the optimum value of power coefficient (C_p), optimal rotor speed (ω_r) and the wind velocity samples (V_w).

2. The samples of wind speed (V_w) are set as input for the training process. On the other hand, the optimal rotor speed and turbine maximum power are

recombined as data pairs {ω_{ropt}, P_{max}}, which are employed as target matrix of the neural networks.

3. . During the training process (learning stage), the estimated optimal rotor speed and maximum power are compared with the orginal optimal rotor speed and maximum power resectively to calculate errors.
4. Back propagation algorithm propagates those calculated errors in backward direction to adjust link weights between nodes to minimize the error of ANNs.

To determine the optimal rotor speed and maximum power at every wind speed, we have to find out all maximum and optimal values of power and rotor speed respectively at any sampled 140 wind speeds. For 140 samples of wind speed 140 data pairs $\{P_{max}, \omega_{ropt}\}$ is generated to train the ANN.

Now the training process starts, by providing sampled wind speed as input to neural network and maximum power and optimal rotor speed data pairs as target output to train neural network both in feed-forward and radial basis function methods.

3.3.4 Implementation of ANN MPPT controller in MATLAB/Simulink

The method used for training is Feed- forward back-Propagation for wind velocity estimation and radial basis function methods for MPPT. After the training process, one Simulink block is generated for neural network simulation to estimate wind speed and another one for neural network simulation to track MPP. The ANN-based wind speed estimation and MPPT controller in Simulink is shown in the following Figure 3.10.

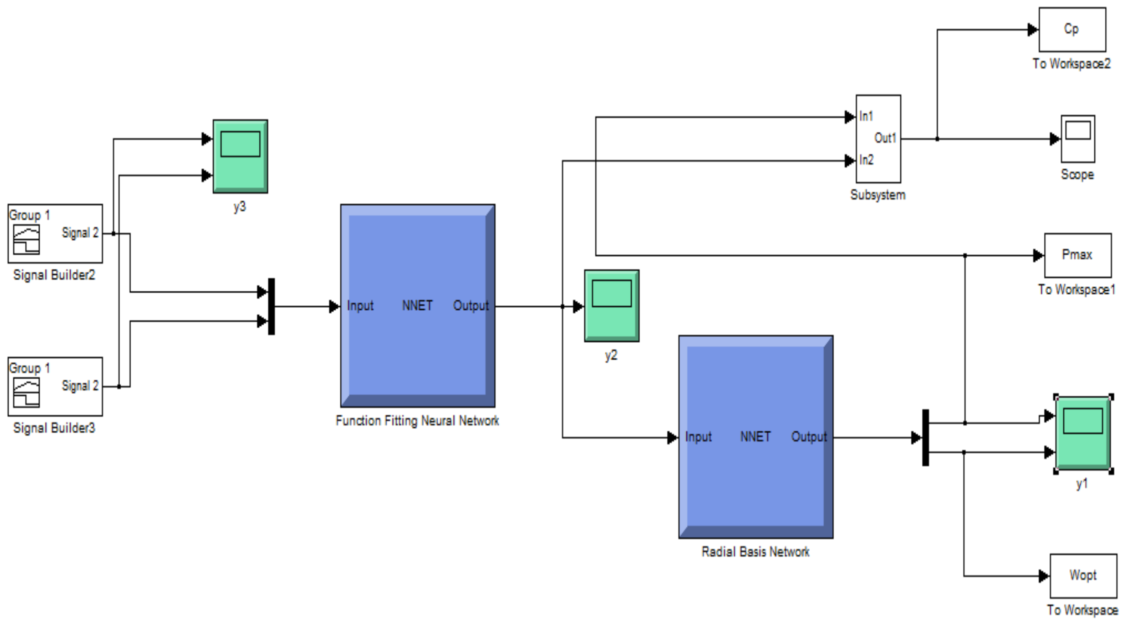

Figure 3.10: ANN-based wind speed estimation and MPPT controller in Simulink

Figure 3.10 shows that the rotor speed and turbine power are presented to neural network to estimate the wind. The estimated wind speed is then feed to the radial basis network to determine both the maximum power and optimal rotor speed corresponding to that estimated wind speed.

The testing is also done by providing rapidly changing input data (turbine power and rotor speed) to evaluate the effectiveness of the proposed controller under rapidly changing wind conditions.

3.4 SIMULATION RESULTS

3.4.1 Simulation results for wind speed estimation

The verification of wind speed estimation is done by applying random test input signals (operating power and rotor speed) to the trained network implemented in Simulink. Figure 3.11 shows the applied input signals, based on the input signals the wind speed is estimated, which is shown in Figure 3.12.

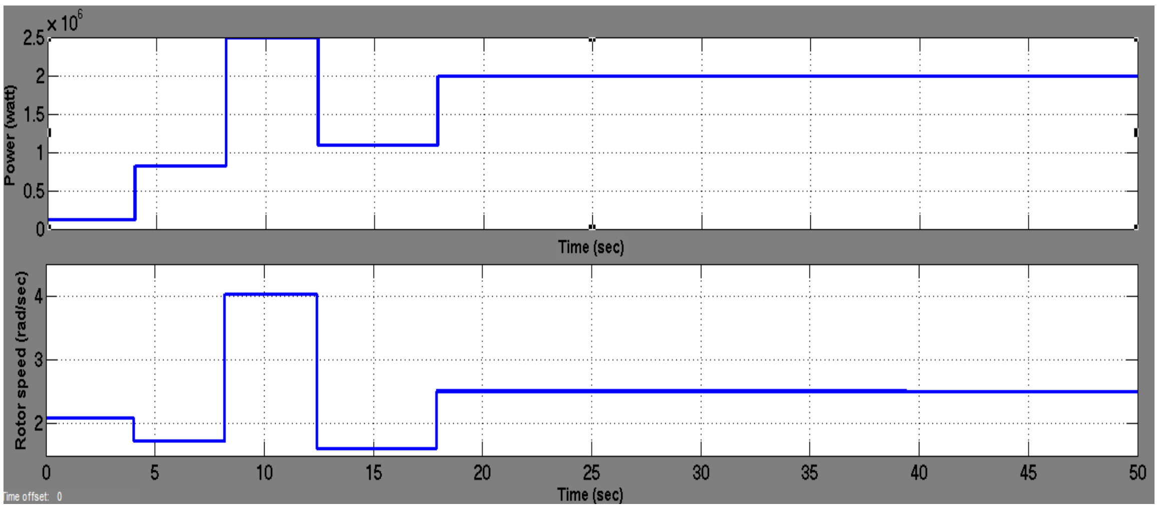

Figure 3.11: Input signal (Pm, ω_r) to the trained ANN.

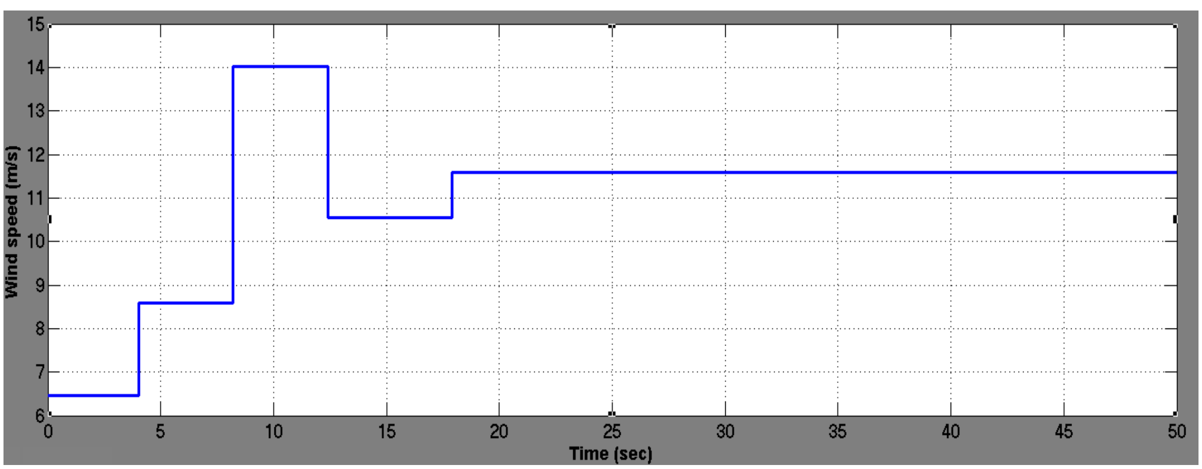

Figure 3.12: Estimated wind Speed

From the Figure 3.11 and Figure 3.12 it is evidient that with the change in the input (turbine power and rotor speed), the trained network can track the change in wind speed. Wind speed estimation error is used as performance criterion of the implemented simulink model. The wind speed error is measured by calculating the difference between the calculated wind speed and simulated wind speed as shhown in table 1.

Table 3.1: Testing using Feed-forward Back-propagation

Input		**Simulation**	**Calculated**	**Error**
Turbine power, Pm (MW)	Rotor speed, ω_r (rad/sec)	Wind speed, V_w (m/s)	Wind speed, V_w (m/s)	(%)
0.124	2.094	6.4546	6.4423	0.190
0.815	1.727	8.5967	8.6120	0.178
2.50	4.029	14.0231	14.019	0.003
1.087	1.604	10.5521	10.495	0.054
2.00	2.508	11.5981	11.550	0.416

From the above table it is clear the trained network is able to estimate the wind speed with very high accuracy. The error in wind speed estimation is very close to zero, the maximum error is only 0.416%.

Figure 3.13 shows a comparison between the original and estimated wind speed during rapid change in wind conditions. The solid line shows the original wind speed and the dased line shows the estimated wind speed. The results shown in Figure 3.13, demonstrates that the proposed controller has the ability to estimate wind speed under rapid change in wind conditions.

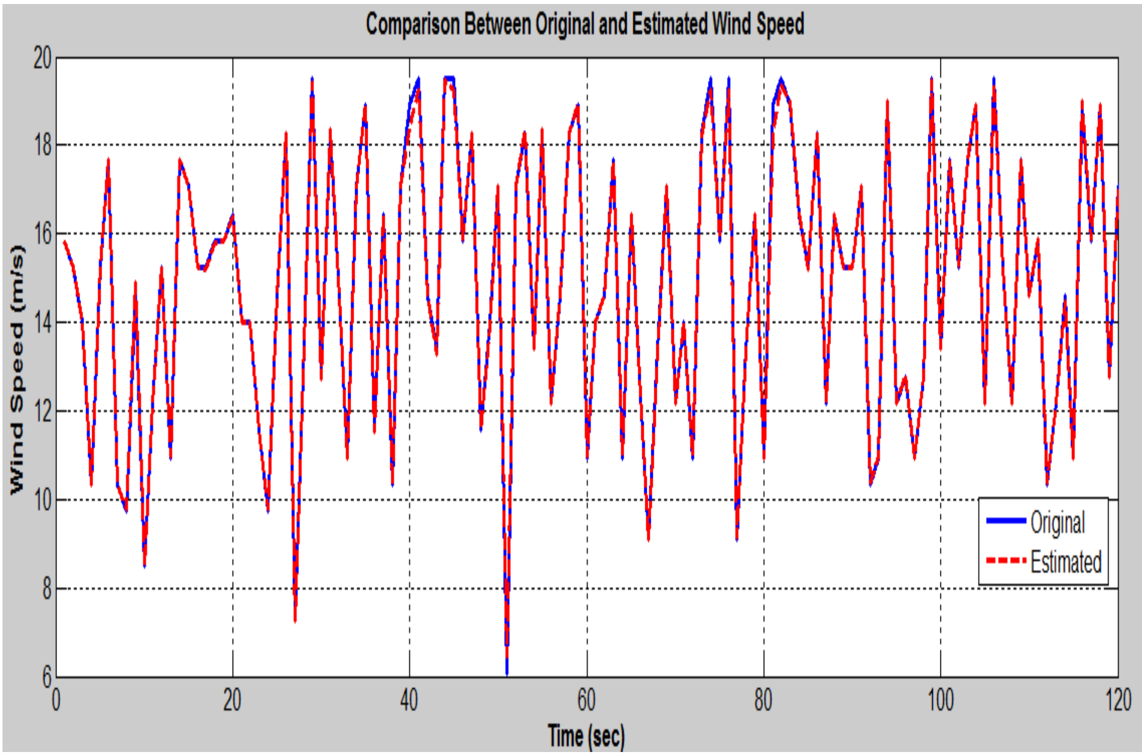

Figure 3.13: Original and estimated wind speed

In Figure 3.14, Simulation result shows the error in wind speed estimation for ANN based wind speed estimator. It can be noticed from the graph that the wind velocity is well estimated with small errors, the maximum error is only 0.22 m/s.

Figure 3.14: Error in wind speed estimation

3.4.2 Simulation results for MPPT

The methods used to test the performance of MPPT controllers are both Feed-forward back-Propagation (FFBP) and Radial basis function (RBF). Testing is done by providing wind speed as input to the trained network. This trained neural network will behave as a controller which gives maximum power and the corresponding optimal rotor speed at any wind speed. Figure 3.15 shows the estimated wind speed, that is used as input to the RBF based MPPT controller to track the maximum power and optimal rotor speed.

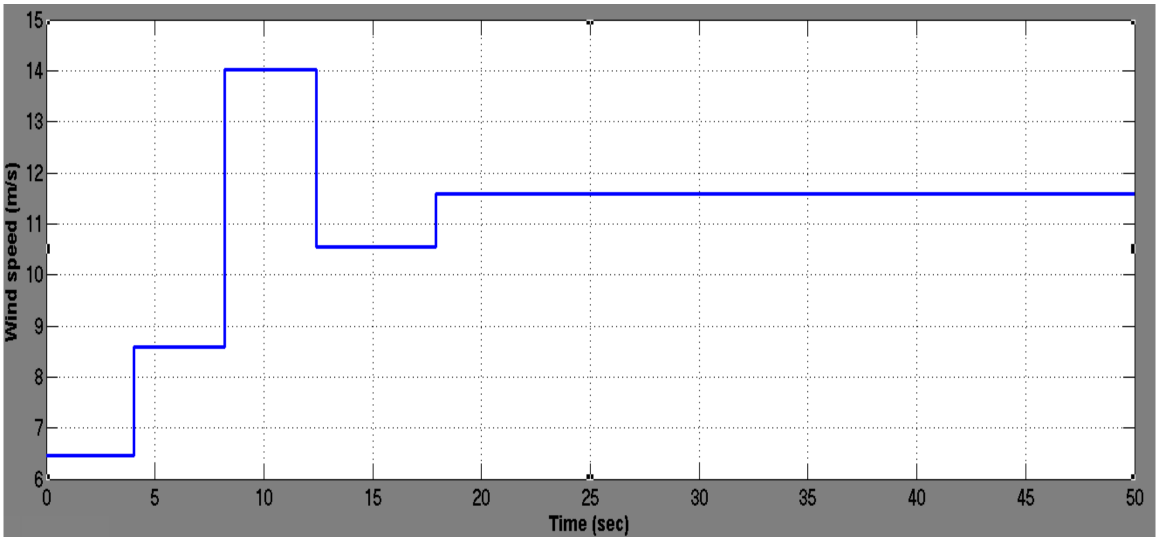

Figure 3.15: Wind speed

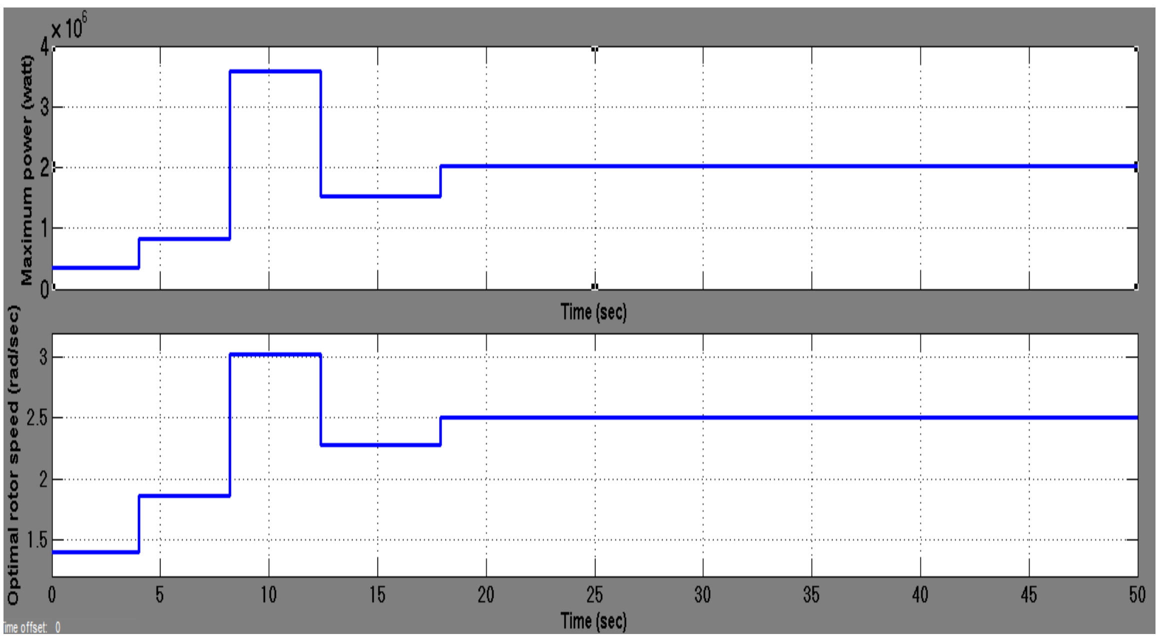

Figure 3.16: Maximum power and optimal rotor speed with respect to the estimated wind speed

When wind speed changes, the controller can track the maximum power point (MPP) and optimal rotor speed properly as shown in Figure 3.16. Figure 3.17 shows that the

ANN based MPPT algorithm is able to maintain the optimum value of power coefficient (C_p) that is almost constant at 0.48.

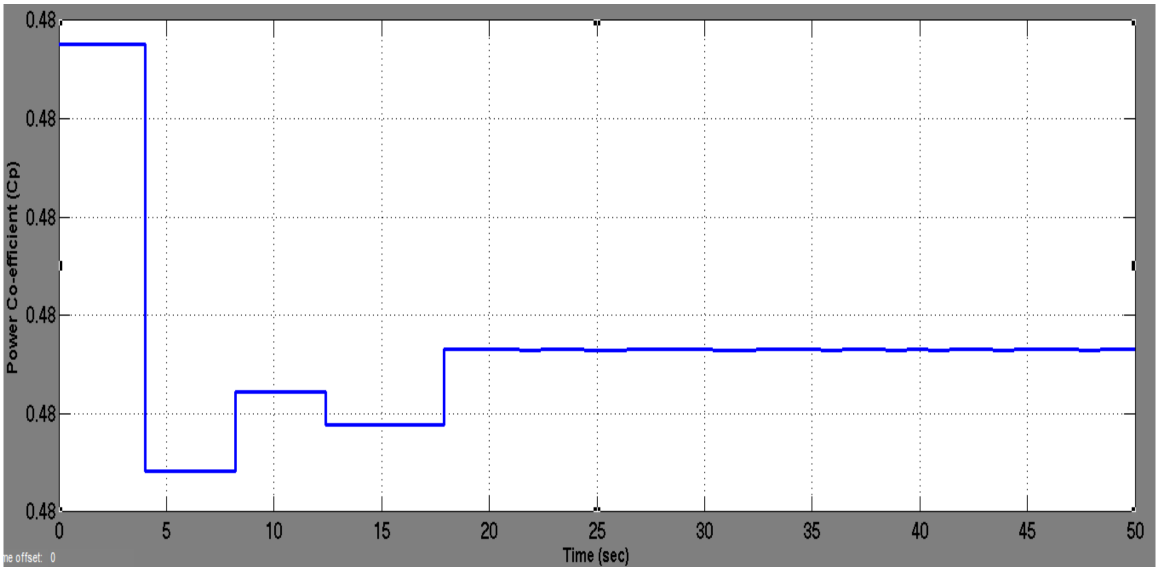

Figure 3.17: Power coefficient (Cp)

Test data was provided to the implemented Simulink network. Testing was carried out on both methods, i.e.; Feed-forward back-propagation and Radial basis function Network. Maximum power point tracking (MPPT) error is used as performance criterion of the implemented FFBP and RBF networks. The MPPT error is measured by calculating the difference between the actual optimal rotor speed and simulated optimal rotor speed as shhown in table 2 and table 3.

