Pitch and Torque Control of Variable Speed Wind Turbine using Self-Learning Neuro Fuzzy Controller

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THESIS

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ABSTRACT

Wind Turbine is one of the renewable source of energy and fast growing industries for power generation in this modern world. In spite of this there are many challenges present regarding its installation cost and control method.

Wind Turbine has to operate with variable nature of wind speed. The foremost part in controlling methods of wind turbine is to extract optimum amount of energy by avoiding mechanical overload on system in all regions of wind profile. The other aspect of control is related to electrical side that is to avoid power and frequency fluctuation when connected to grid. The both objectives of control are usually achieved by two controlling approaches one is Pitch Angle Control and other is Torque Control.

The wind turbine system is nonlinear in nature and conventional control approaches usually build on linearizing the plant at all operating regions of Wind Speed. Therefore classical methods such as PI or PID have good performance when wind turbine profile is linear but during transition from one region the performance is not satisfactory due to non-linearity. The controller gains also need to be tuned in all operating regions of wind profile for controlling pitch angle and voltages for converters / inverters. The designer also has to design two separate controllers each for pitch angle and control voltages of converter/inverter. Hence, control objectives at these operating zones changes and in order to meet these objectives during transition from one region to another is the critical part while designing control techniques for wind turbine. Keeping in view the non-linear nature of wind turbine and power characteristics curve, researchers diverts their attention towards non-linear control approaches. In this research one non-linear method namely Self Learning Neuro Fuzzy Controller is implemented separately each for Pitch Angle as well as Torque Control. The controller behavior is studied using MATLAB/SIMULINK phasor type wind turbine model in which both the pitch angle and torque have been regulate to obtained desired power and rotor speed.

ACKNOWLEDGEMENT

Allah, all praises to Him, is the creator of this universe and by His Benediction I am able to write this in order to thanks and acknowledge for all his blessings which HE, the only worshiper bestowed on me in the shape of loving parents, health, wealth, knowledge, a supportive mentors and teachers which enable me to complete my thesis.

I would like to thanks the continuous sincere and dedicated efforts of Dr. Muhammad Bilal Kadri throughout my thesis. This thesis would be possible without the guidance of my honorable GEC members;

GEC members Names:

- Capt. Dr. Muhammad Junaid Khan (PN)
- Cdr. Dr. Muhammad Farhan(PN)
- Cdr. Dr. Ataullah Memon.

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LIST OF SYMBOLS

λ', Tip Speed ratio

'ω', Rotor rotational speed,

'R', Rotor radius

'v', velocity of Wind Speed

'Cp', power Co-efficient of wind Turbine

'β', Pitch Angle

'Pm', Mechanical Power

'Ir', Rotor Current

'Igc', Grid Side Inverter Current

'Is', Stator Current

'V' Voltage at Grid

'I' Current at Grid

'Vr', Control voltages of Rotor side and

'Vgc' Control voltages of Grid Side Inverter

'uf(t)', Feed Forward Controller Output

'a(t)', Transformed Input Vector

'w(t)', Parameter Vector

'e(t)', System Error'

'γ', Online Learning Rate,

'δ' User Defined parameter

'kp', Proportional Gain

u(t), Total Control Action at time t,

'td', Time Delay of System

'RMSE', Root Mean Square Errors

'NLMS', Normalized Least Mean Square,

'FLMS', Fuzzy Least Mean Square

Chapter # 1

INTRODUCTION

1.1 Motivation:

World is moving toward utilization of renewable energy i.e. wind, thermal, solar etc. in most efficient and sustainable ways. To do so many advance and modern control techniques or approaches continuously developed by the researchers to efficiently utilize these resources.

Similarly many works carried out in the wind energy sector by the controllers to extract maximum energy while avoiding mechanical fatigue on the system. Due to non-linearity in the wind energy power system, control methods like Proportional, PI or PID to some extent meet the objectives when environmental constrains such as noise is avoided while linear wind profile is provided.

Self-Learning Neuro Fuzzy control scheme comprises of Feed Back Error Learning scheme and online updating of controlling parameters is capable to handle non-linearity and physical/environmental constrains.

1.2 Thesis Objective

The objectives of the thesis is to study the self-learning neuro fuzzy control scheme and deploy it on built in Doubly Fed Induction Generator Wind System of Model MATLAB Simulink software. The other objectives includes

1. *In Depth study of wind system and wind profile*
2. *Study the purpose of using Doubly Fed Induction Generator in Wind Energy System*
3. *Study the behavior of already deployed Proportional and PI controllers in MATLAB model*
4. *Development Of Control Algorithm of Self –learning Neuro Fuzzy Controller*
5. *Study & Compare the results obtained of Self-learning Neuro Fuzzy Controller*

1.3 Thesis Organization

The research work has been organized and divided into six chapters. The brief detail of each chapter has been described below.

Chapter # 1: Introduction

This describes the motivation, objective behind the thesis using self-learning neuro fuzzy controller and finally tells the organization of the thesis.

Chapter # 2: Literature Review

The Second chapter starts with the discussion about wind speed regions and operation of wind turbine in these regions. After established basic understanding about behavior of wind turbine and control objectives in the pre - defined operating regions, the already research work carried out by control engineers to achieve control objective in these regions is being discussed.

Chapter # 3: System Review

This chapter discussed the MATLAB/ SIMULINK Model which has been used in this research to test proposed control strategy. The second chapter starts with the description of general diagram of the MATLAB model and converge it to desire tracking characteristics of the model. Then, it enhances the discussion to build a concept regarding working of each component.

Chapter # 4: Self Learning Neuro Fuzzy Controller

This chapter completely focuses discussion on the proposed self-learning Neuro fuzzy control strategy. The discussion begins with block diagram approach of the self –learning scheme and enhances it to the description/working of each block. In the end a summary of steps to incorporate control algorithm has been mentioned for better understanding of the reader.

Chapter # 5: Simulation Results

This chapter demonstrates the results obtain from the MATLAB/ SIMULINK of the already build in proportional and PI controllers and compare with results of propose self-learning Neuro fuzzy control scheme.

Chapter # 6: Conclusion & Future Work

This chapter Conclude the thesis work and suggest future work & recommendations for the betterment in performance of the Self –Learning Neuro fuzzy controller.

Chapter # 2

LITERATURE REVIEW

2.1 Introduction

Nature of wind speed is variable and non-linear. The methods to control wind turbine with unpredictable nature of wind speed are Blade Pitch Angle and Torque Controls. The turbine side control is called “Pitch Control” in which the angles of the turbine blades adjusted while the generator side control is called “Torque Control” in which the current injected to the rotor of the alternator is changed as to meet constant power requirement.[1]

Three methods have been widely used to control pitch angle i.e. (a) passive stall and (b) to change pitch angle of turbine rotor blades [2] (c) Active stall. The main purpose of these methods is to extract maximum energy from wind speed around operating range and waste extra wind energy to avid mechanical damaged or fatigue to the wind turbine.