Table 3.2: Testing using Feed-forward Back-propagation

	Simulation		Calculated		
Wind speed (m/sec)	Pmax (MW)	ωopt (rad/sec)	Pmax (MW)	ωopt (rad/sec)	Error (%)
6.443	0.3473	1.4	0.34910	1.3944	0.42
8.612	0.8297	1.883	0.82477	1.8637	1.04
14.019	3.5787	3.027	3.57990	3.034	0.24
10.495	1.5015	2.387	1.52530	2.2712	5.10
11.55	2.0013	2.649	2.02530	2.4996	5.98

Table 3.3: Testing using Radial basis function

	Simulation		Calculated		
Wind speed (m/sec)	Pmax (MW)	ωopt (rad/sec)	Pmax (MW)	ωopt (rad/sec)	Error (%)
6.4423	0.34929	1.3942	0.34910	1.3944	0.02
8.612	0.82523	1.8569	0.82477	1.8637	0.36
14.019	3.58180	3.0289	3.57990	3.0339	0.16
10.495	1.52610	2.2793	1.52530	2.2713	0.35
11.55	2.02650	2.5052	2.02530	2.4996	0.22

Comparing the results obtained from back propagation and radial basis algorithms, radial basis function method is found to be more accurate.

Figure 3.18 shows the original and estimated maximum power points together during the rapid change in wind speed. The solid line shows the original maximum power and the dashed line shows the estimated maximum power. The results shown in Figure 3.18, demonstrates that the proposed MPPT controller has the ability to track maximum power point under rapid change in wind conditions.

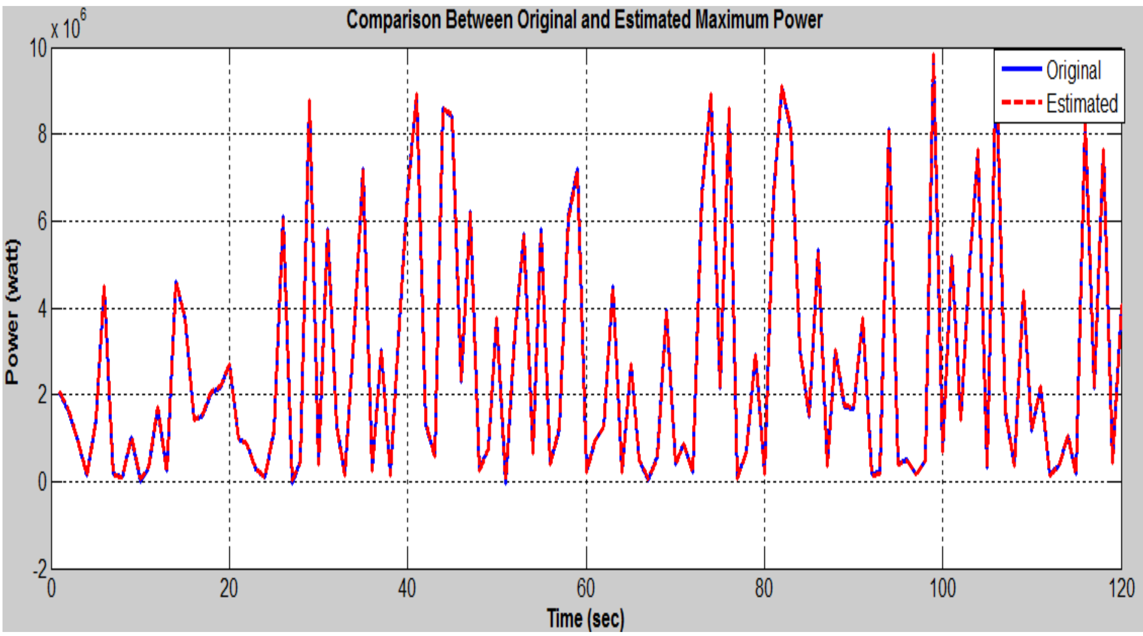

Figure 3.18: Original and estimated maximum power

In Figure 3.19, Simulation result verifies the effectiveness and accuracy of ANN based controller for maximum power point tracking. When wind speed changes the rotor also changes and based on the wind speed the controller can track the rotor speed. The controller is so trained that it can track the MPP correctly with maximum $9.7\text{x}10^{-3}$ watt.

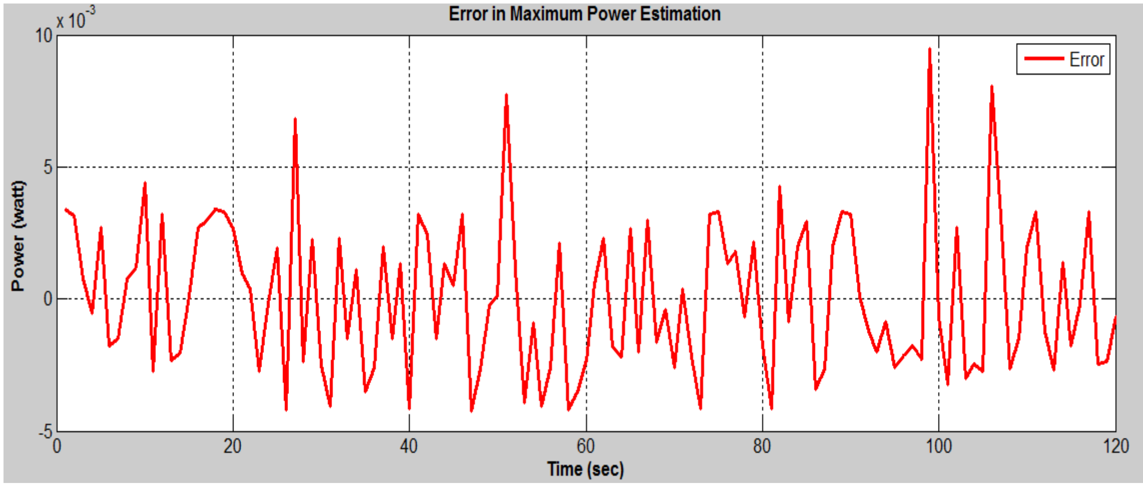

Figure 3.19: Error in maximum power estimation

Figure 3.20 shows the original and estimated optimal rotor speed together. The solid line shows the original optimal rotor speed and the dashed line shows the estimated optimal rotor speed. The results shown in Figure 3.20, demonstrates that the proposed MPPT controller has the ability to track optimal rotor speed under rapid change in wind conditions.

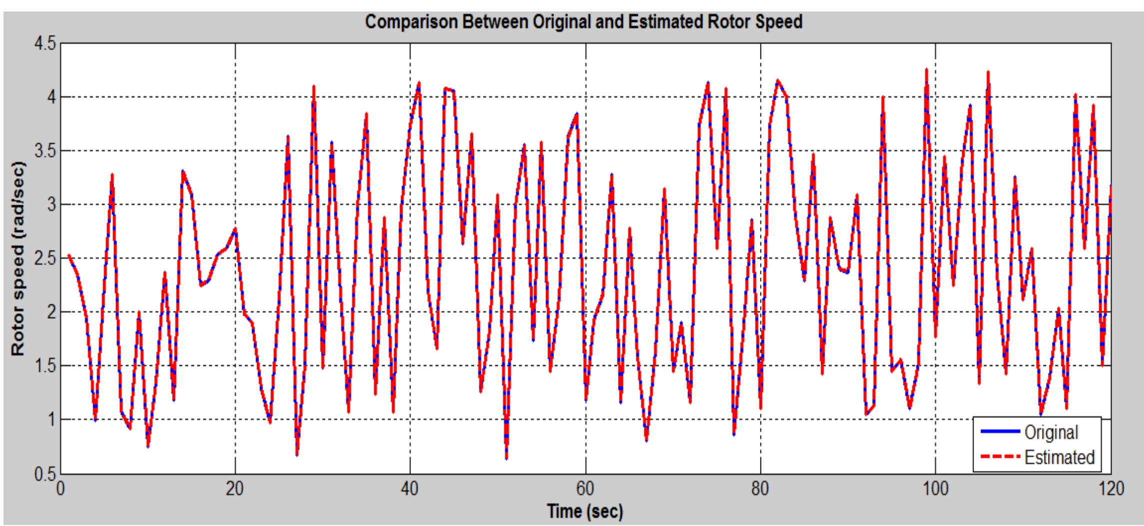

Figure 3.20: Original and estimated optimal rotor speed

In Figure 3.21, simulation result shows that optimal rotor speed is well estimated with very small errors, the maximum error is only 0.01 rad/sec.

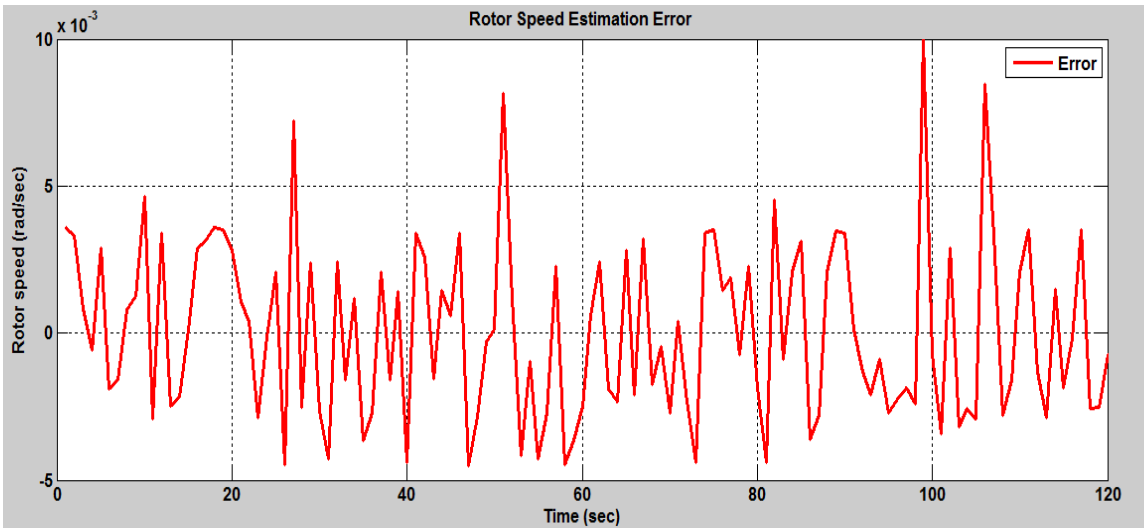

Figure 3.21: Error in optimal rotor speed estimation

The test results confirm the effectiveness and accuracy of the proposed ANN based MPPT algorithm and it has very fast response in rapidly changing wind conditions.

3.4.3 Comparison with the traditional MPPT algorithm

The proposed ANN based MPPT algorithm is compared with the three commonly used MPPT techniques as shown in table 4. TSR methods required both anemometer and system pre-knowledge for wind speed estimation and MPPT; both are considered as drawbacks of MPPT algorithm. PSF methods does not required anemometer but it required system memory. Moreover, PSF method does not support online updating. P & O (also known as HCS) method does not required anemometer and system pre-knowledge for wind speed estimation and MPPT, but tracking is slow and causes oscillation around the MPP. By using proposed ANN based MPPT algorithm, it is possible to overcome all the shortcomings of the conventional MPPT algorithms.

Table 3.4: Comparison between traditional and proposed MPPT algorithms

MPPT algorithm	**Anemometer**	**System Pre-knowledge**	**Tracking speed**	**Oscillation at MPP**	**Online updating**
TSR	Required	Required	Fast	No	No
PSF	Not required	Required	Fast	No	No
P & O	Not required	Not required	Slow	Yes	Yes
Proposed algorithm	Not required	Not required	Fast	No	Yes

3.4.4 Comparison with the previously proposed ANN-based MPPT algorithm

The proposed control algorithm is also applicable for other wind generation systems. A variable speed small wind generation system is considered to evaluate the performance of the proposed algorithm. The rating of the wind system is 1.4 kW and radius of turbine blades is 1m. The test results of the proposed controller and the previously proposed ANN based controller reported in [21] is compared.

Figure 3.22 and Figure 3.23 show the original and estimated wind speed by the proposed controller and the reported controller respectively.

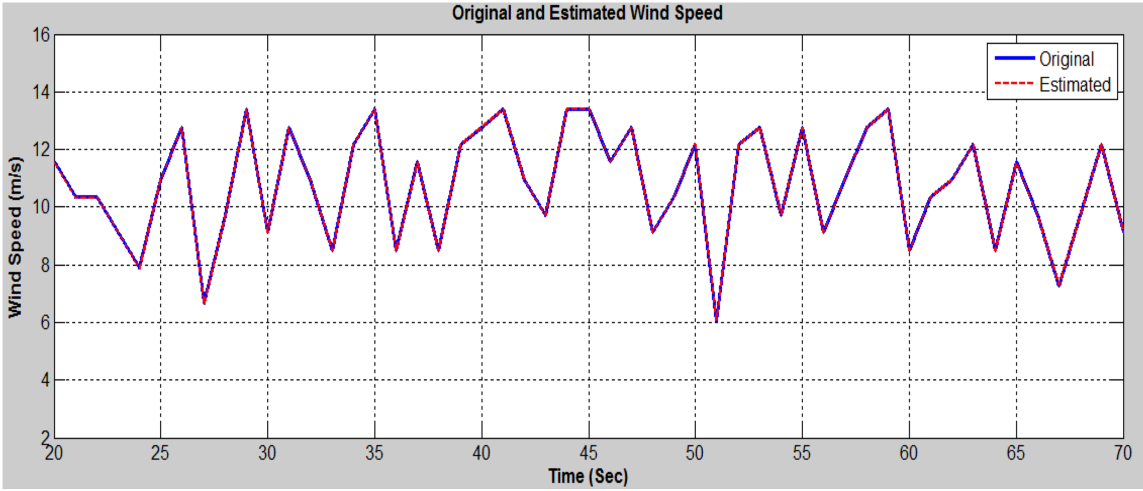

Figure 3.22: Original and estimated wind speed

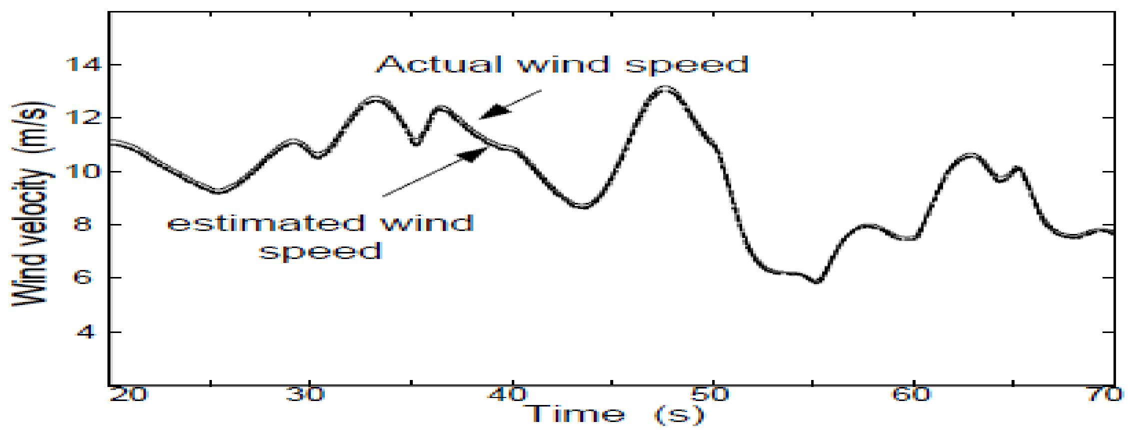

Figure 3.23: Original and estimated wind speed [21]

Figure 3.24 and Figure 3.25 show the wind speed estimation error using proposed controller and the reported controller. The maximum error in wind speed estimation for the proposed controller is 0.11 m/s, which is 0.25 m/s for the reported controller as shown in Table 3.4: Comparison between traditional and proposed MPPT algorithmsTable 3.4.

Table 3.5: Comparison between proposed and reported MPPT techniques

MPPT Techniques	Minimum Wind Speed Error (m/s)	Maximum Wind Speed Error (m/s)
Previous Method	0.02	0.25
Proposed Method	$1.6\text{x}10^{-4}$	0.108

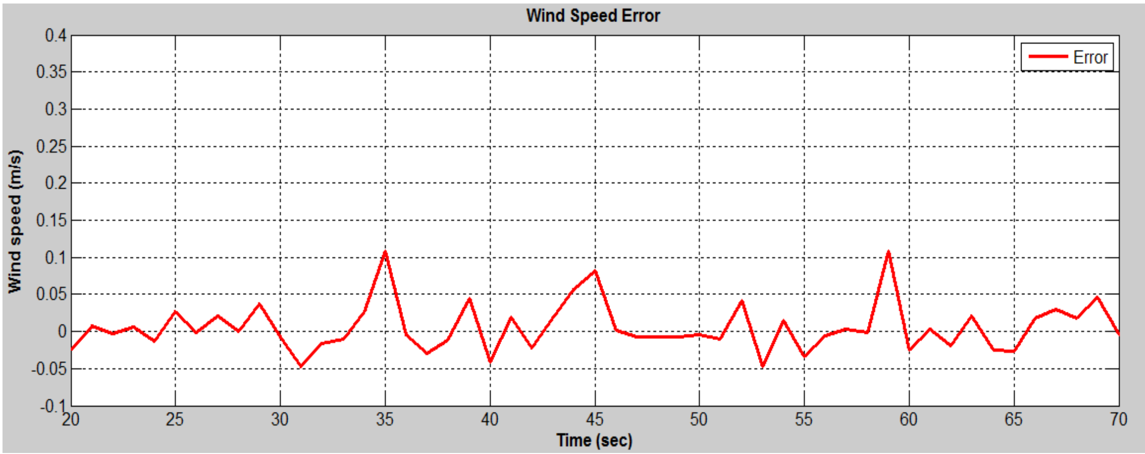

Figure 3.24: Wind speed estimation error

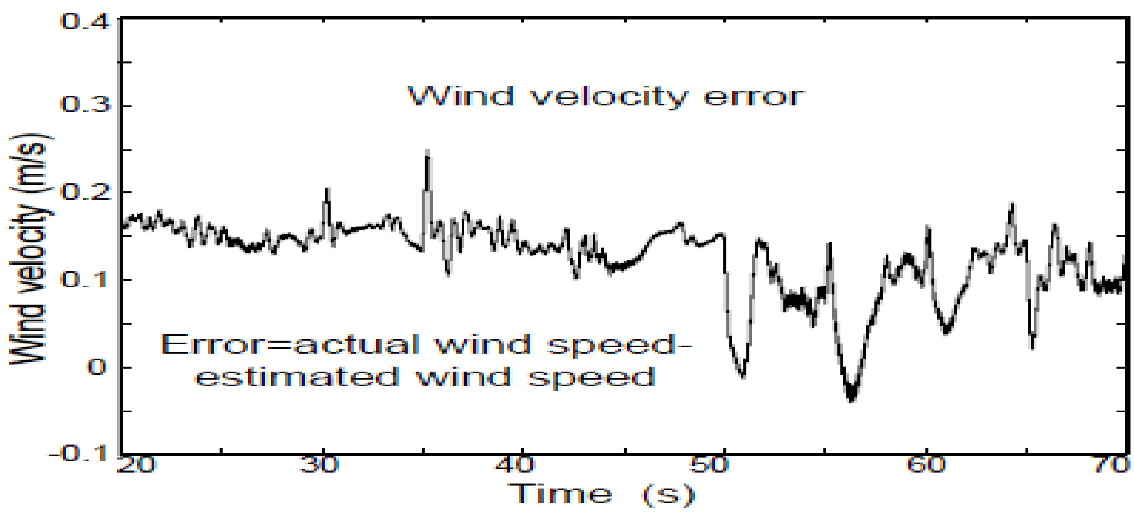

Figure 3.25: Wind speed estimation error [21]

Performance of the proposed controller is superior to the reported controller since it reduces wind speed estimation error. Reported controller has used feed forward back propagation algorithm with five tan-sigmoid neurons in the hidden layer to estimate wind speed while performance has been improved using ten tan-sigmoid neurons in proposed method.

Figure 3.26 shows optimal rotor speed tracked by the proposed ANN based MPPT controller and Figure 3.27 shows the optimal rotor speed for the reported controller.