In passive stall method the rotor blades are fixed at certain angle as compared to variable pitch angle method in which angle of blades continuously adjusted. The passive stall has no control over speed of wind turbine and power, when wind speed rises above rated speed region. The variable pitch angle of rotor blades varies according to wind speed in order to maintain constant power at the output. The two methods are applicable to small power wind turbine whereas high power wind turbines greater than 1 MW active stall is used [3]. In Active stall, the characteristics of both (a) and (b) are merged. The active stall method divert the rotor blades in opposite direction of wind speed when speed rise to the cut off speed. The purpose achieved by pulling rotor blades in opposite direction is to reduce overloading on wind turbine.

In the beginning two control strategies has been discussed. The next step after mentioning the control strategies is their control. Before moving towards controlling aspects, we have to completely understand this point that either both strategies should be active at every wind speed or one control should take over another control during multiple regions of wind speed profile. To overcome this issue we look into wind speed profile.

Wind speed profile curve is shown with different regions of operation in Fig 1. Three regions of turbine operation have been clearly defined in the curve profile. The region below 5 m/sec is the cut off region, region from 5 m/sec up to 15 m/sec is the rated speed region, wind speed above 15 m/sec is the above rated speed region. The speed b/w 20 and 30m/sec for large wind turbine is the cut off speed or shut down region to avoid excessive overloading on the system. The wind turbine model used in this research, reaches to it rated speed when wind speed is between 12 m/sec instead of 15 m/sec

The designers concerns are related to control strategies uses in all three regions of wind speed. In brief, the task is to define that the both control strategy either used separately or in parallel to meet desired performance

2.2 Cut in Region

Region 1 is the region defined on when wind speed is below 5m/sec. At this region the wind turbine is not operated. The Pitch angle of the turbine blade are in such position to generate less aerodynamic torque i.e. the blades are move to opposite direction of the wind speed.

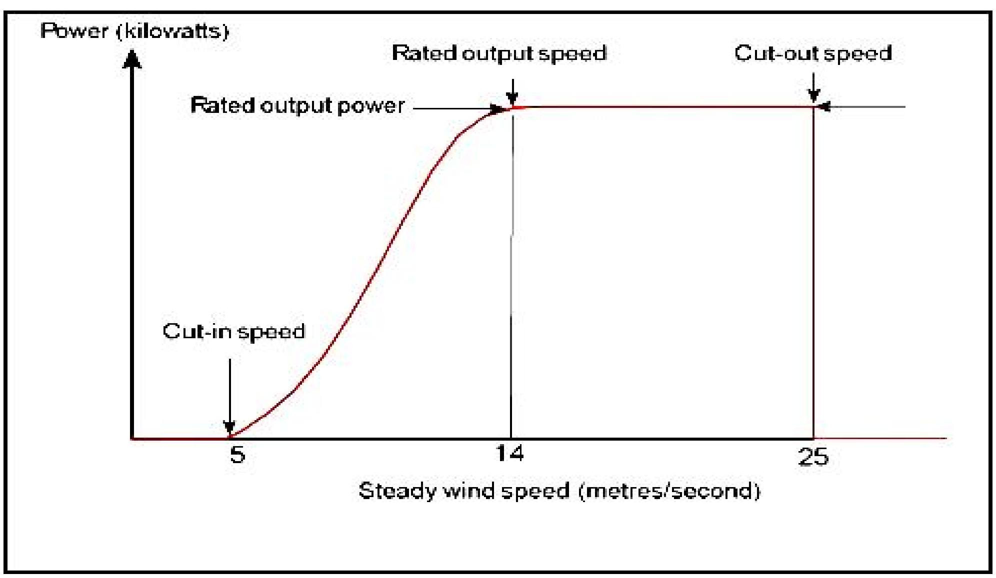


Figure 1: Wind Speed Curve with different region of operation of wind turbine

2.3 Rated Speed Region:

This region defines when wind speed increases from 5m/sec to 15m/sec. In this region turbine blades are put into the direction of wind speed to generate aerodynamic torque. The pitch angle is held at its optimum value, as a result maximum aerodynamic torque achieved.

The maximum aerodynamic torque is get when pitch angle is at its optimum value on which there is a constant value of λ , which is called Tip Speed Ratio.

The tip speed ratio is computed as below [4]

$$\lambda = \omega * R / v, \tag{1}$$

Where ωr is the rotational speed, R is the rotor radius and v is the wind speed.

The combine effect of pitch angle and TSR to control aerodynamic torque is co-operated in a function called Power Co-efficient or Cp.

2.4 Above Rated Speed Region:

This region defines from 15 m/s to 25m/sec, for high power wind speed the region from 20 to 25m/sec is the cut off region or no operation region in order to avoid mechanical stress and fatigue on the system.

In this region the pitch angle is continuously adjusted in order to get less aerodynamic torque as the system already generating rated power. The speed regulation is the objective in this region which is attain by varying pitch angle.

2.5 Discussion regarding Control Strategies in all three Wind profile regions:

To understand which control strategy is useful in the three above mentioned regions, we have to first look into that how much power extracted from wind speed.

The mechanical power captured from the wind speed is directly proportional to wind speed and power co-efficient and is given by.[4]

2

Where,

ρ is the air density,

A is the turbine swept area,

V is the instantaneous wind speed,

C_p is the power co-efficient of wind turbine,

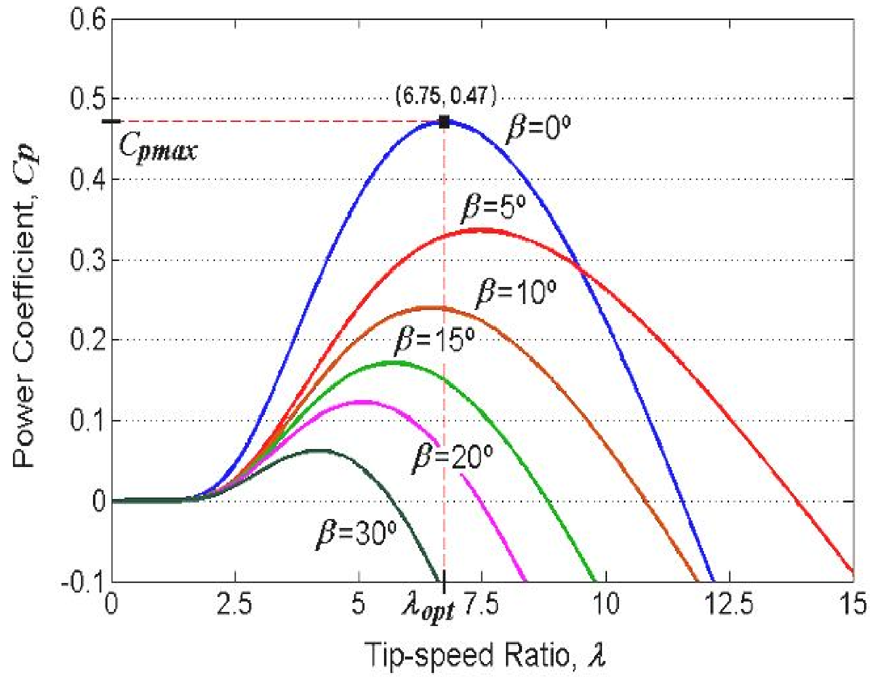


Figure 2: Power Co-efficient Curve

The selection of Cp or optimum value of Cp is the critical part which is need to be determined at low and rated speed region in order to get maximum power from wind speed.

The plot of Cp and tip speed ratio at different values of pitch angle has been shown in Fig.2. The maximum value of Cp is obtained at pitch angle zero, therefore from low to rated wind speed the pitch angle should be kept zero in order to get maximum value of Cp. The pitch angle above rated wind speed should be varied in order to get low power co-efficient because as wind speed is high, as a result its cubic value will be high and from equation 1, power is directly related to wind speed, therefore to maintain optimum value of mechanical power, Cp should be lowered by increasing pitch angle. The maximum value of Cp is given by Betz's limit which is (59%)

At high wind speed i.e. above rated speed, pitch angle control as well as electromagnetic torque control are required to maintain constant frequency at constant power. This is achieved by controlling the frequency of the rotor side injected current. The frequency of the rotor side current is adjusted by varying the modulation index of the PWM (pulse width modulation) voltage at the rotor side inverter as shown in Fig 4.

2.6 Research carried out regarding Control Methods in all three Wind profile regions:

Up till now different control strategies and which strategy is suitable have been discussed, now the next task is to find the control methods. The control methods objectives are to obtained optimum Cp at low and rated wind speed regions while varying torque in these regions and low Cp by varying pitch angle as well as torque at above rated wind speed region.

As from above discussion it has been quite clear that objectives in three regions of wind speed are different.

In order to control multivariable objective either one has to design separate controller for each objective by linearizing the model on every operating point/loop or use one controller by varying its parameters continuously.

The classical methods of control like proportional, integral along derivative control has been used to obtain satisfactory performance but problem occurs during transition from one region to another and when noise added to measured input. This problem has been addressed by using more than one controller in every region or gain scheduling method which is quiet similar to self-tuning or adaptive type controller.

The PID controller implemented to control variable speed of wind turbine in paper namely Effect of Pitch control and Power Conditioning on Power Quality of Variable Speed Wind turbine Generator.[5] In this paper the writer has demonstrated both cases of controlling i.e. pitch angle and torque control using inverter separately as well as combine. Although he has used simple dynamic model of wind turbine but he demonstrate the results of both control strategy to show the importance of controlling both parameters.

In this paper, first the uncontrolled results were obtained for the wind profile which is then compared with both pitch angle and converter/inverter control methods. When only pitch control is applied through PID, the results obtained in with respect to rotor speed shows less fluctuations during high speed region. [5] The results on power and voltage show transient or fluctuation. Similarly when only converter and inverter method applied to the system, it show stabilization in the output but transients and fluctuation are same as that of uncontrolled case. When both control strategies through PID are applied shows better performance as compared to individual control. The overloading on wind turbine in high speed region is controlled by pitch control and transient were reduced by actively converter control.

The gain scheduling controller approach to control pitch angle of variable speed wind turbine has been used by Fabien Lescher, Jing-Yun [2006].[6] They have designed the controller using Linear Matrix Inequalities (LMI) optimization and Linear Parameter Varying (LPV) systems for the whole operating regions. The controller performed satisfactory performance during transition from partial load condition to full load condition.

The non-linear profile of wind speed also encouraged different researchers to divert their work from traditional control towards fuzzy control. The advantages of fuzzy logic over traditional control is that it handle non-linearity of the control quiet well and require less knowledge of mathematical model.

Fuzzy logic controller on both torque and blade control has been implemented in [7] In this paper the author compare its simple fuzzy control strategy (no self-tuning) with PI controller and proof with tabulated results the fuzzy controller superiority over PI. The output power or energy and rotor speed increase with Fuzzy controller as compared to PI Controller but increment is not very large.

Another way to control pitch angle without measured the wind speed is the maximum power tracking point MPPT. [8] This method predicts the turbine rotor speed from the measured electrical power while keeping regards of electrical loses. The predicted wind speed is then transmitted to control logic which generates PITCH angle command. The control logic was deployed using Neuro fuzzy logic but not clearly demonstrates the advantages.

Self-Learning Neuro fuzzy control method already been tested by Tan W W and Dexter in their paper to control the heater voltage of a liquid helium Cryostats.[9] The compare the simulation results obtained by self-learning scheme with the simulation results of gain schedule PI controller. The shows that the performance is maintained during online learning and neuro fuzzy controller is gradually learning to maintained the output around the desired set point

Hence, keeping in view the advantages and superiority of simple fuzzy and Neuro fuzzy controller, we will use a self-learning Neuro fuzzy approach and compare it simple PI or P controller. Neuro fuzzy approach and control methodology has been described in chapter 4.

Chapter # 3

SYSTEM REVIEW

3.1 Introduction:

In modern wind turbine system despite of blade angle control electromagnetic torque control is also used to maintain constant power. Torque control is mainly achieved at rotor side of the generator by controlling voltage of the converter/inverter which controlled the frequency of the injected current in the rotor.

Wind turbine is either directly connected to the grid or indirect connected to the grid with synchronous or asynchronous generator. The main difference b/w direct or indirect connection is the rating of the power electronics converter used in wind turbine. For direct connection to the grid the rating of the power electronics grid should be equal to the grid power rating whereas the power electronics circuit used in the indirect connection to the grid has to bear 30% power of the grid

The main purpose of the power electronics circuit in the wind turbine system is to control the frequency fluctuation of variable speed wind turbine with respect to grid to a fixed frequency.

3.2 AC/DC/AC Inverter Control:

The technique used to control the power electronic circuit in the wind turbine or other power circuit is pulse width modulation or pulse duration modulation technique. The technique actually control the average output voltage deliver to the load. This techniques work on the principle to control the average value by controlling the switching the power device on a fast rate i.e. if the on period of the output either voltage or current is high as compared to off time then the average output value will be high or vice versa.

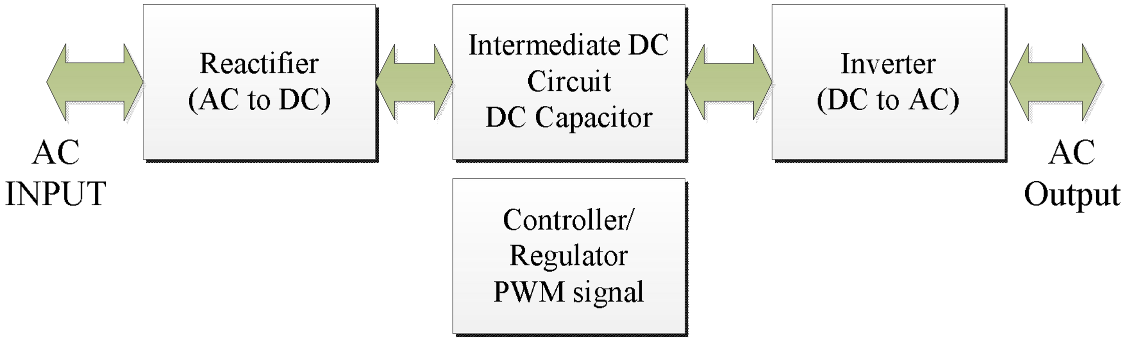


Figure 3: Block Diagram of AC/DC/AC Inverter

The Block Diagram of the PWM includes a bridge or rectifier circuit, then a DC circuit and in the last inverter circuit which converts DC to AC as shown in Fig 3.