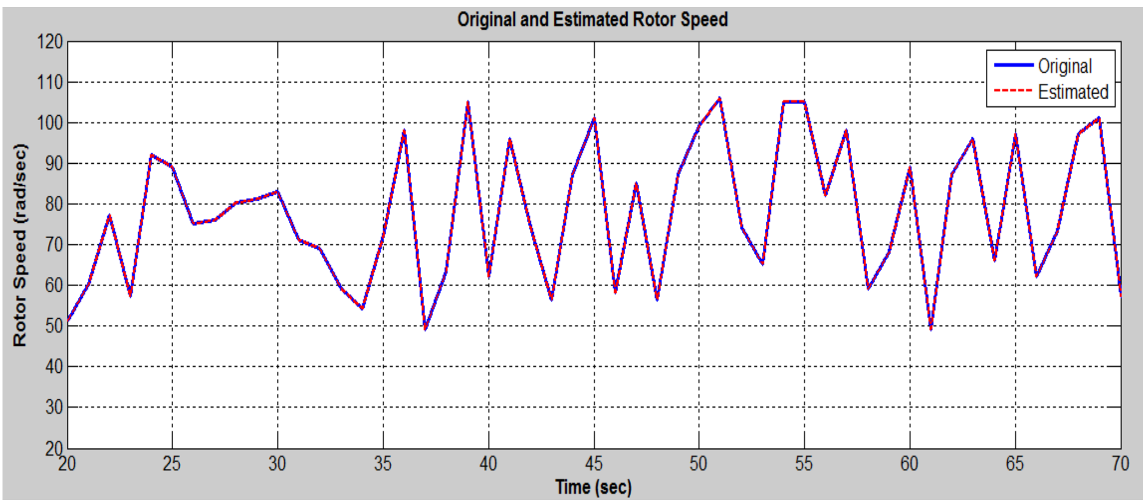

Figure 3.26: Original and estimated optimal rotor speed

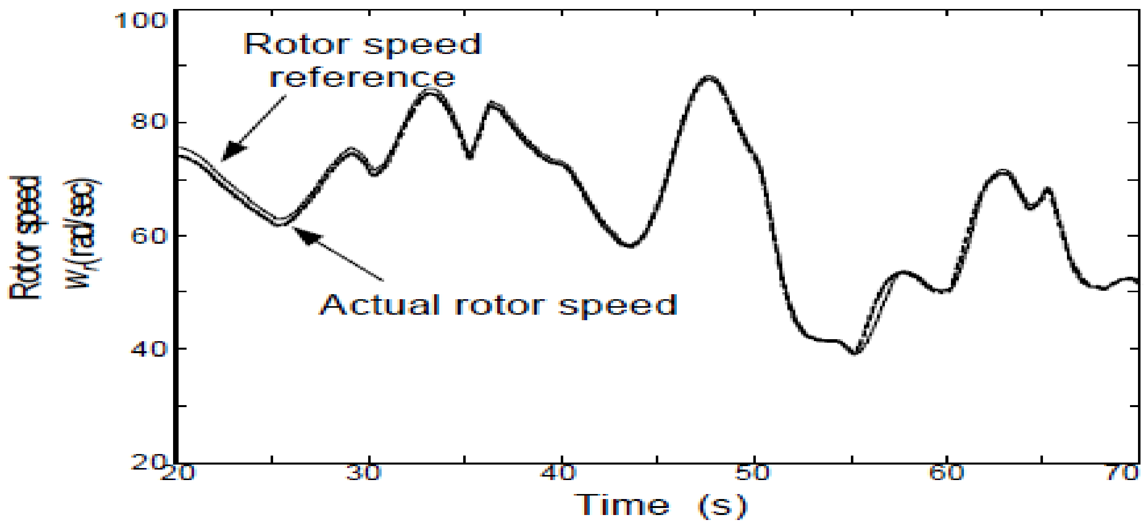

Figure 3.27: Original and estimated optimal rotor speed [21]

From Figure 3.27 it is evident that maximum rotor speed error is around 1 rad/sec. On the other hand maximum error in optimal rotor speed tracking is 3.9x10^{-4} rad/sec as shown in Figure 3.28.

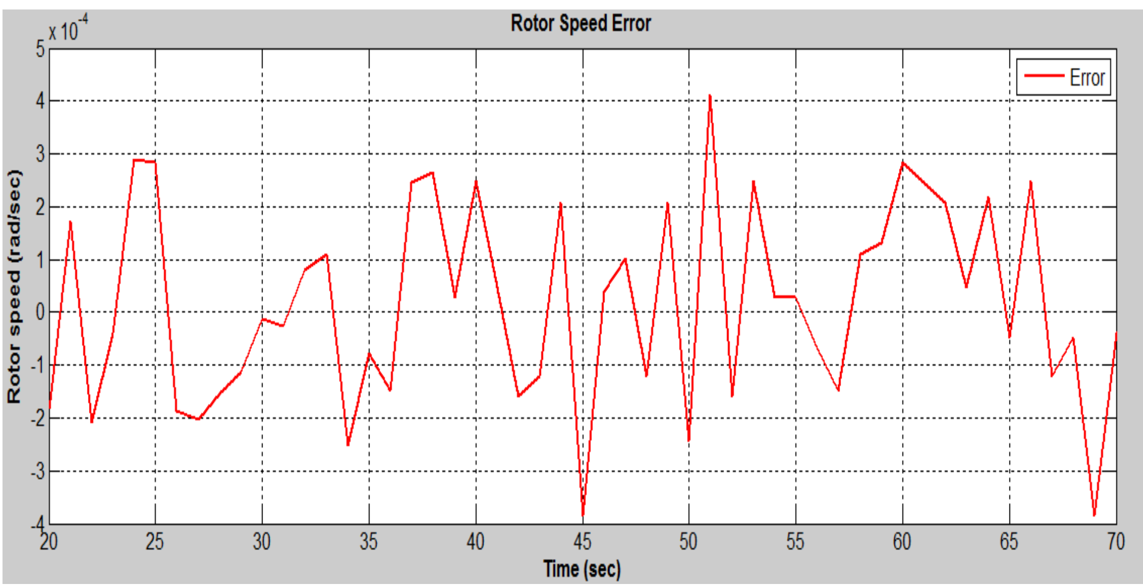

Figure 3.28: Rotor speed estimation error

A comparison between proposed and reported MPPT techniques has been made in Table 3.6 in terms of rotor speed estimation at maximum power point.

Table 3.6: Comparison between proposed and reported MPPT techniques

MPPT Techniques	**Minimum Rotor Speed Error (rad/sec)**	**Maximum Rotor Speed Error (rad/sec)**
Previous Method	0.003	0.5
Proposed Method	$1.35 \mathrm{x} 10^{-5}$	$4.11 \mathrm{x} 10^{-4}$

So in optimal rotor speed tracking, the performance of the proposed ANN based MPPT controller is superior to the reported controller since it reduces wind speed estimation and optimal rotor speed tracking error.

The feasibility of the proposed controller is validated and the simulation results prove the robustness, fast response, and exact wind speed estimation with maximum power point tracking capabilities of the proposed ANN based MPPT algorithm.

CHAPTER 4

ANFIS-BASED MPPT CONTROLLER DESIGN

4.1 INTRODUCTION

Wind energy systems are the nonlinear source of energy, because the turbine output power is the cubic function of wind speed. For a particular wind speed there is a particular curve and each curve has one optimum point called Maximum Power Point (MPP) as discussed in previous chapters. The maximum power point varies with the wind speed. Therefore, accurate on-line maximum power point tracking (MPPT) controller is essential to extract maximum possible power from any wind speed.

Artificial intelligence (AI) techniques are becoming popular in MPPT of photovoltaic and wind systems due to their learning and adaptive control capabilities. AI technique based MPPT algorithms are highly successful comparing to the conventional methods such as tip speed ratio (TSR) control method, power signal feedback method (PSF) and hill-climbing search (HCS) or perturb and observe (P&O) method. Neural network (NN) and fuzzy logic (FL) based MPPT controllers are the commonly used AI techniques. After a proper training an AI technique got the ability to produce accurate output for random input.

Neural network is a powerful tool to deal with nonlinear objective function but it works as a black box. On the other hand by using fuzzy rules and membership function, fuzzy logic controller can convert heuristic and linguistic terms into numerical values. ANFIS integrates neural network and fuzzy logic to take the advantages of both the techniques. Researchers already proved that ANFIS based MPPT controller is very efficient, robust, simple and economical [68]. The accuracy of maximum power point tracking depends on the accuracy of the wind speed measurement. Anemometer is used for wind speed estimation in previously proposed ANFIS based MPPT methods, but the use of anemometer is not economical. Moreover, to measure wind speed accurately numbers of anemometer is required to be placed in different position around the turbine system.

In this chapter, the new intelligent MPPT controller based on the adaptive neuro-fuzzy inference system (ANFIS) is proposed and developed for wind speed estimation and maximum power point tracking. Two series ANFIS network will be used, one for wind speed estimation and the other to track maximum power point. In the proposed algorithm there is no need of anemometer for wind speed measurement.

4.2 ANFIS-BASED MPPT CONTROLLER DESIGN

4.2.1 Adaptive Network-Based fuzzy Inference System (ANFIS)

In comparison to the neural network, ANFIS also has similar type network structure and maps for the input-output data set using the parameters of fuzzy membership functions. A simple ANFIS architecture, based on the two rule Sugeno system with two inputs (X and Y) and single output (F) is shown in Figure 4.1, where A1, A2 and B1, B2 are fuzzy input memberships for input X and Y, respectively and are used to fuzzify the inputs [56].

For a Sugeno ANFIS model the typical rule set with two fuzzy if-then rules can be defined as in (4.1) and (4.2): [69]

$$If\ X\ is\ A_1\ and\ y\ is\ B_1 \quad THEN \quad f_1 = p_1x + q_1y + r_1 \tag{4.1}$$

$$If\ X\ is\ A_2\ and\ y\ is\ B_2 \quad THEN \quad f_2 = p_2x + q_2y + r_2 \tag{4.2}$$

As shown in Figure 4.1, ANFIS consists of five layers; the function of each layer is described below:

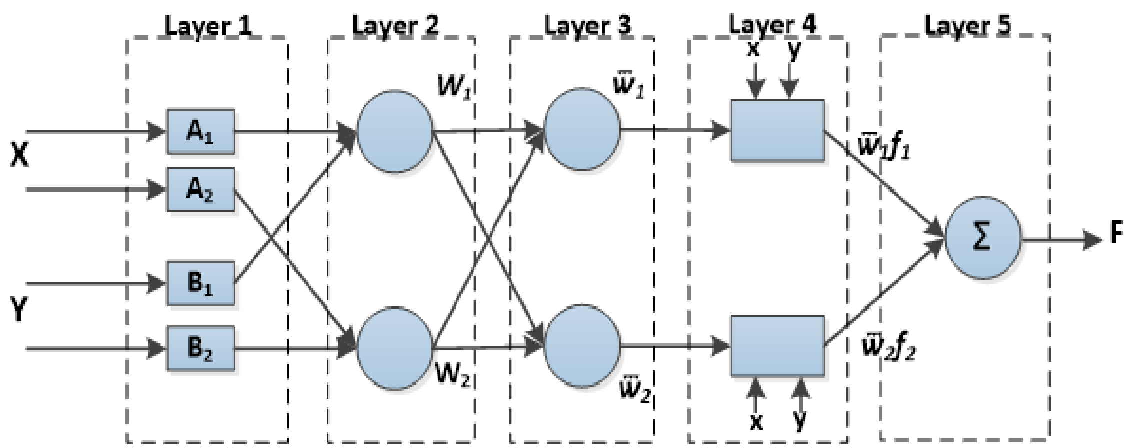

Figure 4.1: ANFIS architecture.

Layer-1:

In layer-1 every node is adaptive node. Adaptive node is the one which has the ability to learn through a process and adjusts its response to a new situation based on its learning process. The number of adaptive node in layer-1 depends on the number of input membership functions. Each input is assigned a certain number of membership functions and each membership function corresponds to a node. The main task of this layer is to fuzzify input parameters using some variables named as large, medium, small etc. Their output is given by:

$$O_{1,j} = \mu_{A_j}(x) \qquad for\ j = 1,2 \tag{4.3}$$

$$O_{1,j} = \mu_{B_{j-2}}(y) \qquad for\ j = 3,4 \tag{4.4}$$

Here, μ is the membership function and $O_{1,j}$ is the membership value for inputs *X* and *Y*. The subscripted 1 and j is used to represent the layer number and node number, respectively.

Membership functions μ_A can be different shaped function like trapezoidal, triangle, Gaussian. The most commonly used membership function is generalized bell (g-bell) and can be define as (4.5).

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-c_j}{a_j}\right|^{2b_j}} \tag{4.5}$$

where a_j is the standard deviation, b_j is a positive number *and* c_j is the mean. These parameters are also termed as **premise** parameter and will to be optimized during the training period. The plot generalized bell shape function is shown in Figure 4.2. The value of a, b, c used for this plot are 2,4,6 respectively.

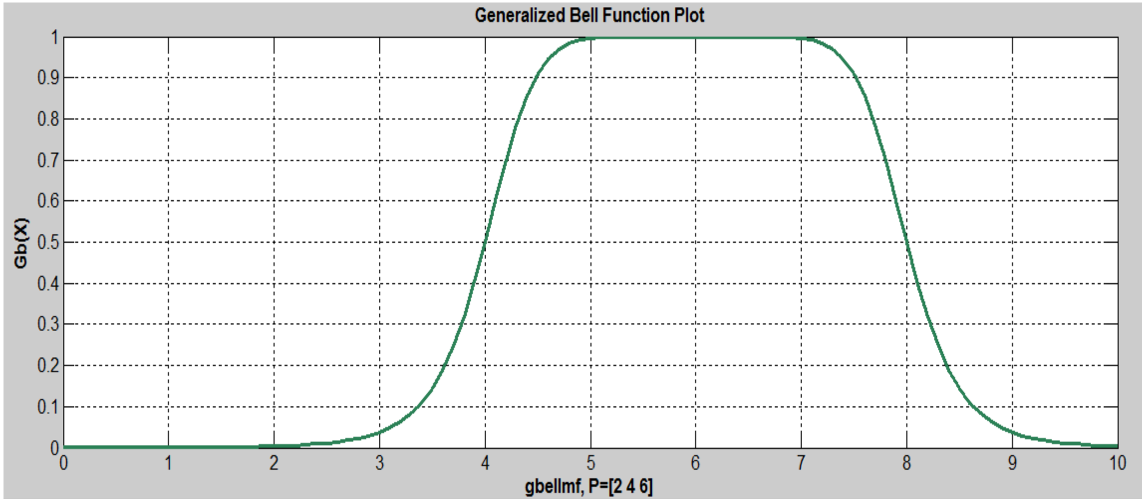

Figure 4.2: Generalized bell shape curve

It has been observed that the wind speed estimation from turbine power vs rotor speed curve follows approximately bell shaped behavior. Though the turbine power vs rotor speed curve for different wind speed is not precisely follow the normal distribution characteristics but for large sample size (more than 30 samples) would guarantee that means will be bell shaped.

Layer-2:

All the nodes in this layer is fixed node and admits the output (membership values) from layer-1, where t-norm is used to "AND" these values, given by (4.6). A t-norm is a binary operation; a function $T_1 = [0, 1] \times [0, 1] \rightarrow [0, 1]$ is called t-norm. The following four properties are to be satisfied for all a, b, c ϵ [0, 1]:

Commutativity : $T_1(a, b) = T(b, a)$

Associativity: $T_1 = (a, T(b, c)) = T(T(a, b), c)$

Monotonicity: T_1 (a, b) ≤ T_1 (a, c) whenever b ≤ c and

Boundary condition: T_1 (a, 1) = 1

$$O_{2,j} = w_j = \mu_{A_j}(x)\mu_{B_j}(y) \quad j = 1,2 \tag{4.6}$$

Output of all the nodes correspond to the firing strength of the rule. Firing strength is a threshold limit above which a rule/ nodes get active and pass the output to other nodes.

Layer-3:

In this layer-3, each node is fixed node and used to perform normalization operation. The j-th node of this layer calculates the ratio between the j-th node activation level and the sum of all activation level, which is known as normalized firing strength. The output of every node can be defined by (4.7).

$$O_{3,j} = \overline{w}_j = \frac{w_j}{w_1 + w_2} \tag{4.7}$$

Output of every node interprets the normalized firing strength of the rule.

Layer-4:

In layer-4, every node is adaptive and the function can be defined as (4.8).

$$O_{4,j} = \overline{w}_j f_j = \overline{w}_j (p_j x + q_j y + r_j) \tag{4.8}$$

Where, p_j, q_j *and* r_j are the resultant parameters (these parameters are referred as consequence parameters), and these need to be minimized during the training period.

Layer-5:

This layer is the output layer. The output signals from layer-4 are summed together to obtain the result at the layer 5. This layer can be described as (4.9).

$$O_{5,j} = \sum_j \bar{w}_j f_j = \frac{\sum_j w_j f_j}{\sum_j w_j} \tag{4.9}$$

Learning Process:

In learning stage to develop algorithm, ANFIS optimize and adapt its parameters by using the training data sets for predicting the output data with very high accuracy. There are two types of parameters for Sugeno-type model [54]

- Nonlinear parameters or membership functions parameters (premise parameters): Premise parameter defines the membership function, gradient descent methods is used in ANFIS to fine tune them.
- Linear parameters or rules parameters (consequent parameters): Consequent parameters define the coefficient of each output equations. Least square technique is used in ANFIS to identify them.

There are numbers of learning methods that have been developed by the researchers. The method used in this thesis work is based on the hybrid learning algorithm that is the combination of gradient descend or back propagation (BP) and least square estimation (LSE) technique to optimize the premise and consequent parameters [56].

In proposed work, forward pass and backward pass are used for learning algorithms:

- In forward pass consequent (linear) parameters are calculated using a LSE algorithm while premise (nonlinear) parameters are held constant.
- In backward pass premise (nonlinear) parameters are calculated using a back propagation algorithm while consequent (linear) parameters are held constant.

The function of LSE learning algorithm is to calculate the square error between training data output and predicted output that is obtained from the Sugeno-type model. The expression of LSE is shown in (4.10).

$$E_{fp} = \frac{1}{2}\sum_{m=1}^{M} E_m = \frac{1}{2}\sum_{m=1}^{M}(O_m - y_m) \tag{4.10}$$

Where, O_m is the target output of node m and y_m is the actual output of node m. This error is used to update the consequence parameters of the Sugeno-type model. The gradient descent method used to propagate the error rates in backward direction to update the premise parameters. When the values of premise parameters are learned, the final output (F) can be expressed as a linear combination of the consequent parameters as shown in (4.11): [69]

$$F = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \overline{w}_1 f_1 + \overline{w}_2 f_2$$

$$= (\overline{w}_1 X)p_1 + (\overline{w}_1 Y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 X)p_2 + (\overline{w}_2 Y)q_2 + (\overline{w}_2)r_2 \tag{4.11}$$

p_1, q_1, r_1, p_2, q_2 and r_2 are the consequent parameters. During the learning process the consequent and premise parameters are updated to attain minimum error between the actual output and desired target output.

4.3 IMPLEMENTATION OF ANFIS ALGORITHMS

A superviesd ANFIS algorithm is used for wind speed estimation and maximum power point tracking (MPPT). Sugeno-type ANFIS model is used for training due to its simplicity and three generalized bell (g-bell) membership function is used to train the ANFIS network.

ANFIS based MPPT algorithms are recently applied in wind energy system. The main draw back of the prevously proposed techniques are, mechanical sensor required for wind speed measurement, which is costly and system pre-knowledge is required that needed memory and varies from one system to the other. In the proposed ANFIS based MPPT methods, two series network is used for maximum power point tracking (MPPT). One network for wind speed estimation and the other to track maximum power point and optimal rotor speed. This method does not required any mechanical sensor for wind speed measurement or any pre-system memory.

4.3.1 Wind Speed estimation using ANFIS

The initial capital cost of the wind energy conversion system installation is pretty high; the capital cost can be reduced by removing the need of the wind velocity sensor (Anemometer). This can be done by using ANFIS based controller to estimate the wind velocity. The proposed training scheme of ANFIS based network to estimate wind speed is shown in the following Figure 4.3.

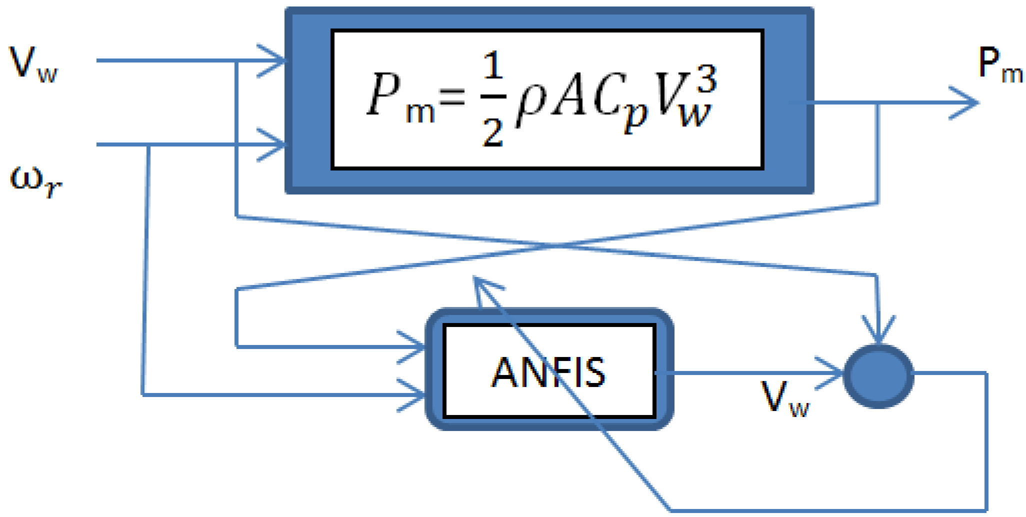

Figure 4.3: The proposed training scheme for ANFIS based wind velocity estimation

Wind speed estimation is done in following steps:

1. The turbine power data (Pm) is generated from the turbine power equation for the preselected rotor speed (ω_r) and the wind velocity samples (V_w).