The main task of the control is to find the control voltage which is to be fed to the inverter so that output varies as desired.

In PWM there are two signal are used which are constantly compare to generate output signal in the form square wave whose frequency can be varied according to desired which either turn on or off the control circuitry on high rate. This fast switching in turn control the average power output delivered to the load which is can be either grid side or rotor side for variable speed wind speed turbine.

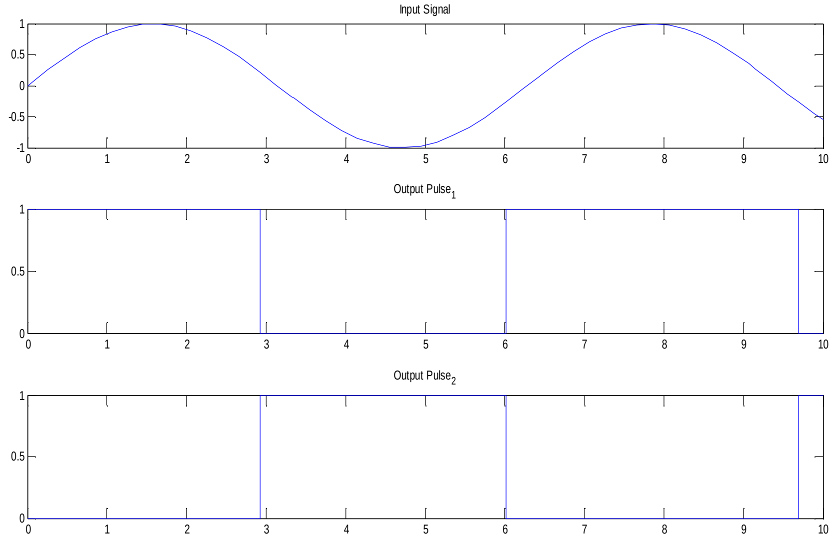


Figure 4: PWM SIGNAL

3.3 Induction Generator:

Induction generator or motor works on the principle of electromagnetic induction of voltage on the stator or rotor due to magnetizing field in the air gap b/w rotor and stator.

In fixed speed wind turbine squirrel cage induction generator normally used and directly connected to the grid. In this connection speed is kept constant (usually varies to 1 to 2%) as compared to the grid frequency. The system is not capable to bear the turbulence of the wind speed which will ultimately result in power fluctuation. The other major disadvantage of fixed speed wind turbine is that, when short circuit occurs in the network and generator capacity is low then generator will overs peed and causing drop in the terminal voltage by absorbing too much reactive power from the network. The only foremost advantage of using fixed speed wind turbine is the construction of the generator which is simple and competitive in term of cost /per kilowatt hour.[10]

To bear turbulence and power fluctuation usually two type of variable speed wind turbine has been used. Both systems have been shown below in Fig 5 & fig 6

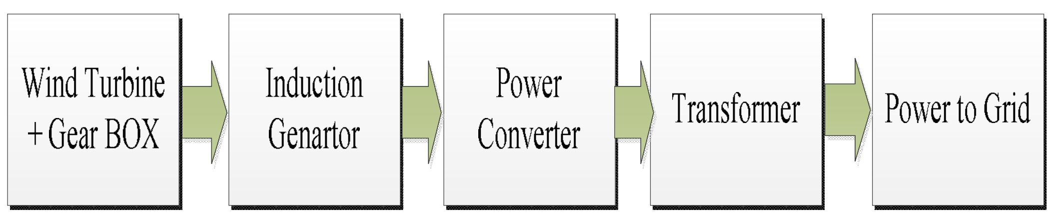


Figure 5: Variable Speed Wind Turbine with Direct Connection to Grid

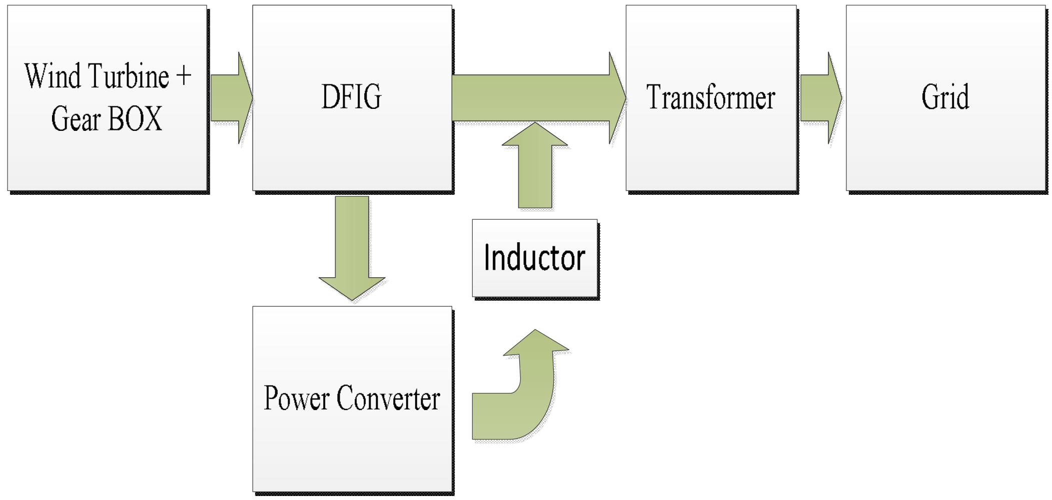


Figure 6: Variable Speed Wind Turbine with DFIG Induction Generator

3.4 Doubly Fed Induction Generator:

A three phase induction machine can be used as a doubly fed induction motor. In this case the motor rotates on a synchronous speed (the speed at which the motor shaft rotates with respect to magnetic flux around it) and this speed can be varied by adjusting the ac current feed into the rotor winding of the machine. The machine can be used a doubly fed induction generator, in this case the mechanical power applied to the machine shaft through prime mover is converted to electrical energy and is transmitted to network via both stator and rotor windings as shown in Fig.7

There are two main reason of using DFIG in the system.[10]

A. The primary reason of selecting DFIG (Doubly fed induction generator in which both stator and rotor are connected to grid) instead of SFIG (Singly fed induction generator in which only stator is connected to the grid or network) in the model is, as the system under investigation has to maintained constant frequency at variable speed with respect to grid or the network in order to remain synchronized.

B. The secondary reason of using DFIG is that the size and cost of the power electronics devices used in AC/DC/AC inverter has to handle 30% of the generator rated output power whereas the power electronics devices used in SFIG type wind turbine model has to bare 100% of the generator rated power

The frequency at the stator of DFIG is given by, [10]

$$f_{stator} = \frac{n_{rotor} * N_{pole}}{120} \pm f_{rotor} \quad , \qquad 3$$

Where,

f rotor is the frequency of the ac current that need to be fed into the doubly fed induction generator rotor winding

f stator to be equal to the frequency of the grid or network, expressed in Hz

n rotor is the frequency of the rotational speed of the generator rotor expressed in rotation per minutes (r/min)

N pole is the number of magnetic pole per phase in the doubly wound induction generator

3.5 MATLAB Model:

The Block Diagram of Wind Turbine System has been shown in Figure 7, consists of wind turbine, gear train, and DFIG. The stator of DFIG is directly connected to grid and rotor has been connected to grid via AC/DC/AC inverter and inductor.