2. The rotor speed and turbine power are recombined as data pairs {ω_r, Pm}, which are employed as input matrix of the ANFIS network. On the other hand, the samples of wind speed (V_w) are set as target for the training process

3. Training starts with some rules and proceeds iteratively. During the training process (learning stage), in forward pass consequent (linear) parameters are calculated using a LSE algorithm while premise (nonlinear) parameters are

held constant. The estimated wind speed is compared with the actual wind speed to calculate the estimation error.

4. Back propagation algorithm propagates that calculated error in backward direction to update the premise parameters to minimize the error of ANFIS. The training process is completed when the error goal is reached or the total number of iteration exceeds the pre-determined number.

Figure 4.4 shows the overall ANFIS structure is a 5 layer network for wind speed estimation. The input is two column matrix consists of turbine power (P_m), rotor speed (ω_r) and the output is single column matix of wind velocity (V_w).

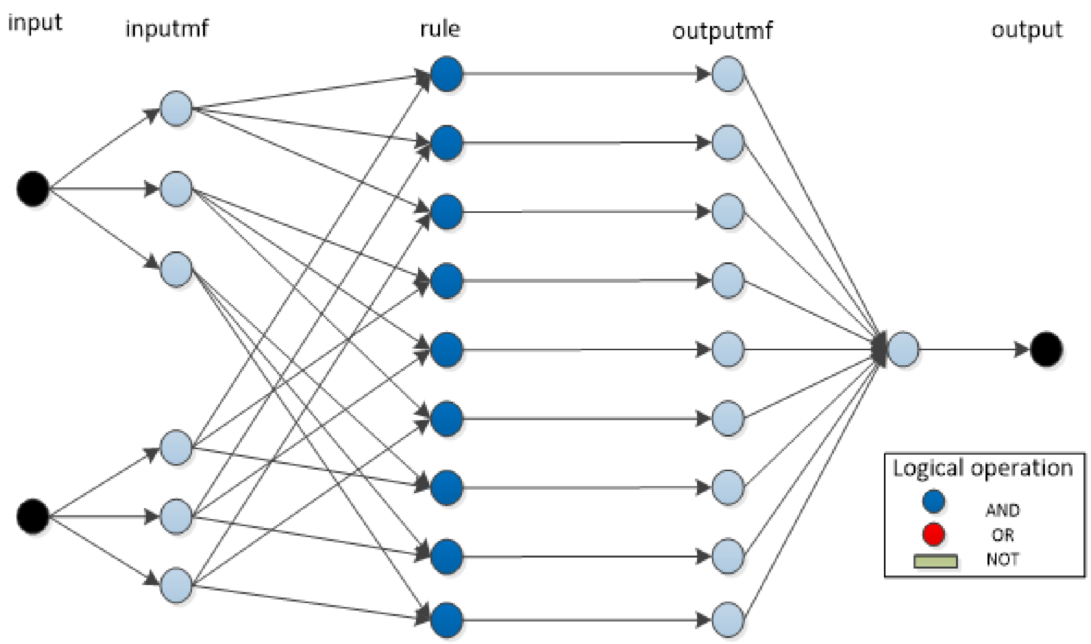

Figure 4.4: Wind velocity estimation ANFIS model structure

4.3.2 Testing of trained ANFIS network

ANFIS-based wind speed estimation is developed in MATALB/Simulink using three generalized bell (g-bell) membership functions. Neural network and fuzzy logic based hybrid learning algorithm is used to train the network. Least square error algorithm and gradient descend method are used to adapt the consequent parameters and the premise parameters of the membership functions respectively. The ANFIS network is trained for 300 epochs and the root mean square error (RMSE) tolerance set to 10^{-3}. Figure 4.5 shows that the error reached to a value of 1.05x10^{-3} in about 300 epochs. Though the RMSE value reaches close to the targeted error tolerance, the network is said to be well trained and ready to use for any input data.

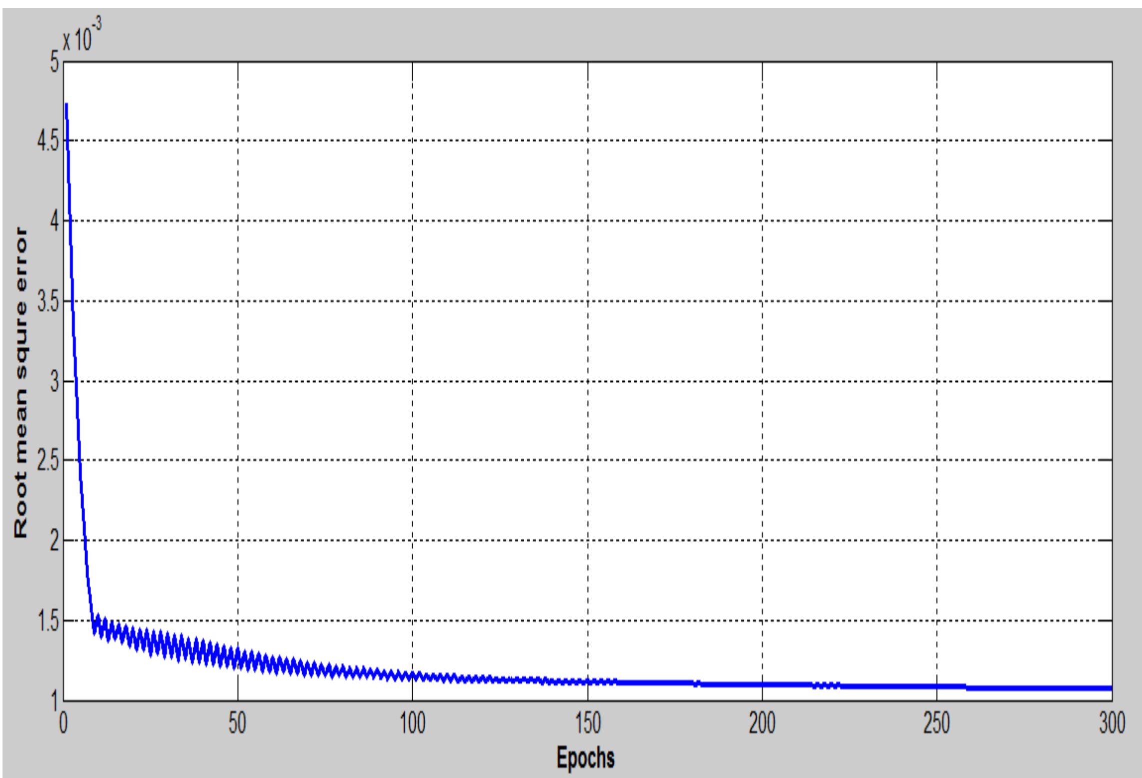

Figure 4.5: Training error versus epochs for the ANFIS based wind speed estimation

4.3.3 Maximum power point tracking (MPPT) using ANFIS

For a particular wind speed (V_w), there are different turbine power and rotor speed. There is a optimum power point called maximum power point (P_{max}) for a particular V_w. The rotor speed corresponding to that maximum power point is termed optimum rotor speed (ω_{opt}). To extract maximum possible power from a particular wind speed, the rotor must be operated at the optimum rotor speed. The proposed training scheme of ANFIS based MPPT controller is shown in Figure 4.6.

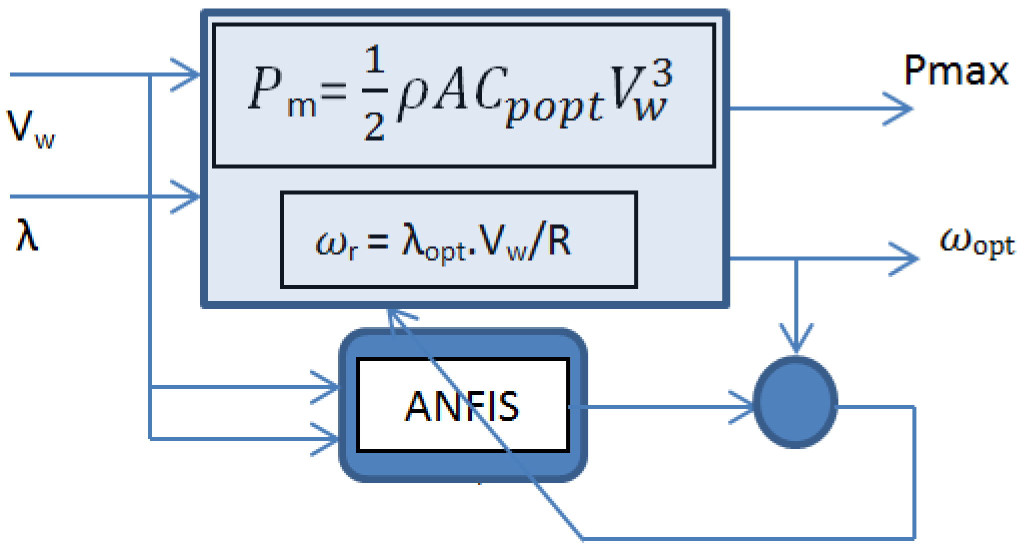

Figure 4.6: The proposed training scheme for ANFIS based MPPT

Maximum power point tracking is done in following steps:

1. The training data, turbine maximum power (P_{max}) and optimal rotor speed (ω_{ropt}) are generated from the turbine power equation for the preselected wind velocity samples (V_w).

2. The optimal rotor speed and turbine maximum power are recombined as data pairs {ω_{ropt}, P_{max}}. For training, , the samples of wind speed (V_w) are employed as input matrix of the ANFIS network and the data pairs {ω_{ropt}, P_{max}} are set as target.
3. Training starts with some rules and proceeds iteratively. During the training process (learning stage), in forward pass consequent (linear) parameters are calculated using a LSE algorithm while premise (nonlinear) parameters are held constant. The tracked optimal rotor speed is compared with the actual optimal rotor speed to calculate the optimal rotor speed tracking error.

4. Back propagation algorithm propagates that calculated error propagates in backward direction to update the premise parameters to minimize the error of ANFIS. The training process is stopped when the targeted error goal is reached or pre-specified number of epochs exceeds.

4.3.4 Testing of trained ANFIS network

The ANFIS-based MPPT is developed in MATALB/Simulink using three generalized bell (g-bell) membership functions. Neural network and fuzzy logic based hybrid learning algorithm is utilized to train the network. Least square error algorithm and gradient descend (also known as back propagation) method are used to adjust the consequent parameters and the premise parameters of the membership functions respectively. The ANFIS network is trained for 300 epochs and the root mean square error (RMSE) goal set to 10^{-5}. Figure 4.7 shows that the error reach to a value of

$1.0x10^{-5}$ in about 300 epochs. Though the RMSE value reaches close to the targeted error, the network said to be well trained and ready to use.

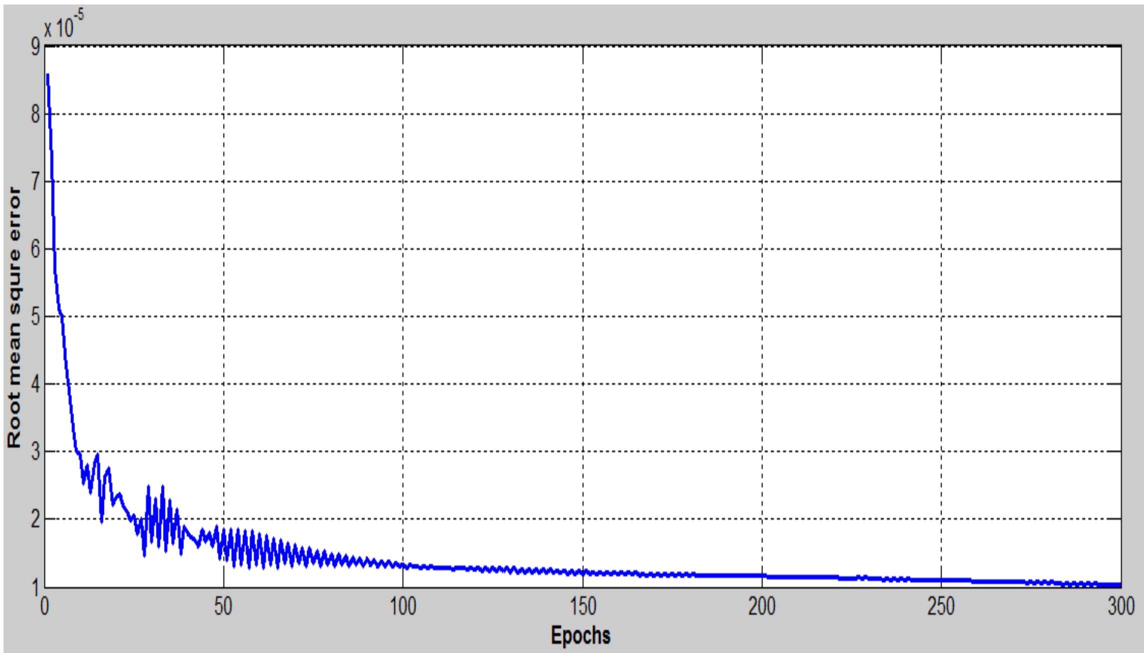

Figure 4.7: Training error versus epochs for the ANFIS

4.3.5 Implementation of ANFIS MPPT controller in MATLAB/Simulink

After the training process, one Simulink block is generated for ANFIS network simulation to estimate wind speed and another block for ANFIS network simulation to track optimal rotor speed. The ANFIS-based wind speed estimation and MPPT controller in Simulink model is shown in Figure 4.8 .

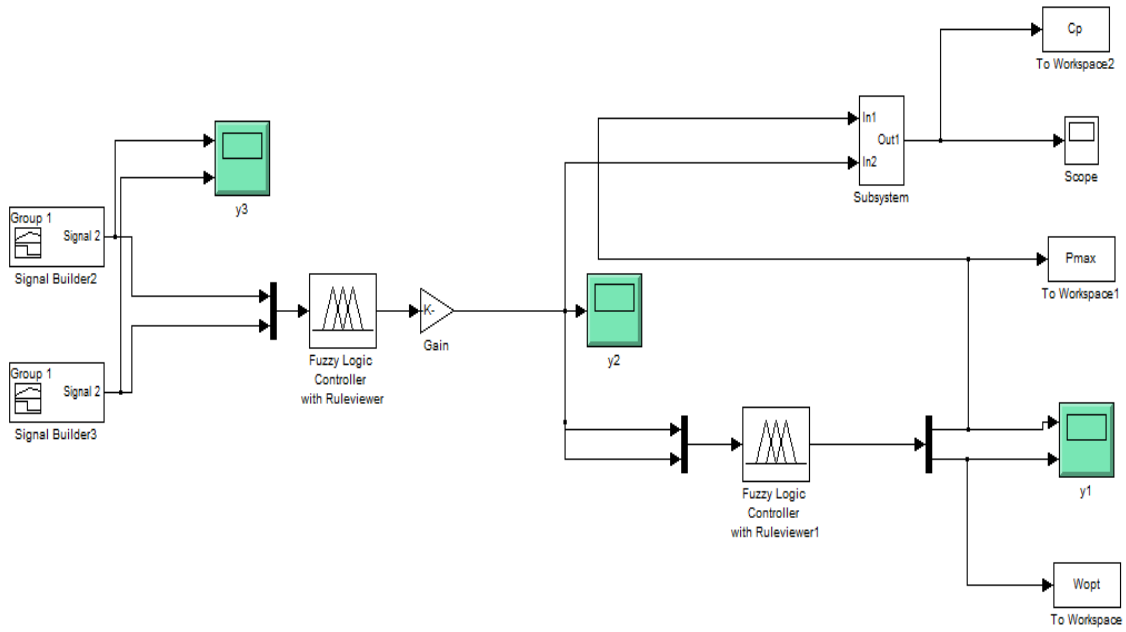

Figure 4.8: ANFIS-based wind speed estimation and MPPT controller in Simulink

Figure 4.8 shows that the rotor speed and turbine power are presented to the first ANFIS based fuzzy logic controller network to estimate the wind speed. The estimated wind speed is then feed to the ANFIS based fuzzy logic controller network to determine the maximum power as well as the optimal rotor speed based on the estimated wind speed.

The testing is also done by providing rapidly changing input data (turbine power and rotor speed) to evaluate the effectiveness of the proposed controller under rapidly changing wind conditions.

4.4 SIMULATION RESULTS

4.4.1 Simulation results for wind speed estimation

The verification of wind speed estimation is done by applying random test input signals (operating power and rotor speed) to the trained network implemented in Simulink. Figure 4.9 shows the applied input signals. Based on the applied input signals the wind speed is estimated, which is shown in Figure 4.10.

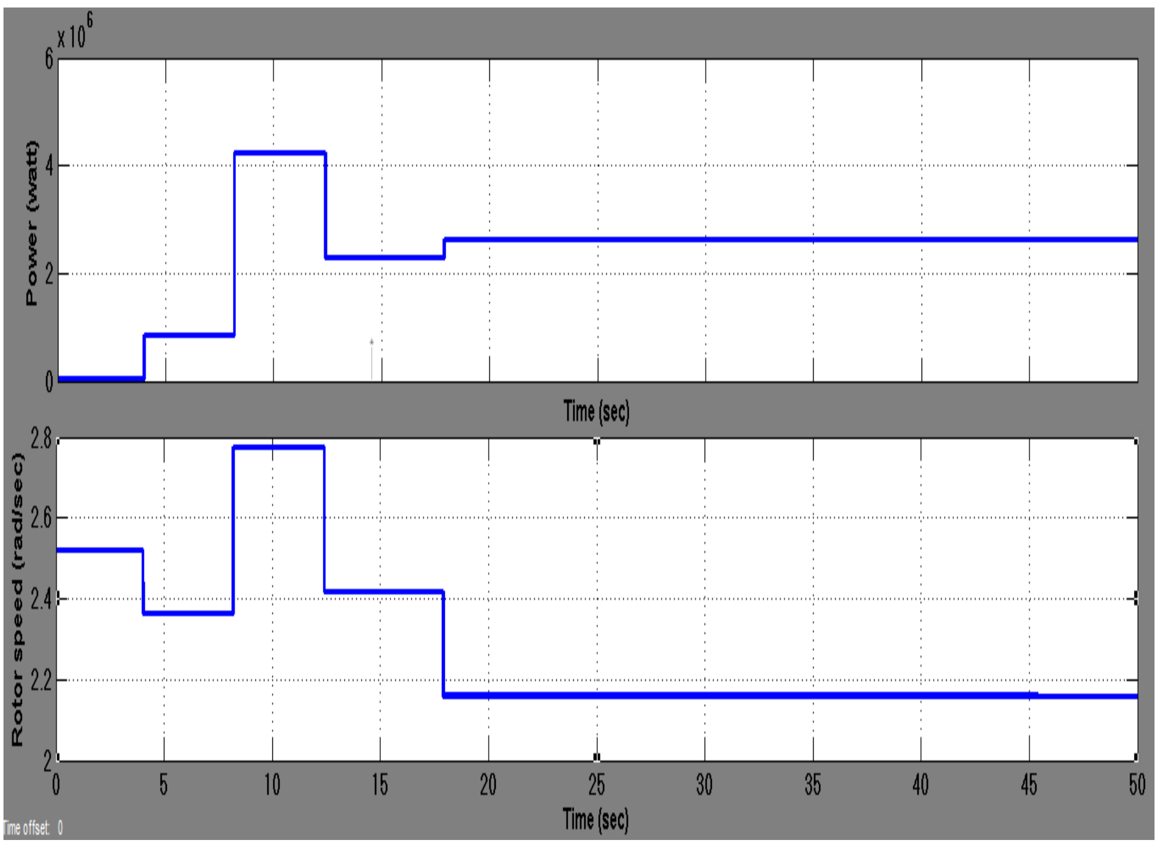

Figure 4.9: Input signal (Pm, ω_r) to the trained ANFIS network

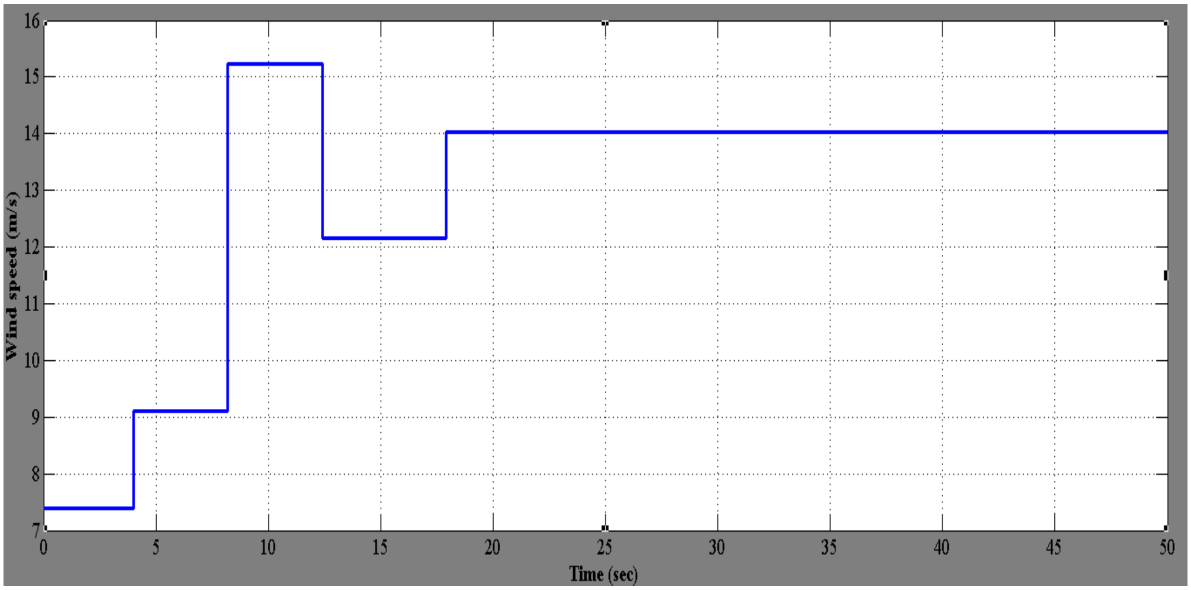

Figure 4.10: Estimated wind velocity

Wind speed estimation error is used as performance criterion of the implemented controller. The wind speed error is measured by calculating the difference between the actual wind speed and simulated wind speed as shhown in table 4.1.

Table 4.1: Testing using Feed-forward Back-propagation

Input		**Simulation**	**Calculated**	**Error**
Turbine power, Pm (MW)	Rotor speed, ω_r (rad/sec)	Wind speed, V_w (m/s)	Wind speed, V_w (m/s)	**(%)**
0.06525453	2.5192	7.2924	7.2804	0.016
0.8668858	2.3649	9.1219	9.1150	0.075
4.224699	2.7763	15.2124	15.230	0.11
2.293007	2.4164	12.2100	12.190	0.16
2.628508	2.1593	13.9700	14.007	0.26

From the above table it is evident that the trained ANFIS network is able to estimate the wind speed with high accuracy. The error in wind speed estimation is very close to zero, the maximum error is only 0.26%.

Figure 4.11 shows the comparison between the original and estimated wind speed together. The solid line and dashed line represent the actual and estimated wind speed respectively. Simulation results verify the effectiveness of trained ANFIS network in wind speed estimation under the rapidly changing wind condition.

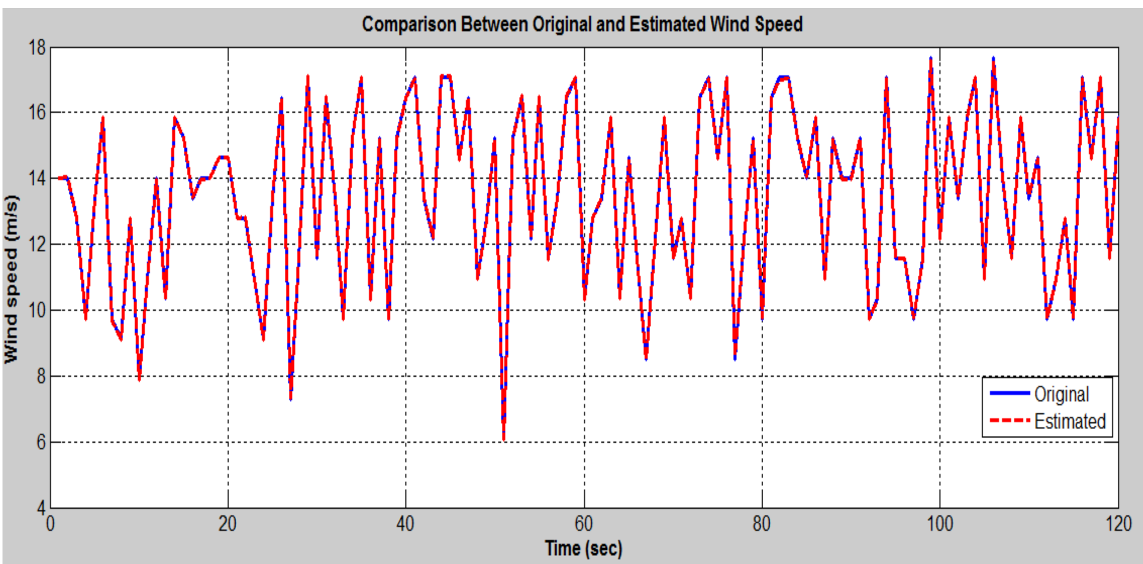

Figure 4.11: Original and estimated wind speed

Figure 4.12 shows the wind speed estimation error. From Figure 4.12 it can be seen that there is a small error in wind speed estimation, the maximum error in wind speed estimation is 0.09 m/s.

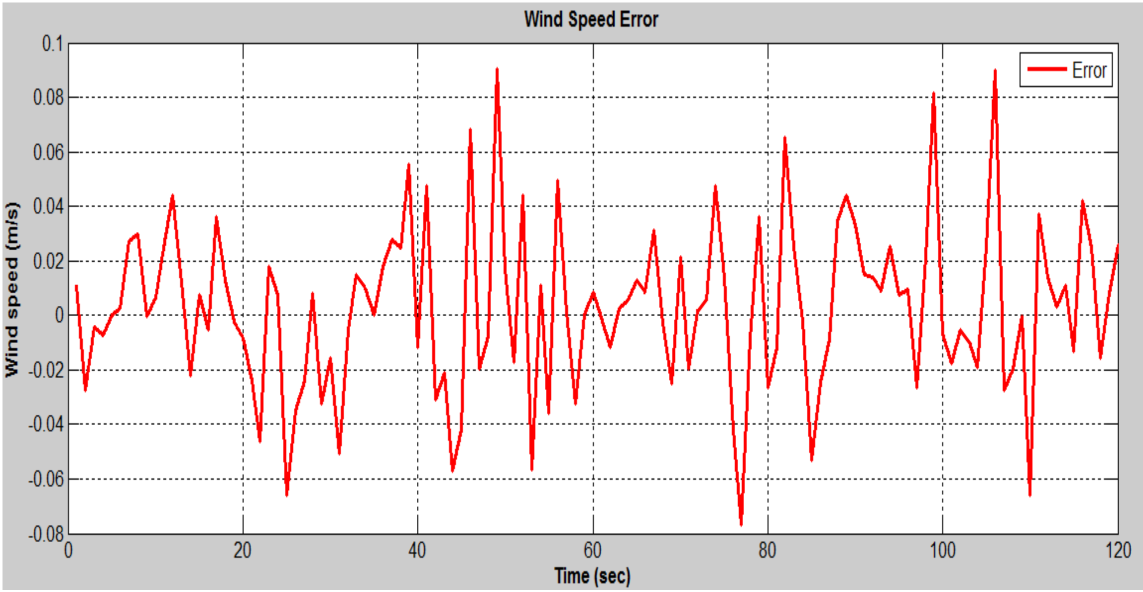

Figure 4.12: Error in wind speed estimation

4.4.2 Simulation results for maximum power point tracking

The verification of maximum power point tracking is done by applying random test input signal (wind speed) to the trained ANFIS network implemented in Simulink. Figure 4.13 shows the applied input signals. Based on the applied input signal the maximum power point and optimal rotor speed is tracked, which is shown in Figure 4.14.

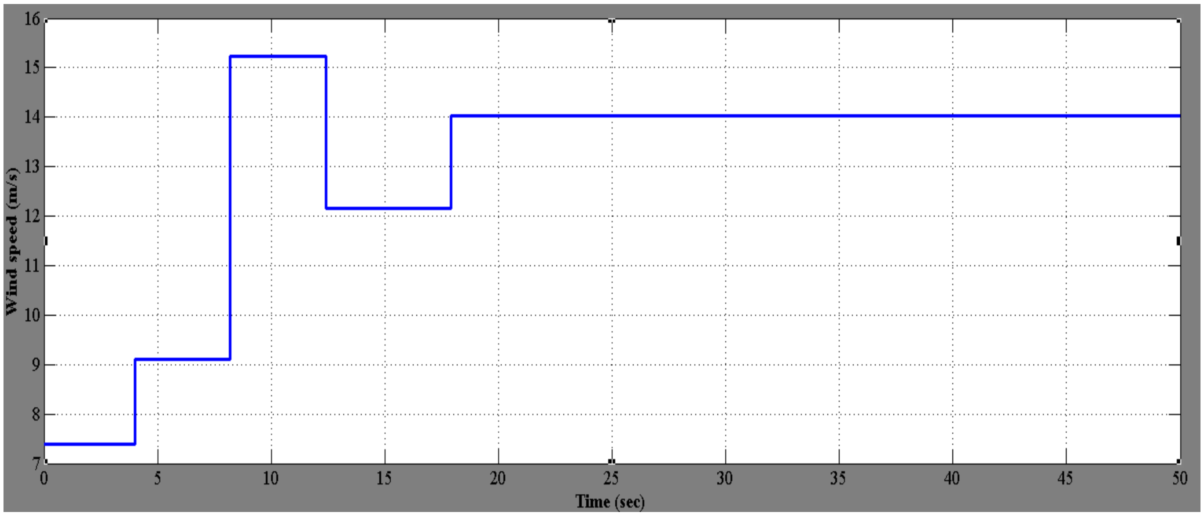

Figure 4.13: Estimated wind speed

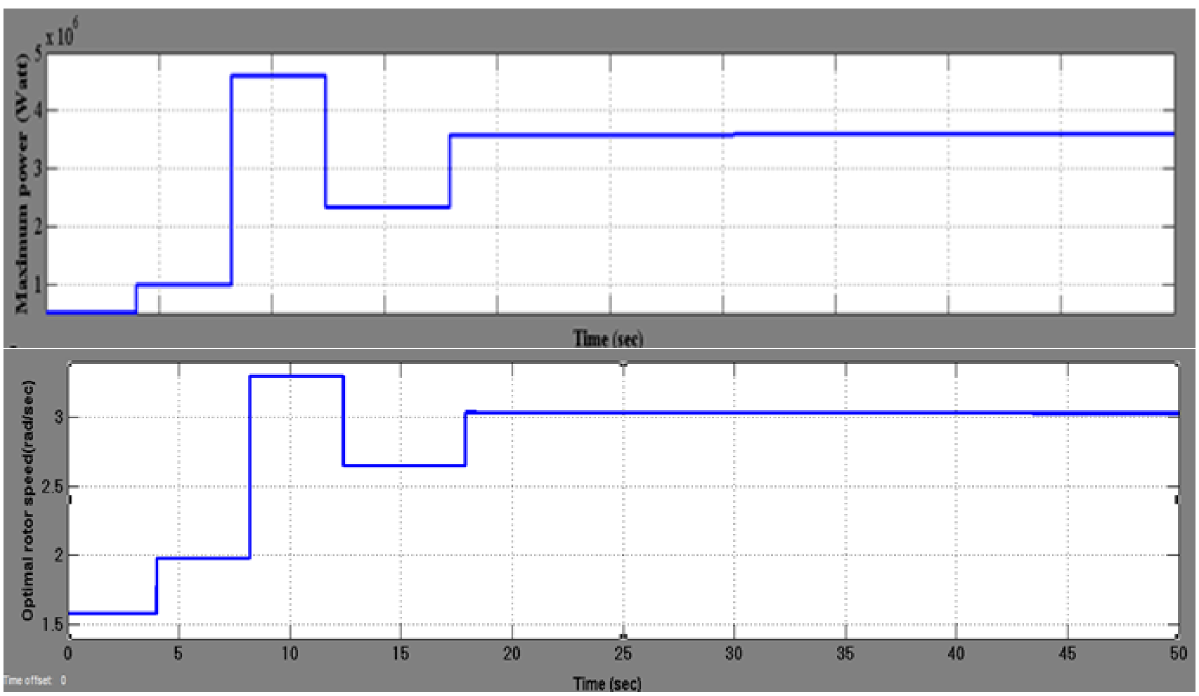

Figure 4.14: Maximum power and optimal rotor speed with respect to the estimated wind speed

The variation of power coefficient (C_p) over the range of transient is shown in Figure 4.15. The C_p value is calculated based on the relation between the tracked maximum power corresponding to the wind speed ($C_p = P_{max}/0.5*\rho*A*Vw^3$). The result proved that the ANFIS based MPPT algorithm is able to maintain the optimum value of C_p, that is almost constant at 0.48.

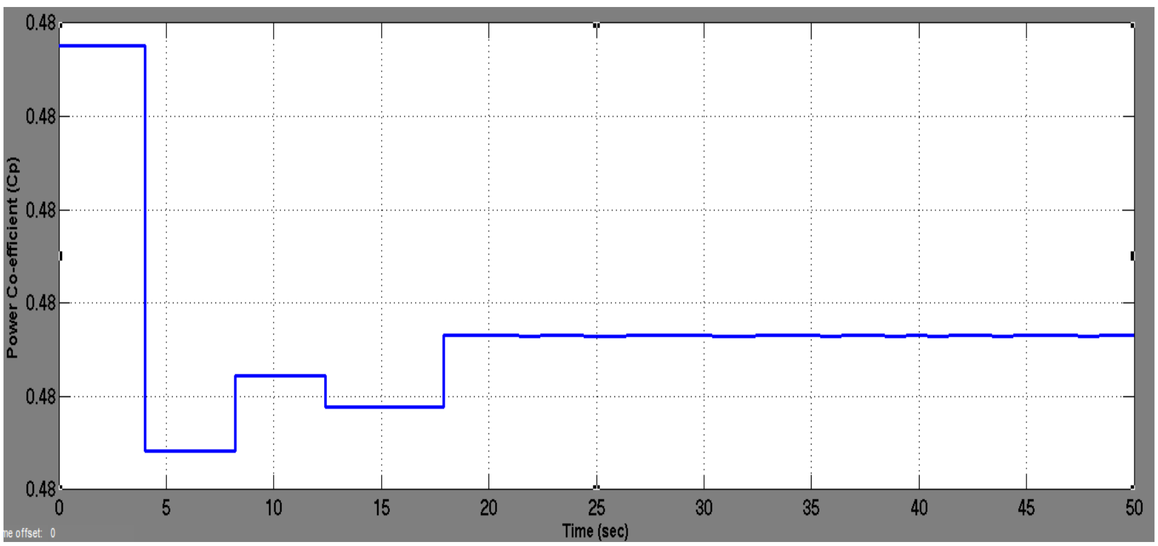

Figure 4.15: Power coefficient Cp

Maximum power point tracking error is used as performance criterion of the implemented MPPT controller. The maximum power point tracking error is measured by calculating the difference between the actual optimal rotor speed and simulated optimal rotor speed as shown in table 4.2.

Table 4.2: Testing using trained ANFIS network

	Simulation		Calculated		
Wind speed (m/sec)	Pmax (MW)	ωopt (rad/sec)	Pmax (MW)	ωopt (rad/sec)	Error (%)
7.2805	0.50300	1.5823	0.5020	1.5798	0.15
9.1150	0.98556	1.9792	0.9830	1.9779	0.11
15.230	4.57390	3.3008	4.5700	3.3009	0.01
12.190	2.36000	2.6494	2.3520	2.6451	0.16
14.007	3.54140	3.0316	3.5390	3.0394	0.20

Figure 4.16 shows the original and estimated maximum power points together during the rapid change in wind speed. The solid line shows the original maximum power and the dashed line shows the estimated maximum power. The results shown in Figure 4.16, validates the effectiveness of the proposed MPPT controller that has the ability to track maximum power point under rapidly changing wind conditions.

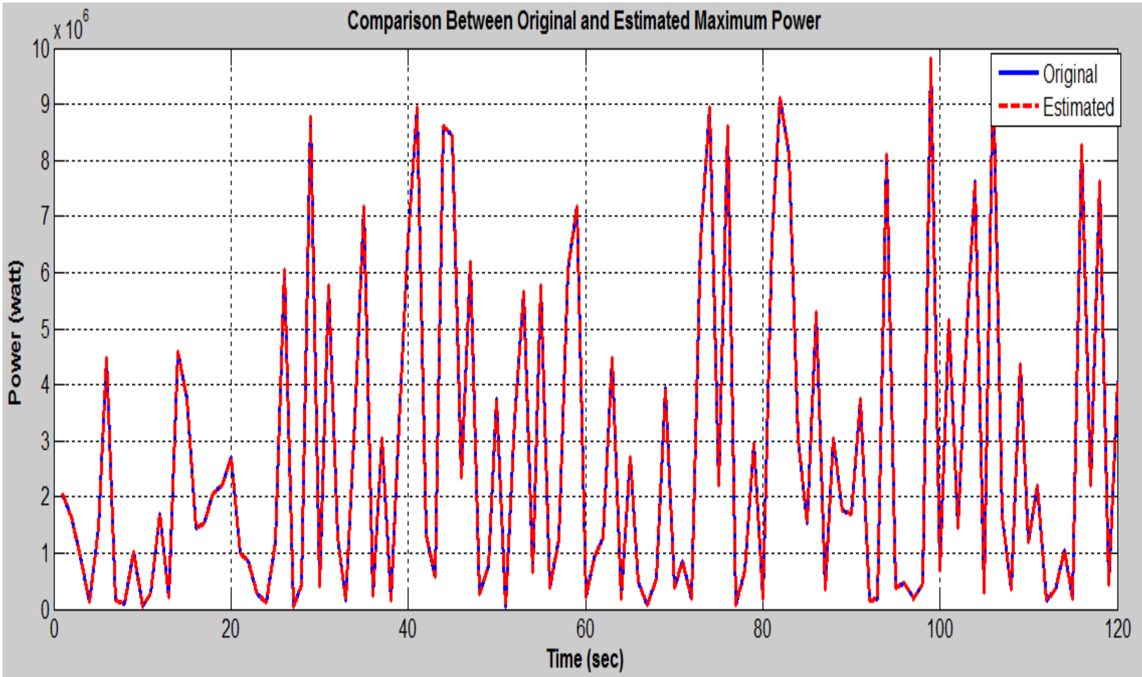

Figure 4.16: Original and estimated maximum power

In Figure 4.17, simulation result shows the error in maximum power point (MPP) tracking. The proposed MPPT controller has the ability to track MPP accurately; the maximum error in maximum power point tracking is $1.23\text{x}10^{-4}$.

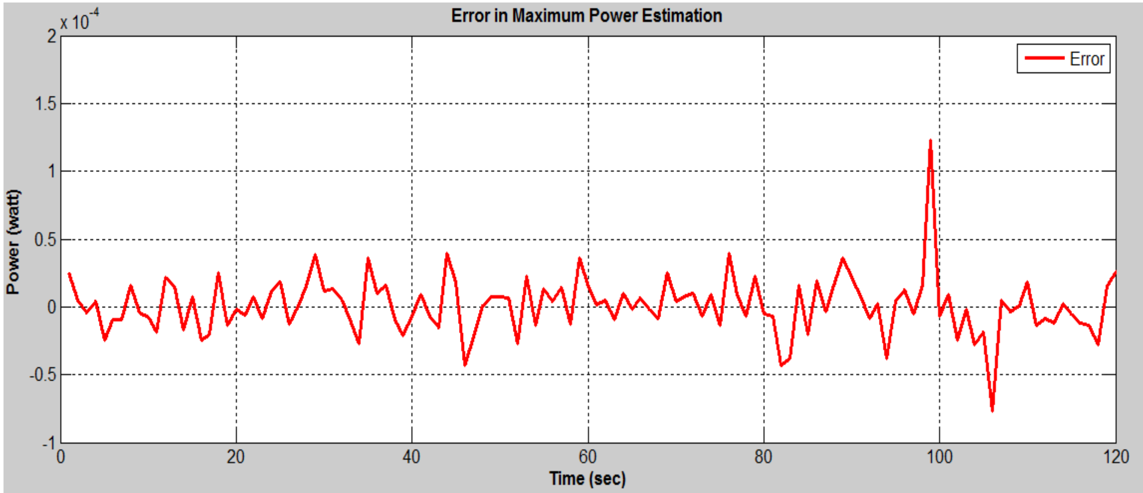

Figure 4.17: Error in maximum power estimation

Figure 4.18 shows the original and estimated optimal rotor speed together. The solid line shows the original optimal rotor speed and the dashed line shows the estimated optimal rotor speed. The results shown in Figure 4.18, validates the effectiveness of the proposed MPPT controller that has the ability to track optimal rotor speed correctly under rapidly changing wind conditions.