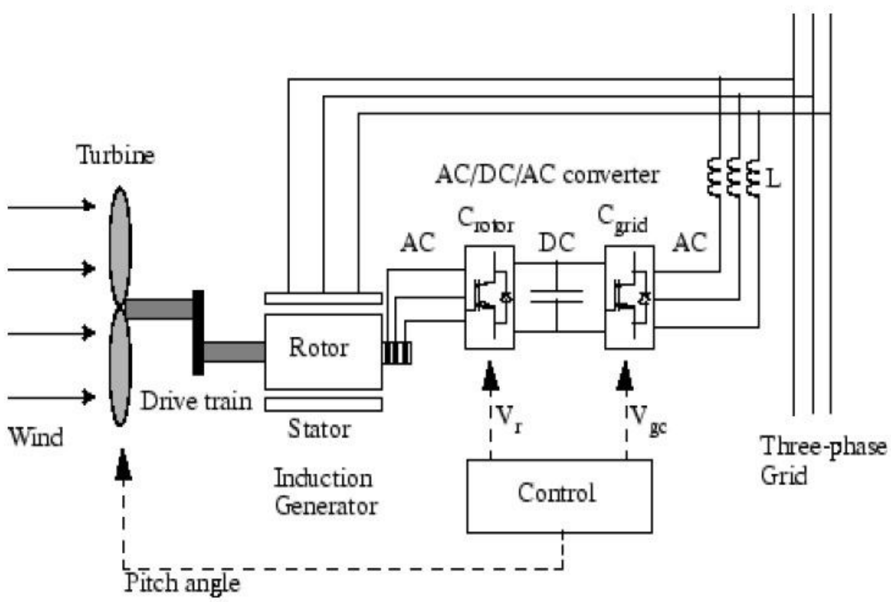


Figure 7: Wind turbine with DFIG Generator

Control system consists of both pitch and torque control which transmits the pitch angle command and control voltages to rotor and grid side inverter in order to control electrical power and the mechanical power of wind turbine and reactive/active power or voltage at grid side terminal.

Electrical inputs and outputs of the system has been shown in Fig.8, i.e. rotor current Ir, Grid Side Inverter current Igc, Stator Current Is, voltage & current at Grid 'V' and 'I' and control voltages as 'Vr' and 'Vgc' and rotor speed 'ωr'.

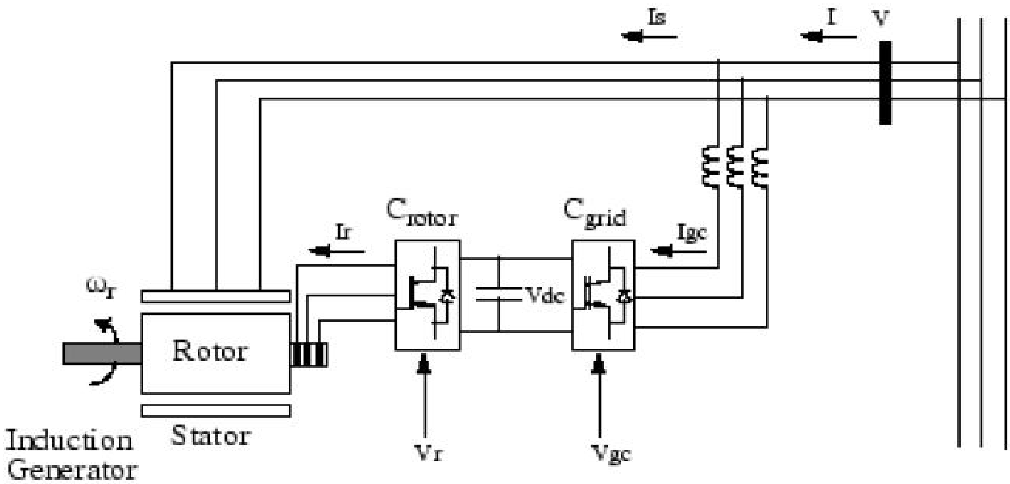


Figure 8: Wind turbine and DFIG Generator with Electrical Parameters

Matlab Simulink model used in this thesis has been shown in Fig 9 in which the pitch angle command generated through simple proportional controller and torque command through PI controller.