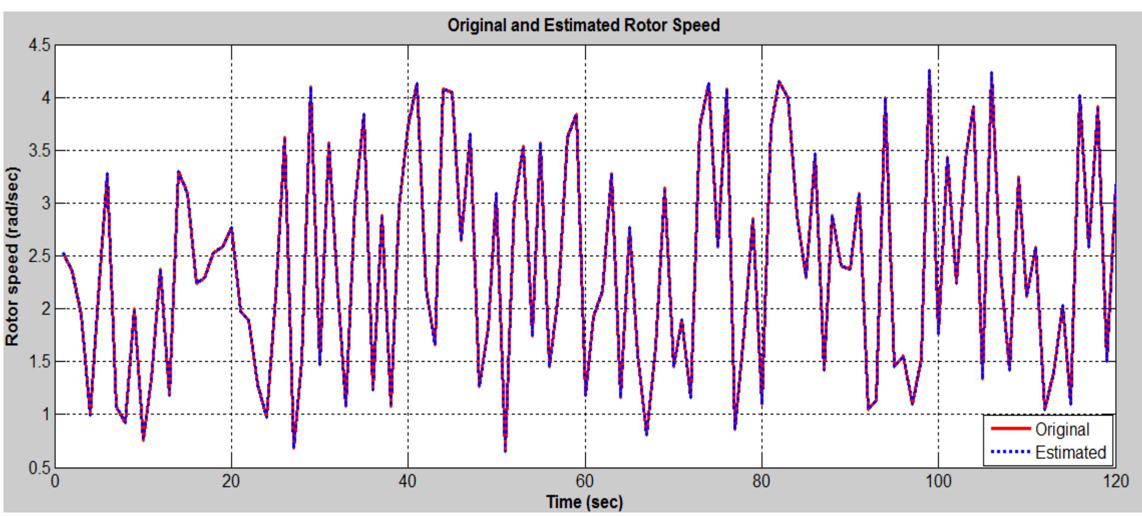

Figure 4.18: Original and estimated optimal rotor speed

In Figure 4.19 shows the error in optimal rotor speed tracking. Simulation result proved that the proposed MPPT controller tracks optimal rotor speed correctly under rapidly changing wind conditions. The maximum error in optimal rotor speed tracking is $1.5\text{x}10^{-4}$rad/sec.

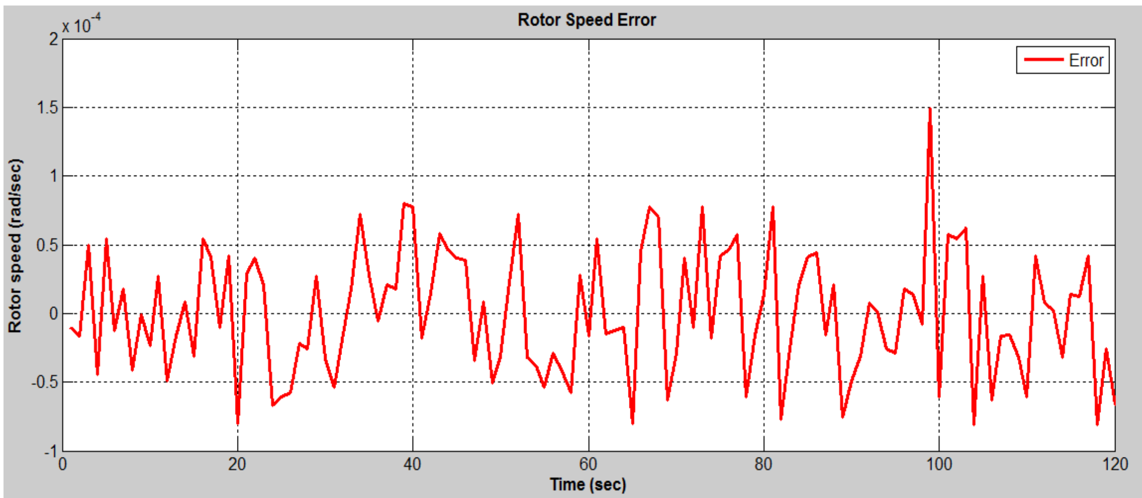

Figure 4.19: Error in optimal rotor speed estimation

The methods used for ANFIS based MPPT is good enough to estimate the wind speed and to track the maximum power as well as optimum rotor speed and good performance is achieved.

4.5 COMPARISON OF ANN AND ANFIS BASED MPPT CONTROLLER

ANN based MPPT controller used feed forward back propagation and radial basis function network for wind speed estimation and maximum power point tracking respectively. ANFIS combines both the advantages of neural network and fuzzy logic system, back propagation algorithm is used to minimize the error of the controller system.

The performance of ANN and ANFIS based controller is compared based on their estimation and tracking accuracy. The solid line and dashed line curve in Figure 4.20 represents the wind speed estimation error of ANN and ANFIS controller respectively. The wind speed estimation error of ANN controller is greater than the ANFIS controller.

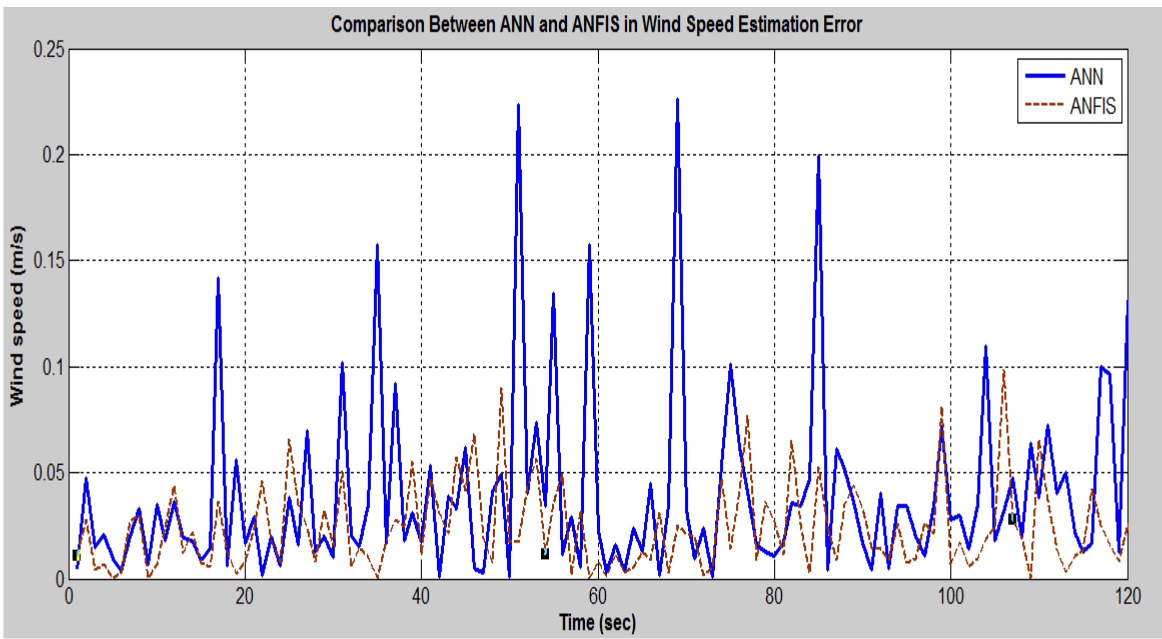

Figure 4.20: Wind speed estimation error for ANN and ANFIS based controller

The maximum wind speed estimation error for ANN is about 0.22 m/s, that is around 0.1 m/s for ANFIS controller. From Table 4.3, we can conclude that ANFIS based controller is more accurate and robust than ANN controller in wind speed estimation.

Table 4.3: Comparison between ANN and ANFIS based wind speed estimation

MPPT Techniques	Minimum Wind Speed Error (m/sec)	Maximum Wind Speed Error (m/sec)
ANN	2.1 x10^{-3}	0.23
ANFIS	4.2 x10^{-5}	0.0988

The simulation results for maximum power point tracking using ANN and ANFIS based controller are shown in Figure 4.21. The solid line curve represents the maximum power point tracking error of ANN based MPPT controller, on the other hand the dashed line curve presents the maximum power point tracking error of ANFIS based MPPT controller. The maximum power point tracking error for ANN is 0.0095 that is 1.23x10^{-4} for ANFIS controller. Table 4.4 noticed that the maximum power point tracking of ANFIS based MPPT controller is better than the ANN based MPPT controller.

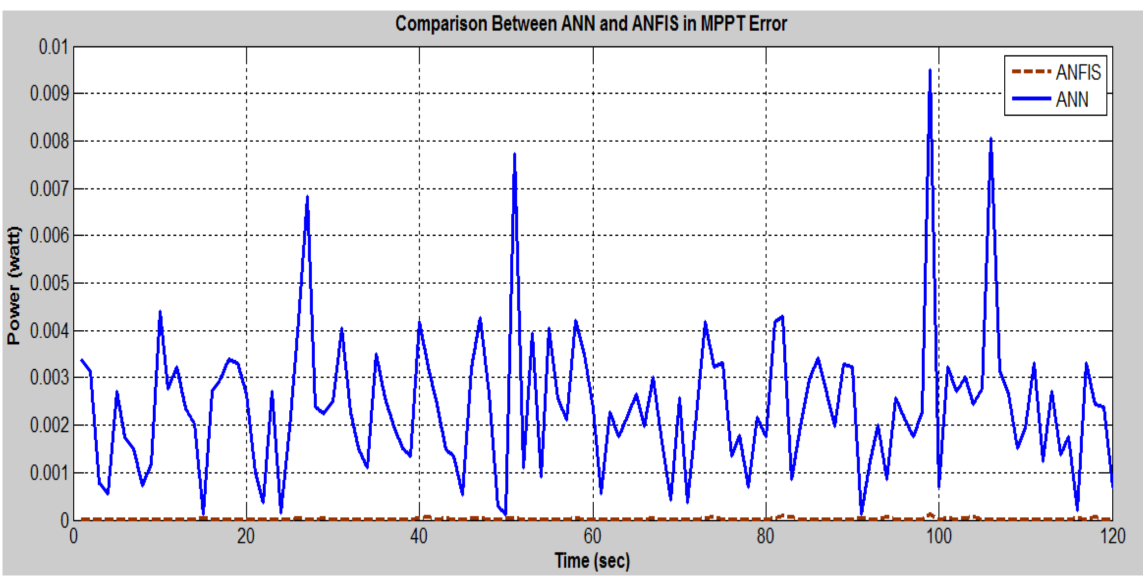

Figure 4.21: Maximum power tracking error for ANN and ANFIS based controller

Table 4.4: Comparison between ANN and ANFIS based maximum power point (MPP) tracking

MPPT Techniques	Minimum MPPT Error (watt)	Maximum MPPT Error (watt)
ANN	3.56 x10^{-4}	9.5 x10^{-3}
ANFIS	2. 3 x10^{-6}	1.23 x10^{-4}

The accuracy of optimum rotor speed tracking depends on maximum power point (MPP) tracking. If the accuracy in MPP tracking is very much accurate then the rotor speed estimation will be also accurate and vice-versa. The simulation results for optimum rotor speed tracking using ANN and ANFIS based MPPT controller are shown in Figure 4.22. The solid line and dashed line curve in Figure 4.22 represents the optimal rotor speed estimation error of ANN and ANFIS based MPPT controller respectively.

Table 4.5: Comparison between ANN and ANFIS based rotor speed estimation

MPPT Techniques	Minimum Rotor Speed Error (rad/sec)	Maximum Rotor Speed Error (rad/sec)
ANN	3.702 x10^{-4}	0.0100
ANFIS	1.1300 x10^{-6}	1.4875 x10^{-4}

The maximum error in optimal rotor speed tracking for ANFIS is about 1.4875x10^{-4}, which is 10x 10^{-3} for ANN. From Table 4.5, we can conclude that ANFIS based controller is more accurate and robust than ANN controller in optimal rotor speed tracking.

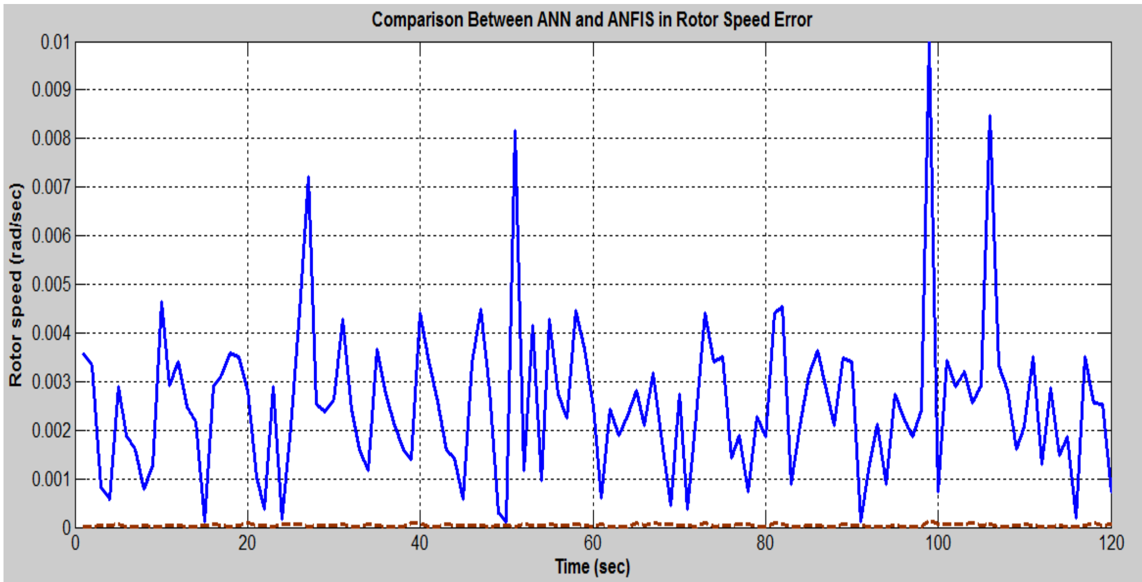

Figure 4.22: Optimal rotor speed error for ANN and ANFIS based controller

From the above comparison between ANN and ANFIS based MPPT controller, it can be concluded that the effectiveness and accuracy in terms of wind speed estimation, maximum power point and optimum rotor speed tracking, ANFIS based MPPT controller is superior than the ANN based MPPT controller.

CHAPTER 5
IMPLEMENTATION OF THE MPPT ON A PMSG WIND GENERATOR SYSTEM

5.1 INTRODUCTION TO PMSG WIND SYSTEM

Variable-speed wind turbine has the advantage to follow the variation of wind speed and produce the maximum power under the normal operation through maximum power point tracking (MPPT). Variable-speed wind turbine can use both synchronous generator and doubly-fed induction generator. The synchronous generator can either be permanent magnet synchronous generator (PMSG) or excited magnet synchronous generator. The excited magnet synchronous generator requires an extra DC power supply to the rotor windings produce a rotating magnetic field. The magnetic field can be control by regulating the flow current of the rotor windings. The generator output varies with the rotor speed and the exciting DC current. In contrast, the magnetic field of a PMSG cannot be controlled. The PMSG has been considered as a system which is used to convert the mechanical energy obtained from the wind to electrical energy. In a PMSG, the field winding of the rotor is replaced by a permanent magnet. The advantages of PMSG are-

i). Reduced field copper loss.

ii). Higher power density.

iii). Lower rotor inertia.

iv). Increase robustness.

v). The system is simple and reliable.

vi). It has high quality output and does not need to compensate for reactive power.

The demerits are loss of flexibility of field flux control and possible demagnetization effect and its cost.

A PMSG connected to a power grid is shown in Figure 5.1. The shaft of the wind turbine is directly coupled with the rotor of the generator. There are number of topologies of grid connected PMSG wind turbine, the most popular strategy is the back-to-back converter. The generator side and grid side back-to-back converters are connected to each other through a DC link capacitor. The output power transfers through an AC-DC-AC stage, which consists of a diode bridge rectifier, a boost converter, and a grid-side inverter, which is connected to the grid. Though the generator is fully decoupled from grid, by using active filter the power factor can be corrected. Therefore, before injecting the power to the grid, the inverter can improve the quality of the output power with a unit power factor. Converter grid connection is also advantageous because it allows the variable speed operation of wind turbine that enables the MPPT to increase the efficiency of the wind system.

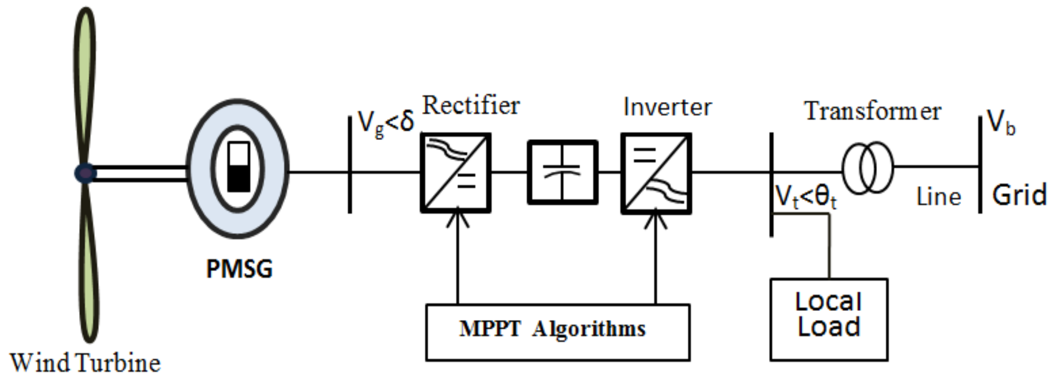

Figure 5.1: PMSG system configuration

Due to the low cost and high reliability of diode bridge rectifier, it is employed instead of a controlled rectifier. A boost converter controls the DC side voltage and current for MPPT and steps up the voltage for grid connection. Finally, the captured power is transferred to the grid via an inverter.

5.1.1 Testing Procedure of the MPPT on a PMSG wind system

The ANFIS based MPPT algorithm is implemented on a PMSG wind system to evaluate the effectiveness of the proposed MPPT technique. MPPT means for controlling wind turbine to track the maximum power point at different wind conditions during operation. The control generation for PMSG wind system using MPPT technique is shown in Figure 5.2. The MPPT algorithm determines the optimal rotor speed corresponding to the maximum power point at different wind speeds during operation. PI controllers along with MPPT techniques are used to extract maximum possible power at any wind speed. Based on the relation between optimal rotor speed and DC output voltage (as shown in 5.3), the optimal DC voltage is generated. The generator side converter and grid side converter is controlled based on the output of the MPPT algorithm. The optimal rotor speed (output of MPPT algorithm) is compared with the operating rotor speed to calculate the error. The calculated rotor speed error is used as input of PI controller then the PI controller adjusted the operating rotor speed to the optimal rotor speed and maximum power extraction is achieved. Similarly, the grid side converter duty ratio is adjusted based on the optimal DC voltage and the operating DC voltage. The difference between optimal DC voltage and operating DC voltage is used as input to the other PI controller, which is used to vary the duty ratio of the grid side converter.

5.2 IMPLEMENTATION OF ANFIS-BASED MPPT TO PMSG WIND SYSTEM

The arrangement of the developed ANFIS-based controller for MPPT of a PMSG wind system is shown in Figure 5.2. The input of the proposed ANFIS based MPPT is the estimated wind speed (V_w). The output of the ANFIS based MPPT controller will determine the optimal rotor speed (ω_{ropt}) corresponding to maximum power point at any wind speed. Based on the optimal rotor speed the DC capacitor voltage will be calculated from equation (5.3). The duty ratio of generator side and grid side converters will be controlled based on the optimal rotor speed (ω_{ropt}) and calculated optimal DC voltage (V_{dc0}).

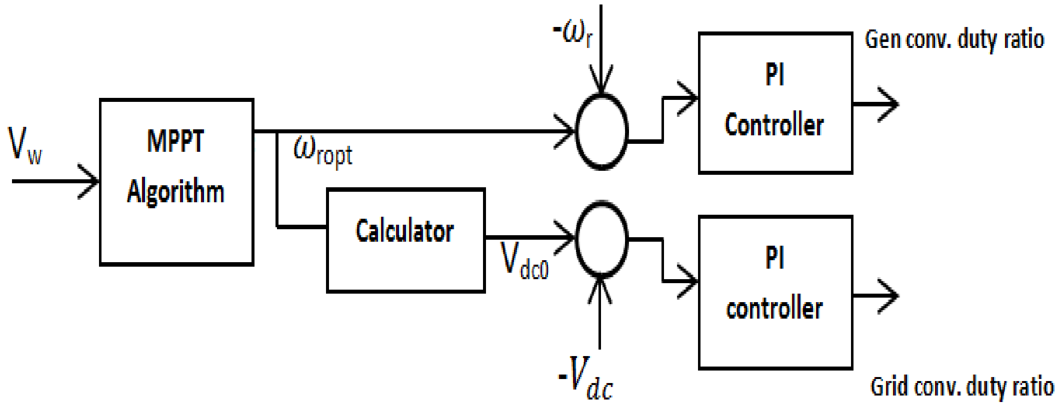

Figure 5.2: ANFIS based MPPT control generation for PMSG wind system

Both wind speed (V_w) and optimal rotor speed (ω_{ropt}) are the cubic function of the maximum power output,

$$P_{max} \propto V_w^3 \propto \omega_{ropt}^3 \tag{5.1}$$

For constant flux (ϕ_c), the phase back emf of PMSG system can be defined as (5.2).

$$E_b = K\phi_c\omega_r \tag{5.2}$$

Here, ω_r is the rotor speed that is proportional to the back emf E_b and K is a co-efficient.

For a non-salient PMSG wind system, the phase terminal voltage (V_{ac}) can be defined as (5.3).

$$V_{ac} = E_b - I_{ac}(R_s + j\omega_e L\_s) \tag{5.3}$$

Here, I_{sc}, R_s, L_s and ω_e are the phase current, stator resistance, stator inductance and electrical angular frequency respectively. Electrical angular frequency $\omega_e = p\omega_r$, p is the number of pole pairs.

The AC and DC side voltage amplitude of diode bridge rectifier can be expressed as in (5.4).

$$V_{dc} = \left(\frac{3\sqrt{3}}{\Pi}\right) V_{ac-amp} \quad (5.4)$$

Solving equations (5.2) and (5.4), the relation between DC voltage and rotor speed can be defined as (5.5).

$$V_{dc} \propto \omega_r$$

(5.5)

At maximum power point,

$$V_{dc-opt} \propto \omega_{ropt}$$

(5.6)

Here, V_{dc-opt} is the optimum rectified DC voltage for a given wind speed.

From equation (5.1) and (5.6), the relation between maximum power and DC voltage can be expressed as shown in (5.7).

$$P_{max} \propto V_{dc-opt}^3 \quad (5.7)$$

The DC output power of the rectifier is,

$$P_{dc} = \eta_r \eta_T \eta_G \, P_{max} \tag{5.8}$$

Here, η_r, η_G and η_T are the efficiency of the rectifier, generator and converter respectively. Combining equation (5.7) and (5.8), we get

$$P_{dc} \propto V_{dc}^3 \tag{5.9}$$

By substituting the DC output power, $P_{dc} = V_{dc} I_{dc}$ in equation (5.6), we can write,

$$I_{dc} \propto V_{dc}^2 \tag{5.10}$$

The converters are controlled with optimal rotor speed and DC output voltage. Based on the values of optimal rotor speed (ω_{ropt}) and operating rotor speed (ω_r) the set points of the generator side PI controller is adjusted, which results in maximum power extraction. On the other hand depending on V_{dc0} and V_{dc}, the set points of grid side PI controller are adjusted to maintain the DC link voltage at constant value. The proposed ANFIS based MPPT controller is extremely fast and able to generate set points rapidly.

5.3 NONLINEAR PMSG WIND SYSTEM MODEL

For actual system implementation, the system dynamics have to be considered in details due to the random variation in wind speed. The system model considered in this research includes the dynamics of generator stator, the drive train dynamics, and converter and DC link dynamics.

5.3.1 The Synchronous Generator

In or to develop the mathematical model of PMSG, it is required to develop the following assumptions:

i). The conductivity of the permanent magnet is zero

ii). Saturation is neglected

iii). Induced electromotive force (EMF) is sinusoidal

iv). Eddy currents and hysteresis losses are negligible

v). There are no field current dynamics

With the assumptions above, the wind turbine causes the rotor of the PMSG to rotate. The voltage-current-flux relationship of PMSG wind system can be written as-

$$\varphi_d = -x_d i_{std} + x_{afd} i_{fd} \tag{5.1}$$

$$\varphi_q = -x_q i_{stq} \tag{5.2}$$

$$\varphi_{fd} = -x_{afd} i_{std} + x_{ffd} i_{fd} \tag{5.3}$$

$$v_{std} = -R_{st} i_{std} - \omega \varphi_q + \frac{\dot{\varphi}_d}{\omega_0} \tag{5.4}$$

$$v_{stq} = -R_{st} i_{stq} + \omega \varphi_d + \frac{\dot{\varphi}_q}{\omega_0} \tag{5.5}$$

$$x_{afd} i_{fd} = \varphi_0 \tag{5.6}$$

Here, φ_0 is the produced flux due to the permanent magnets and it is constant. The d-axis and q-axis fluxes are denoted as φ_d and φ_q respectively.

Now, From Equation (5.3) and (5.6) we can write,

$$\varphi_d = -x_d i_{std} + \varphi_0 \tag{5.7}$$

The voltages in the direct axis (d-axis) and quadrature axis (q-axis) coordinate system, can be described as follows:

$$V_{stq} = -R_{st} i_{stq} + L_{stq} \frac{d}{dt} i_{stq} - \omega L_{std} i_{std} + \omega \frac{d}{dt} \varphi_{std} \tag{5.8}$$

$$V_{std} = -R_{st} i_{std} + L_{std} \frac{d}{dt} i_{std} - \omega L_{stq} i_{stq} + \omega \frac{dy}{dx} \varphi_{std} \tag{5.9}$$

Where,

Vstq is the q-axis stator terminal voltage in *volt*

Vstd is the d-axis stator terminal voltage in *volt*

i_{std} is the d-axis stator current in ampere

i_{stq} is the q-axis stator current in ampere

ω is the angular velocity of generator rotor in *rad/sec*

R_{st} is the equivalent resistance of the stator winding

L_{std} is the stator equivalent inductance in d-axis

L_{stq} is the stator equivalent inductance in q-axis

$\frac{d}{dt}\varphi_{std}$ is the amplitude of the flux linkages in *v/rad/sec*

The voltages refer to the d-q axis of PMSG system is shown in Figure 5.3

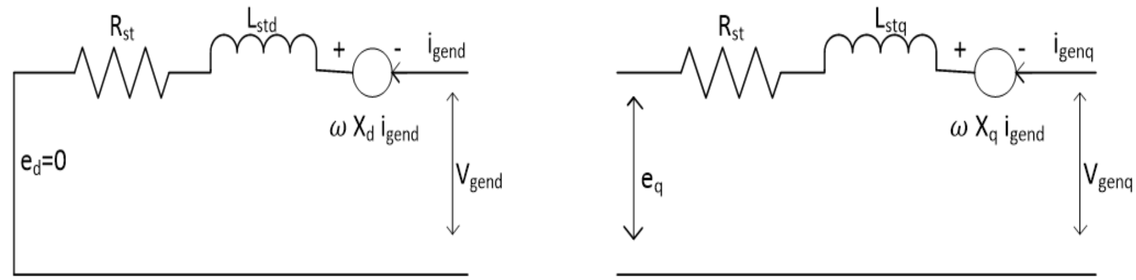

Figure 5.3: PMSG equivalent circuit in synchronous frame

The dynamic model of PMSG can be represented in rotating reference frame with the help of following equations.

$$\frac{di_{std}}{dt} = \frac{\omega_0}{x_d}\left[-R_{st}i_{std} + \omega L_{stq}i_{genq} - v_{std}\right] \tag{5.10}$$

$$\frac{di_{stq}}{dt} = \frac{\omega_0}{x_q}\left[-R_{st}i_{stq} - \omega L_{std}i_{gend} + \omega E_f - v_{stq}\right] \tag{5.11}$$

Here, i_{gend} , i_{genq} are the d-axis, q-axis generator current respectively and E_f is the voltage due to permanent magnet residual flux.

The equation of rotor angle for the PMSG system can be written as-

$$\dot{\theta} = \omega_0(\omega - 1) \tag{5.12}$$

5.3.2 The Derive Train

Already gearbox less operation of PMSG systems are adopted and becoming popular due to its higher reliability, less noise and more efficiency. The two-mass drive train model is shown in Figure 5.4 H_{tb} and H_{gen} denotes the turbine and generator inertia constant respectively. The shaft stiffness coefficient and torsional angle of shaft connecting the turbine with the generator is represented by K_{ss} and θ_{ss} respectively.

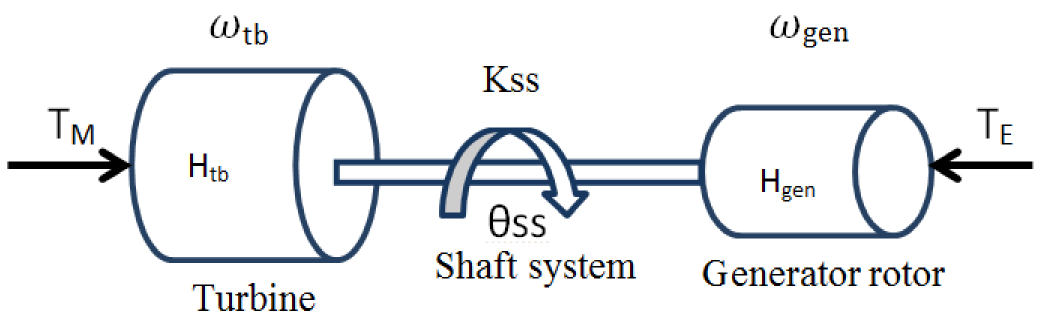

Figure 5.4: The two-mass drive train model

The electromechanical equations of the turbine-generator rotor are written in terms of the differential equations,

$$2H_{tb}\frac{d\,\omega_{tb}}{dt} = Pm - K_{ss}\theta_{ss} - D_{tb}\Delta\omega_{tb} \tag{5.13}$$

$$2H_{gen}\frac{d\,\omega_{gen}}{dt} = K_{ss}\theta_{ss} - P_{elec} - D_{gen}\Delta\omega_{gen} \tag{5.14}$$

$$\frac{d\theta_{ss}}{dt} = \omega_b(\omega_{tb} - \omega_{gen}) \tag{5.15}$$

The terms D_{tb}, D_{gen} refer to damping coefficients of the turbine and generator respectively. The expression for the input power P_m is given in Equation (2.5), while the generator electrical output power P_{elec} is expressed as-

$$P_{elec} = L_m i_{qr} i_{std} - L_m i_{dr} i_{stq} \tag{5.16}$$

5.3.3 The Converters

The inverter output current in the d-q axes are written in terms of inverter internal and terminal voltages as,

$$\frac{dI_{invd}}{dt} = \frac{\omega}{L_{inv}}[v_{invd} - v_{terd} - R_{inv}I_{invd} + \omega L_{inv}I_{invq}] \tag{5.17}$$

$$\frac{dI_{invq}}{dt} = \frac{\omega}{L_{inv}}[v_{invq} - v_{terq} - R_{inv}I_{invq} + \omega L_{inv}I_{invd}] \tag{5.18}$$

The real power transfer from generator to the grid can be successfully completed through DC-link capacitor by keeping its voltage constant. The current in DC-link is discontinuous which produces voltage ripples in DC-link capacitor. By using large size capacitor those ripples can be eliminated but control will be slow. A small size capacitor can speed up the control but there will be some ripples. So depending on the application the optimum size of the capacitor should be selected; because it’s a trade-off between fast control and voltage ripple.

The terminal voltage V_{ter} and inverter internal voltage V_{inv} are broken up along the d-q axes and substituted in equation (5.10) and (5.11). By equating the input and output power to the dc capacitor gives,

$$C_{dc}V_{dc}\frac{dV_{dc}}{dt} = P_{ip} - P_{op} - P_l \tag{5.19}$$

The dc capacitor input and output power expressed in terms of component currents are written as,

$$P_{ip} = v_{sd}i_{sd} + v_{sq}i_{sq} \tag{5.20}$$

$$P_{op} = v_{invd}I_{invd} + v_{invq}i_{invq} \tag{5.21}$$

By controlling modulation indices (duty cycles) and the converter firing angles both the converters can be controlled,

$$v_{sd} = m_1 V_{dc} cos \propto_{rec} \qquad v_{invd} = m_2 V_{dc} cos \propto_{inv} \tag{5.22}$$

$$v_{sq} = m_1 V_{dc} sin \propto_{rec} \qquad v_{invq} = m_2 V_{dc} sin \propto_{inv} \tag{5.23}$$

Substituting the above Equations in Equation (5.19) gives the differential equation of the dc capacitor as,

$$\frac{dV_{dc}}{dt} = \frac{1}{C_{dc}}[m_1 i_{sd} \cos \propto_{rec} + m_1 i_{sq} sin \propto_{rec} - m_2 I_{id} cos \propto_{inv} - m_2 I_{invq} sin \propto_{inv} \tag{5.24}$$

5.4 SIMULATION RESULTS

A grid connected 2.5 MW permanent magnet synchronous generator (PMSG) system is considered to verify the competence of the proposed ANFIS-based MPPT controller. In the implementation of the proposed ANFIS based MPPT controller detailed nonlinear modeling has been considered. MATLAB/Simulink simulation is used to verify the effectiveness of the proposed MPPT controller. The PMSG wind system parameters and the control parameters are shown in table 6 and table 7 respectively.

Table 5.1 PMSG wind system parameters

Items	Specification
System power rating	2.5 MW
Wind speed range	6 m/s -19.5 m/s
Air density	1.225 kg/m³
Turbine radius	37.5 m
Blade pitch angle	0°
Generator inertia constant	0.5 p.u.
Turbine inertia constant	3 p.u.
Pole pairs	40
Maximum rotor speed	40
Maximum power coefficient	0.48
Turbine efficiency	100%
Converter efficiency	99%

Table 5.2 Control parameters

Items	**Specification**
PI control in rectifier	
Proportional gain factor	-3
Integration gain factor	0
PI control in inverter	
Proportional gain factor	-1
Integration gain factor	-0.1

To evaluate the performance of the proposed ANFIS based MPPT controller on a grid connected PMSG system, stair-case wind speed variation is considered. Stair-case wind speed variation verifies the competence of the proposed MPPT controller for the worst case of step-up or step down change in wind conditions. The randomly changing wind velocity is considered for two minutes duration as shown in Figure 5.5. For each sample period the change in wind speed remain constant. From 45 sec to 50 sec the wind speed increases linearly.

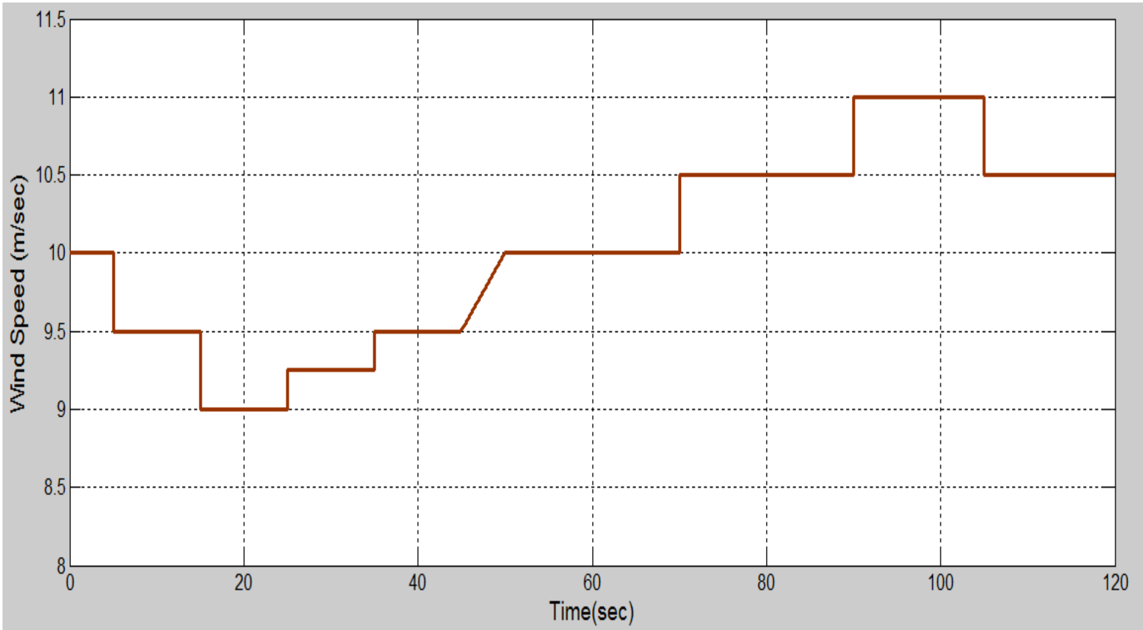

Figure 5.5: Wind speed variation over a period of 120s

With the change in wind speed, the turbine output changes. The variation in turbine output power with respect to the change in wind speed is shown in Figure 5.6.

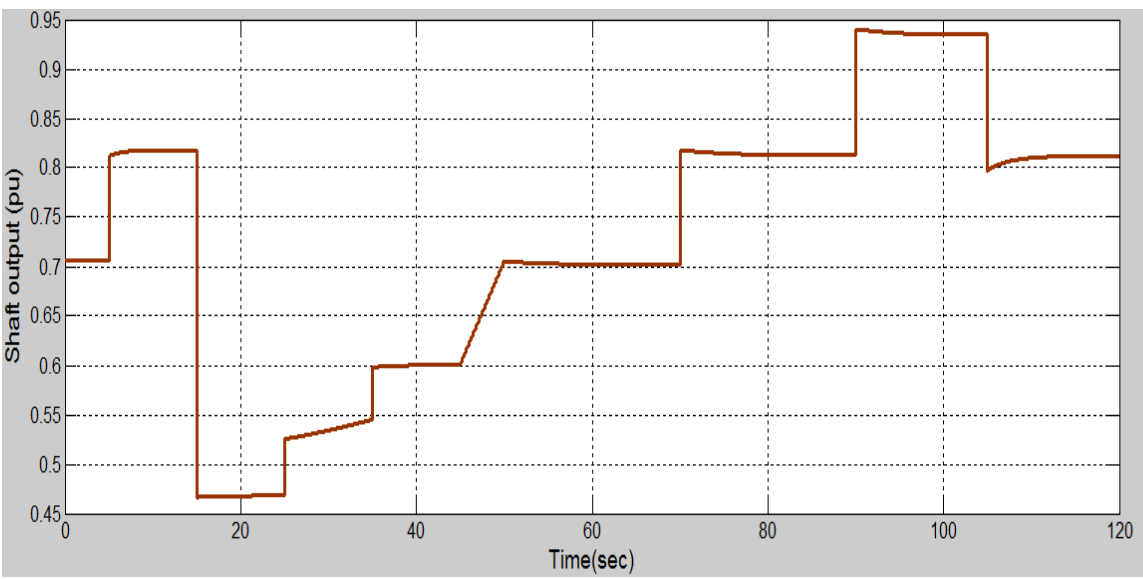

Figure 5.6: Shaft power variation with the wind speed change

The result confirm that the proposed MPPT controller is able to track the maximum power point with the change in wind speed correctly as a result the shaft output power is changing according to the wind speed variation. From Figure 5.7, it is noticed that the generator power output follows the change in wind speed properly.

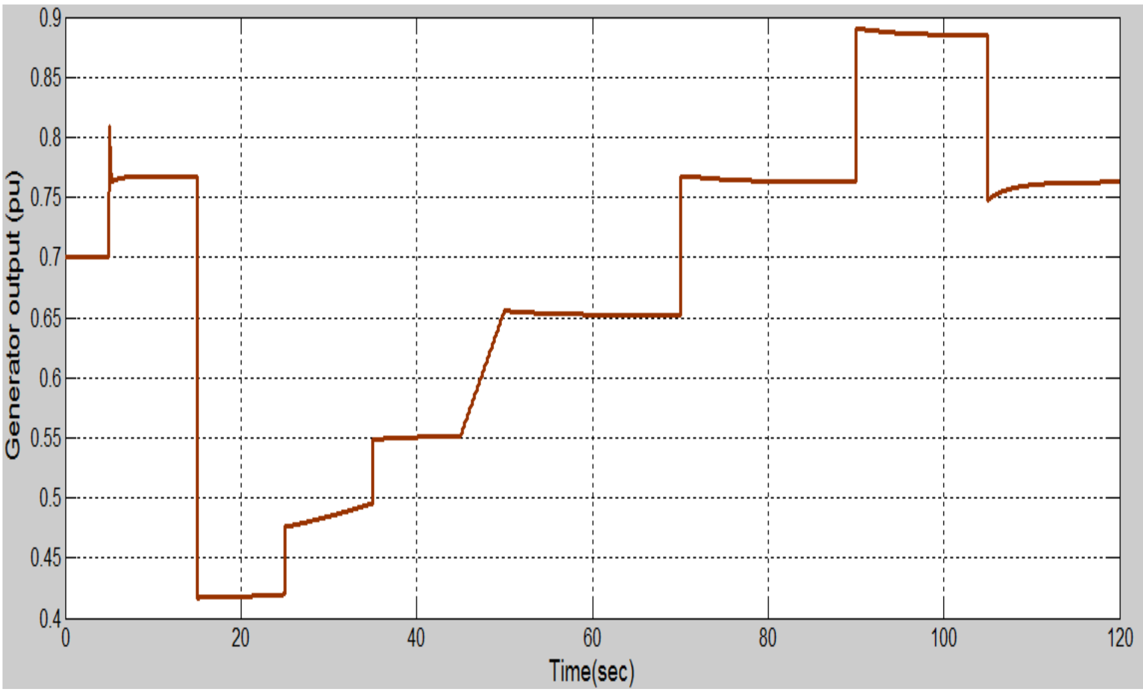

Figure 5.7: Generator output power following the wind speed variation

According to Figure 5.2, MPPT algorithm sets the reference value of optimal rotor speed and converter DC voltages to the PI controller of the generator side converter and grid side inverter. Figure 5.8 and Figure 5.9 demonstrates the change in modulation indices (duty ratio) m1 and m2 for both the converters respectively.