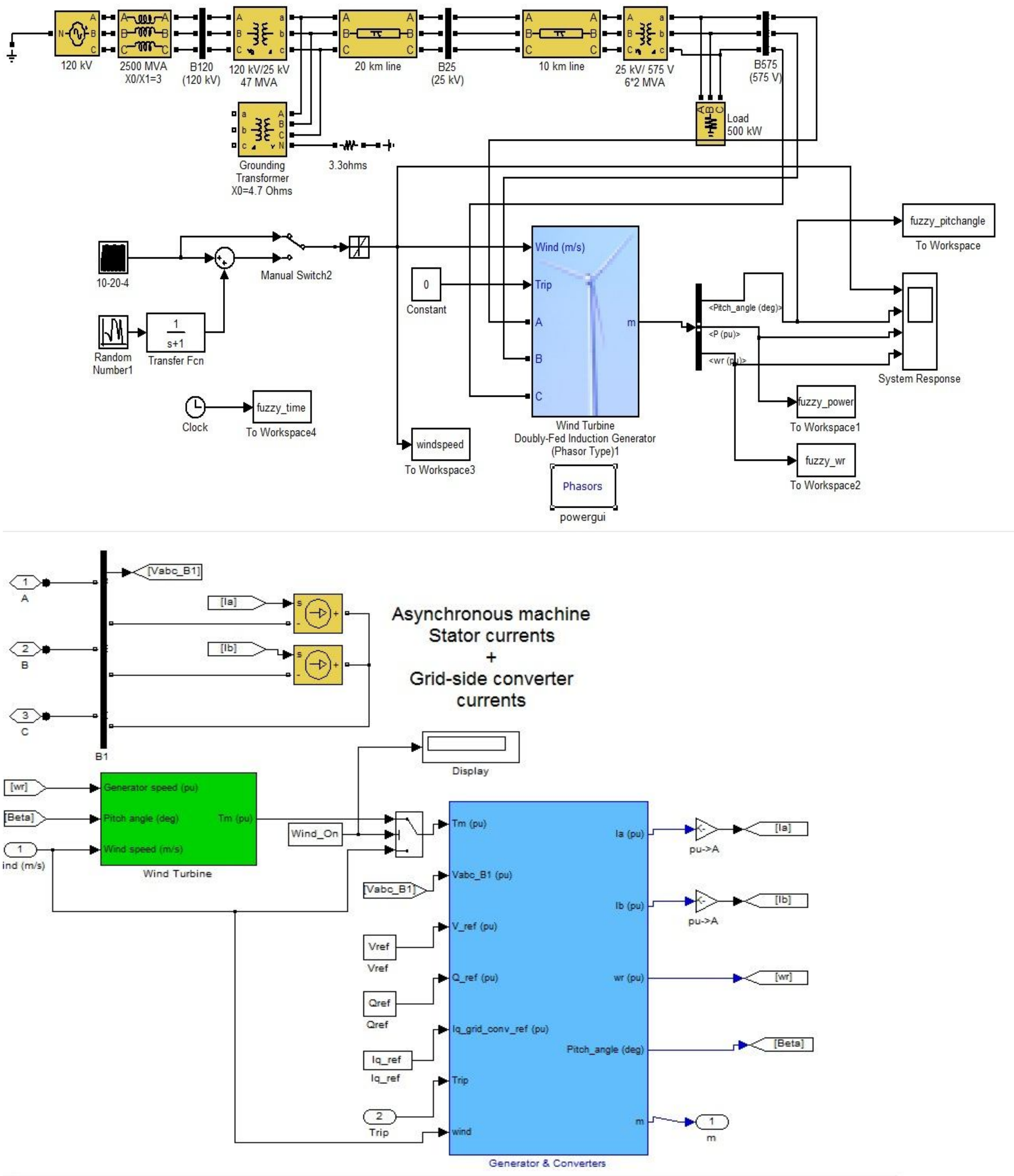
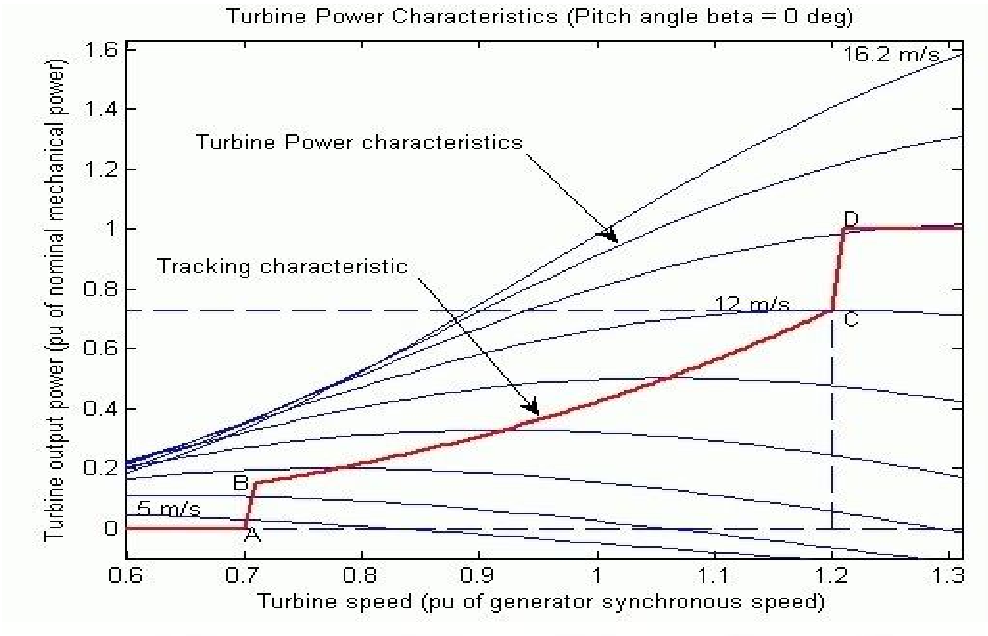


Figure 9: Simulink/ Matlab Model of Wind Turbine

The input to the pitch controller is the error signal of rotor speed ‘ωr’ while torque controller inputs are the error signal of power. The error signal of power is obtained by measure generated power and mechanical plus electrical losses. The resultant of measured parameter is then subtracted from reference power. Now the question arises how to obtain reference power signal. In this model reference power.

Red line is the tracking characteristics curve used for power tracking in MATLAB /our model. The tracking characteristic is defined by four points: A, B, C and D. From zero speed to speed of point A the reference power is zero. Between point A and point B the tracking characteristic is a straight line, the speed of point B must be greater than the speed of point A. Between point B and point C the tracking characteristic is the locus of the maximum power of the turbine (maxima of the turbine power b/w turbine speed curves). The tracking characteristic is a straight line from point C and point D. The power at point D is one per unit (1 pu) and the speed of the point D must be greater than the speed of point C. Beyond point D the reference power is a constant equal to one per unit (1 pu).

The proposed strategy for controlling pitch angle and torque control which has been applied in place of simple proportional and PI controllers will be discussed in chapter 4.



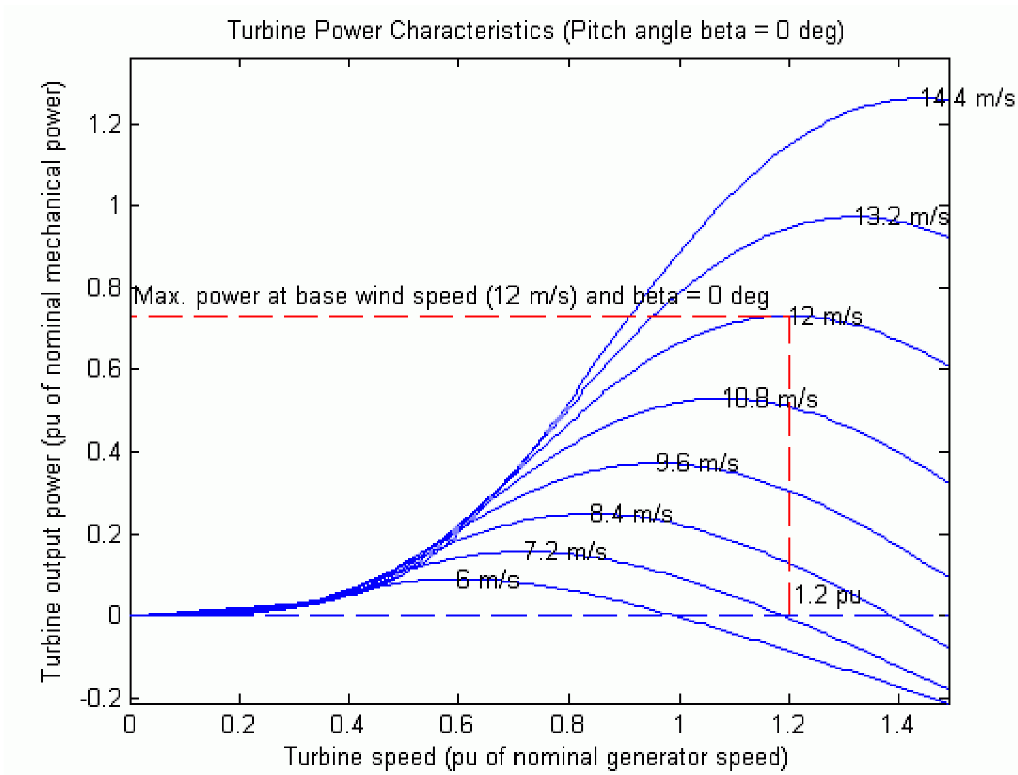


Figure 10: Mechanical power and Turbine speed on different wind speed with desired trajectory curve

Chapter # 4

SELF-LEARNING NEURO FUZZY CONTROLLER

4.1 Introduction

In this chapter we will explain in a generalized way the Self Learning Neuro fuzzy control method. In starting we will discuss the block diagram approach and further demonstrate each components of block diagram separately. In the end a summary of sequence of task need to be performed will be presented which will result in through understanding of reader.