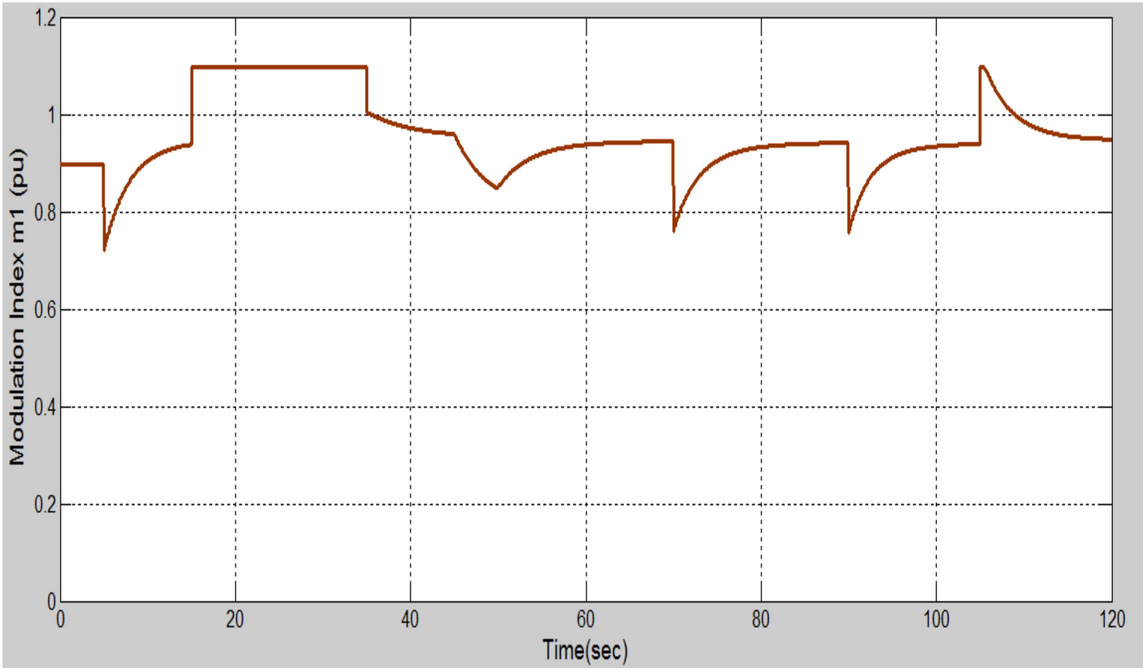

Figure 5.8: Variation in the generator side converter duty ratio

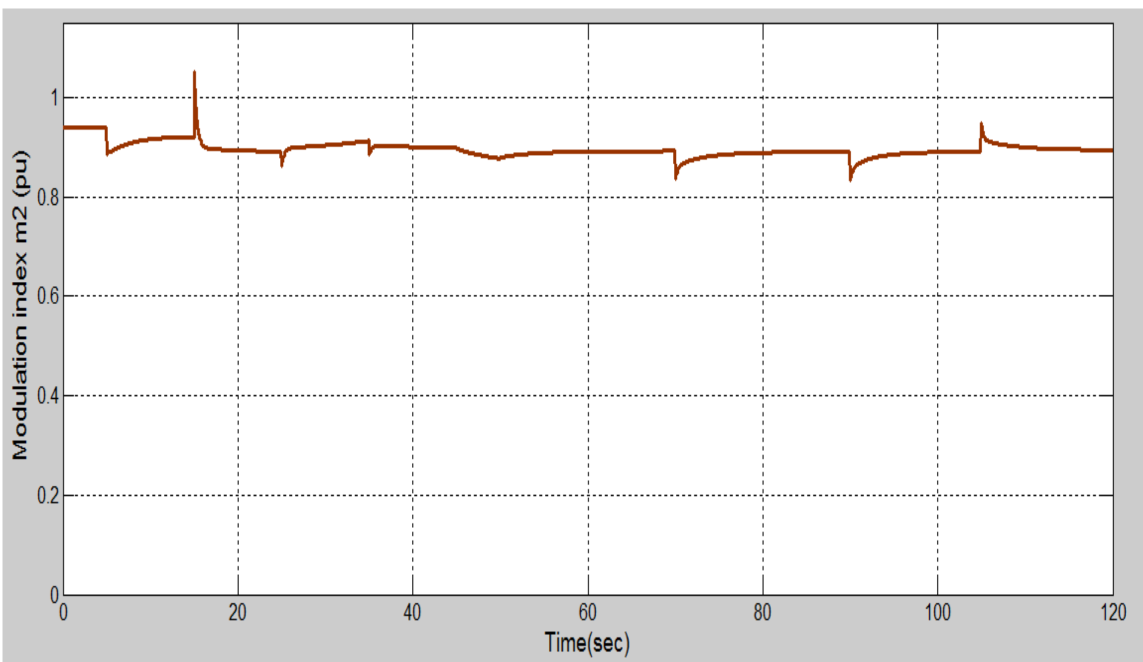

Figure 5.9: Variation in duty ratio for grid side converter

The PI controller gains of the converters have been tuned properly to restore the system variables to their quasi-steady values without any oscillation. Figure 5.10 and Figure 5.11 shows the variation of converter DC voltage and output power respectively. The converter DC voltages changes following the random variation in wind speed.

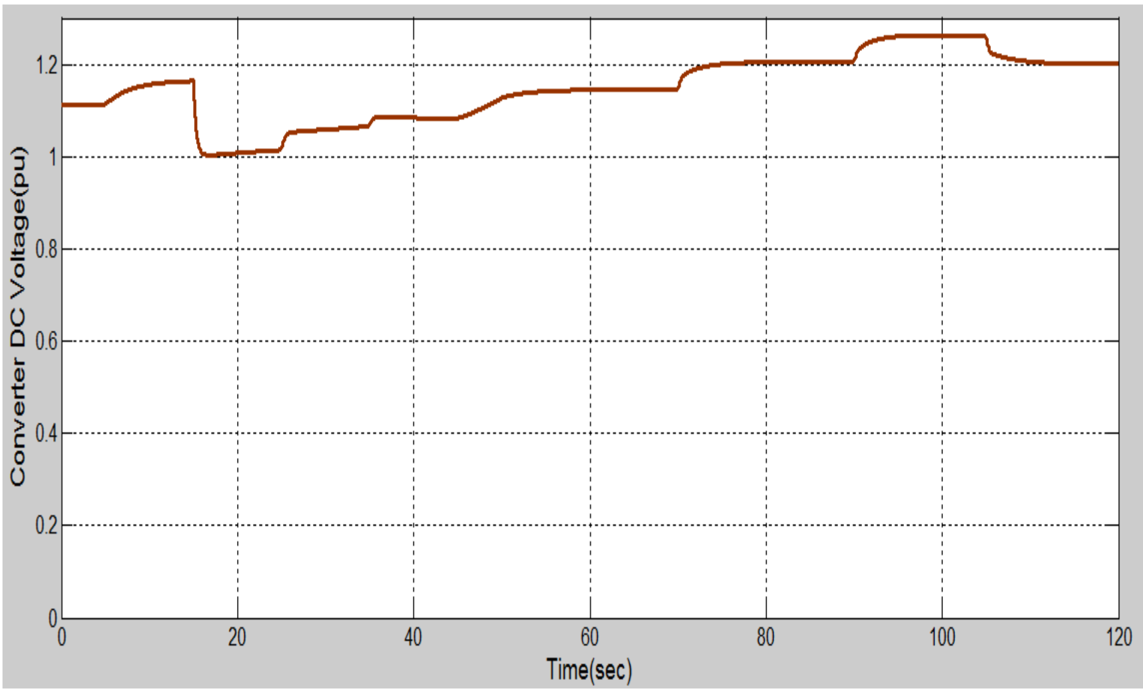

Figure 5.10: DC voltage of the converter

On the other hand Figure 5.11 noticed that the converter output tracks the shaft output correctly; there are few spikes due the sharp change in the wind speed.

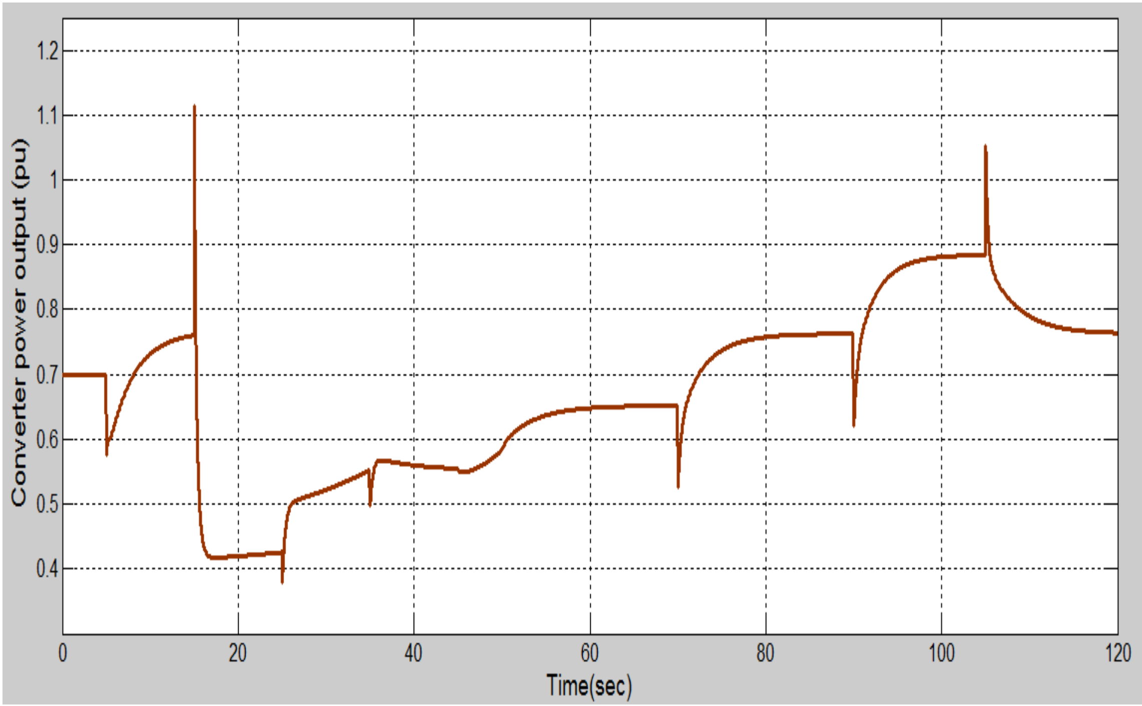

Figure 5.11: DC output power of the converter

Figure 5.12 presents that the proposed ANFIS based MPPT controller is able to track the maximum power point appropriately maintaining the optimum value of the power coefficient (C_p). During the whole range of operation period (120 sec), the value of power coefficient remains close to 0.48 with very small deviation.

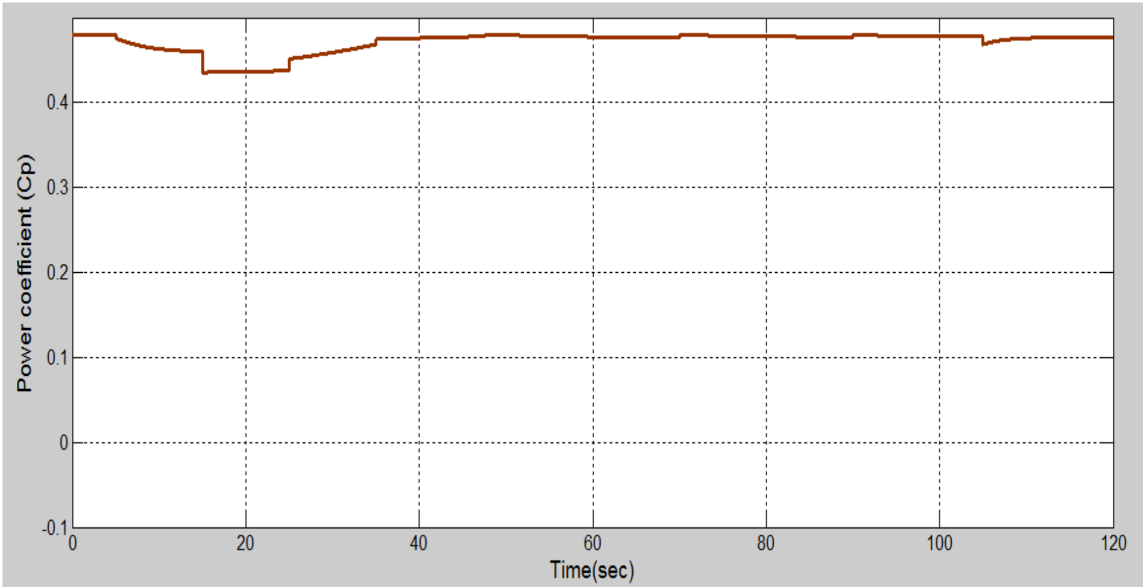

Figure 5.12: Change in power coefficient for random wind speed variation

The proposed ANFIS based MPPT is shown to present a good slowly varying transient speed profile shown in Figure 5.13 following the random change in wind speed even when all the system dynamic relations are included in system modeling.

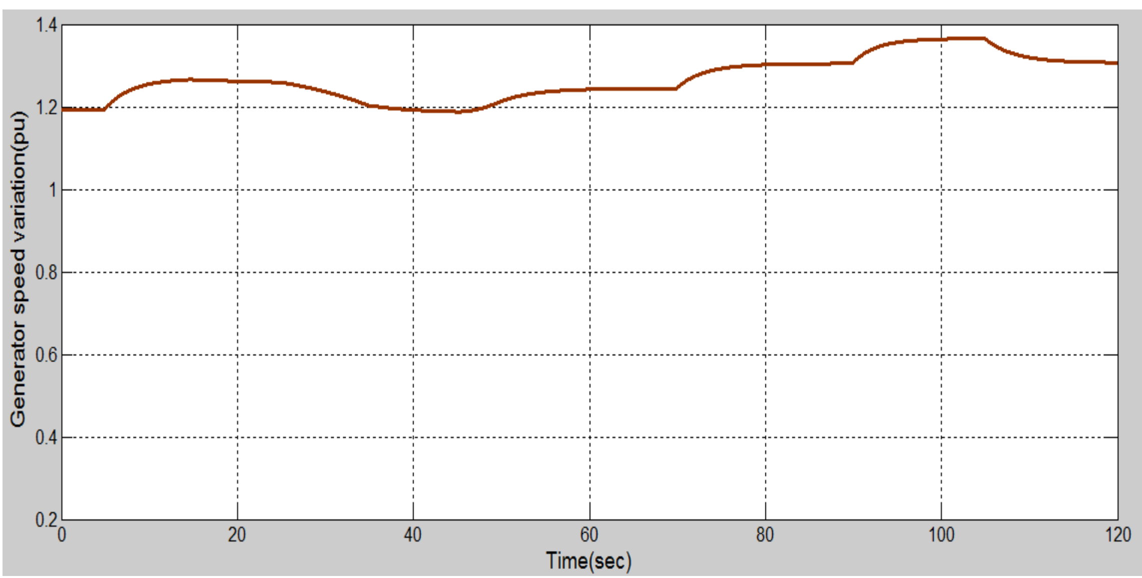

Figure 5.13: Speed variation of generator

The proposed ANFIS based MPPT algorithm is tested on a permanent magnet synchronous generator (PMSG) wind system. The PMSG wind system is controlled based on the optimum relationship between rotor speed and DC voltage. To implement the proposed MPPT controller detailed nonlinear modelling has been considered. The simulation results noticed that the MPPT controller is able to extract maximum power even in rapidly changing wind conditions and during the maximum power extraction, the optimum value of power coefficient is maintained. The proposed MPPT technique does not require any mechanical sensor for wind speed measurement or system pre-knowledge.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

Wind speed sensor-less both ANN and ANFIS based maximum power point tracking (MPPT) algorithm has been developed in this work. The effectiveness of the proposed ANN based MPPT controller is compared with the previously proposed controller. A comparison is also made between the proposed ANN and ANFIS based MPPT controller. The performance of the ANFIS based MPPT algorithm has been tested on a grid connected PMSG wind system.

From the comparison between the proposed and the reported ANN based MPPT controller it has been observed that the proposed controller is better than the reported controller both in wind speed estimation and maximum power point tracking. Comparing the results of the proposed ANN and ANFIS based MPPT controller, it has been observed that the ANFIS based MPPT controller shows better accuracy both in wind speed estimation and maximum power point tracking. By testing the performance of the proposed ANFIS based MPPT controller on a PMSG wind system, it has been observed that MPPT controller is very accurate in controlling PMSG wind system to operate close to the maximum value of power coefficient (C_p).

Two series network is used for both ANN and ANFIS based MPPT algorithm. One network for wind speed estimation and the other for maximum power point and optimal rotor speed tracking. The proposed MPPT algorithm does not require any mechanical sensor for wind speed estimation or the system pre-knowledge. Moreover, the proposed MPPT algorithm is also applicable for any other wind system. Two series network may made the MPPT algorithm little complex, but it can estimate wind speed and track both maximum power point and optimal rotor speed with great accuracy.

Comparisons were done between the ANN and ANFIS based MPPT controller technique and found that ANFIS based controller can provide superior performance over ANN based MPPT controller. ANFIS based MPPT controller is selected and implemented on a grid connected PMSG wind energy system, test results confirm the effectiveness and accuracy of the proposed MPPT algorithm and it has very quick response in transient condition.

6.2 FUTURE WORK

- The algorithm can be tested on a lab-machine with all necessary sensors and controllers can be installed to test the performance of both the proposed ANN and ANFIS-based MPPT controller.

- In both the proposed MPPT algorithm two series networks have been used, one for wind speed estimation and other to track maximum power point and optimal rotor speed. If it can be done using a single network, then the complexity of the proposed MPPT controller will be reduced.
- It will be interesting to compare the proposed MPPT algorithm with the other existing MPPT techniques.
- Real time implementation of the proposed MPPT controller will be more interesting to study.

NOMENCLATURE AND SYMBOLS

DC	Directional Current
AC	Alternating Current
PMSG	Permanent Magnet Synchronous Generator
PI	Proportional plus Integral
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
FFBP	Feed Forward Back Propagation
RBFNN	Radial Basis Function Neural Network
AIT	Artificial Intelligence Technique
WECS	Wind Energy Conversion System
P_m	Turbine mechanical power
V_w	Wind speed
ρ	Air density
A	Wind turbine blades swept area
C_p	Power coefficient
λ	Tip speed ratio
λ_{opt}	Optimum tip speed ratio
β	Blade pitch angle
R	Radius of wind turbine rotor
ω	Mechanical angular velocity of the wind turbine rotor
ω_{opt}	Optimum rotor speed
MPP	Maximum Power Point

MPPT	Maximum Power Point Tracking
φ_0	Flux due to permanent magnet
φ_d	d-axis flux
φ_d	q-axis flux
Vstq	q-axis stator terminal voltage in *volt*
Vstd	d-axis stator terminal voltage in *volt*
i_{std}	d-axis stator current in ampere
i_{stq}	q-axis stator current in ampere
R_{st}	Equivalent resistance of the stator winding
L_{std}	Stator equivalent inductance in d-axis
L_{stq}	Stator equivalent inductance in q-axis
WT	Wind Turbine
RE	Renewable Energy
RES	Renewable Energy Source
DG	Distributed Generation
C_{pmax}	Maximum power coefficient
ω_r	Rotor Speed
ω*	Rotor speed corresponding to the maximum power
FS-VP	Fixed Speed Variable Pitch
FS-FP	Fixed Speed Fixed Pitch
VS-FP	Variable Speed Fixed Pitch
VS-VP	Variable Speed Variable Pitch
HCS	Hill Climbing Search

P&O	Perturb and Observe
MSE	Mean Squared Error
P_{max}	Maximum power
TIP	Tip Speed Ratio
RMSE	Root Means Square Error
PSO	Particle Swarm Optimization

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LIST OF PUBLICATIONS

The following papers will be published from the work described in this thesis:

<u>Conferences:</u>

[1] "An Efficient wind speed sensor-less maximum power point tracking (MPPT) controller using Artificial Neural Network" (under preparation)

[2] "An Efficient wind speed sensor-less maximum power point tracking (MPPT) controller using Adaptive Neuro-Fuzzy Inference System" (under preparation)

[3] "Comparison between Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System in wind speed sensor-less maximum power point tracking (MPPT)" (under preparation)

<u>Journals:</u>

[4] "Performance evaluation of ANN based Maximum Power Point Tracking Controller for grid connected PMSG wind system" (under preparation)

[5] "Performance analysis of ANFIS based Maximum Power Point Tracking Controller for grid connected PMSG wind system" (under preparation)

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