4.2 Self Learning Neuro Fuzzy Controller:

The Neuro Fuzzy control strategy as shown in Fig.11 has been used to replace proportional controller of pitch angle and PI controller for torque controller used in MATLAB model.[11]

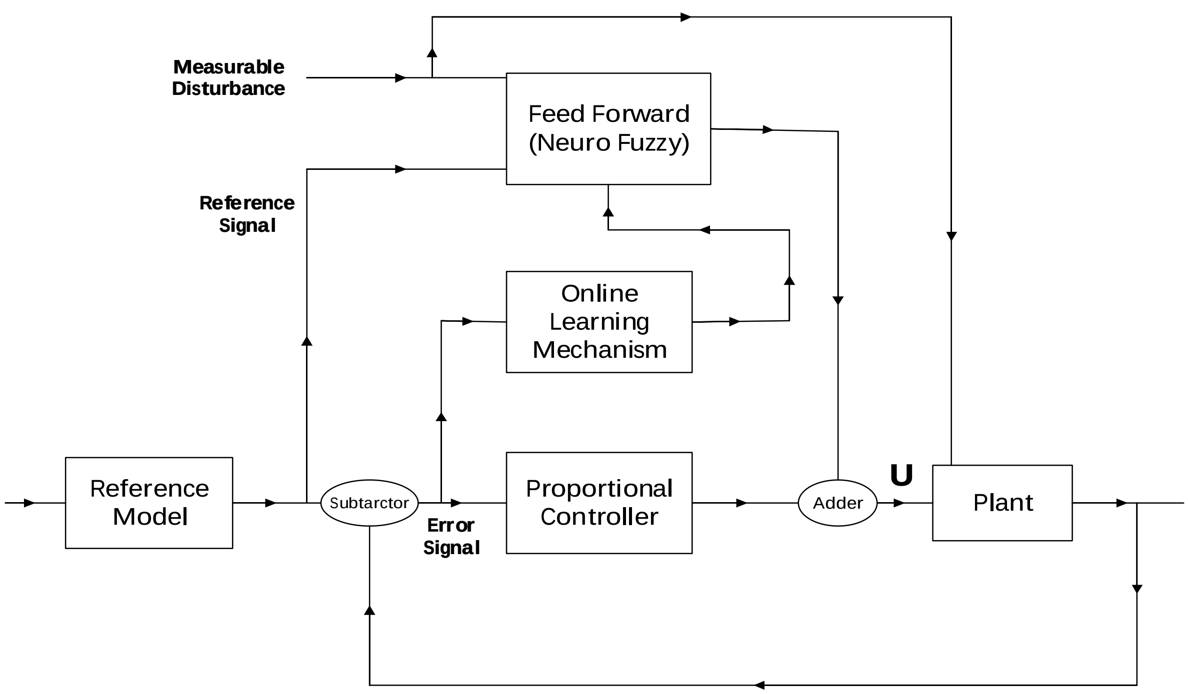


Figure 11: Self Learning Neuro Fuzzy Control Scheme

The self - learning neuro fuzzy scheme consists of four components.

(a) Rreference Model
(b) Neuro Fuzzy Feed Forward Controller
(c) Proportional Controller
(d) Online Learning Scheme

A. Reference Model:

The purpose of the reference model is to generate reference signal suitable for tracking by the controller. It can be any order of filter which provides a practical achievable reference trajectory for the plant keeping in view the physical constraints and plant dynamics.. It is generally a low pass/order filter which filters the step changes in the set point trajectory; hence controller is able to track it.

B. Feed Forward Controller:

The feed forward controller is a Neuro Fuzzy controller defined according to fuzzy relational model which combines fuzzy linguistic reasoning with neural network.

Fuzzy system comprises of if then rules and fuzzy sets. The fuzzy sets are the membership functions (Triangular, Gaussian etc.) of the inputs. In this paper triangular membership functions with partition of unity has been used for each input.

Rotor speed variation in our case is from 0 to 1.3, we made 14 triangular memberships functions with each of width 0.2 as shown below. Similarly, wind speed variation is from 0 to 30 m/sec, hence 12 Gaussian membership functions with width of 5 have been selected for wind profile.

The function representing Gaussian membership function can be written and shown in Fig 12

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2*\sigma^2}} \qquad 4$$

where

c *is the peak of gaussian membership function*

σ *is the width of the gaussian membership function*

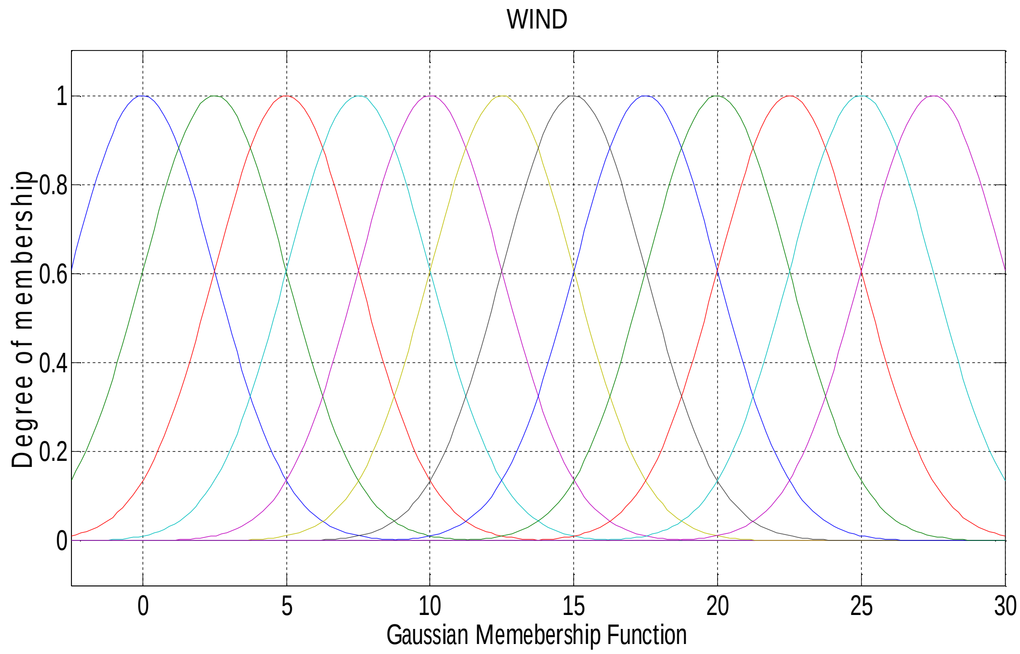


Figure 12: Gaussian Membership Function of Wind Speed

The function representing triangular membership function can be written as and depicted in

$$f(x;a,b,c)=\begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases} \qquad 5$$

where

a *is the start point of traingular membership function*

b *is the peak of the traingular mebership function*

c *is the end point of the traingular membership function*

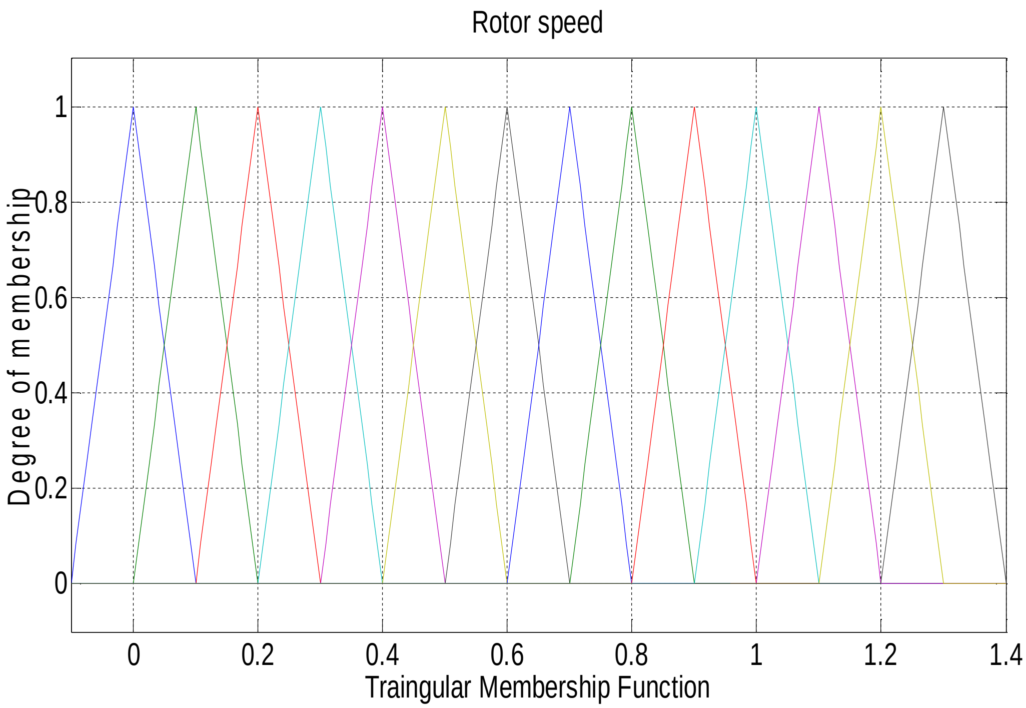


Figure 13: Triangular Membership Function of Rotor Speed

Now if each input universe of discourse consists of 'Pj' fuzzy membership functions and contains p number rules:

$$Rule\ 1: If\ \ x_1\ is\ A_{11},\ x_2\ is\ A_{21},,,,,,,\ and\ x_n\ is\ A_{n1},\ then\ u_f\ \ is\ w_1$$
$$Rule\ 2: If\ \ x_1\ is\ A_{12},\ x_2\ is\ A_{22},,,,,,,,\ and\ x_n\ is\ A_{n2},\ then\ u_f\ \ is\ w_2$$
$$Rule\ i: If\ \ x_1\ is\ A_{1i},\ x_2\ is\ A_{2i},,,,,,,,\ and\ x_n\ is\ A_{ni},\ then\ u_f\ \ is\ w_i$$
$$\vdots$$
$$Rule\ p: If\ \ x_1\ is\ A_{1p1},\ x_2\ is\ A_{2p2},,,,,,,,,and\ x_n\ is\ A_{npn},\ then\ u_f\ \ is\ w_p$$

Then, the output of feed forward controller will be (if weighted average defuzzification method is used for the case of partition of unity b/w triangular membership function) is given by

$$u_f(t) = \sum_{i=1}^{p} a_i(x(t))w_i(t) \qquad 6$$
$$u_f(t) = a^T(t)w(t),$$

Where

$u_f(t)$ *is feed forward control action at time t,*

$x(t) = [x_1, x_2, , , , , x_p]$ *is input vector at time t,*

$ai(x(t)) = \mu A_{1i_1}(x_1(t)) * \mu A_{2i_2}(x_2(t)) * * * * \mu A_{ni_n}(x_n(t)),$

is product of the membership grades of the input antecedent in the i^{th} *rule*

$a(t) = [a_1, a_2, , , , a_p]$ *is transformed input vector at time t,*

$w(t) = [w_1(t), w_2(t), , , , , w_p(t)]$ *is parameter vector.*

C. Proportional Controller:

The exact inverse plant model is difficult to obtain practically (if not impossible) without to compensate model mismatches and unmeasured disturbances, therefore proportional controller has been added in the feedback path to compensate finite modeling errors and unmeasured disturbances. The choice of controller in the feedback path either PI or PID as describe by TAN and Dexter [12] depend on user, proportional controller is selected in this because in order to tune few parameters of the feedback controller.

D. On Line Learning Scheme:

The goal of the online strategy is to find the values in the parameters vector, so that Neuro fuzzy controller is trained to act as the inverse plant model.

The online learning scheme is basically comprises of two separate scheme one is error back propagation algorithm and other is recursive NLMS or FLMS algorithm for parameter up gradation.

In order to train the feed forward controller, the weights regarding each rule should be present to the feed forward controller so that it should track the desired set point. As the parameter vector is unknown in the starting therefore an estimated parameter vector is presented to the controller so that it can generate an estimated desired control action first, which is fed to the plant. Due to estimated control action, a nonzero feedback error occurs due to inherent system 'td' delay. Now a new signal is required to track the desired output, which is given by

$$\tilde{u}_f(t) = u_f(t - t_d) + \gamma e(t) \qquad 7$$

where 'γ' the online learning rate, e(t) is the error signal and is the estimated desired control action. This error signal is used for model mismatches, and this approach in which error is propagate back is called **Feedback error learning scheme.**

Now

$$\{x(t - t_d), \tilde{u}_f(t)\}, \qquad 8$$

pair will be used in the Normalized Least Mean Square (NLMS) or Fuzzy Least Mean Square (FLMS) recursive learning mechanism to update the parameter vector. The choice whether to use NLMS or FLMS depends on computational demand.

NLMS algorithm is computationally undemanding but it has one disadvantage that it may corrupt the value of the parameter which was previously updated correctly. NLMS do so because it uses instantaneous pair of input and output data.

The NLMS equation to updated parameter is as follows

$$w(t) = w(t-1) + \frac{\delta a(t-t_d)}{a^T(t-t_d)a(t-t_d)}\varepsilon(t), \qquad 9$$

To alleviate the disadvantage of NLMS developed FLMS which take into account the strength and frequency of the particular rule that was occurred in the training data [11]

The FLMS equation to updated parameter is as below

$$w(t) = w(t-1) + \delta\frac{S(t-1)a(t-t_d)}{a^T(t-t_d)S(t-1)a(t-t_d)}\varepsilon(t), \qquad 10$$

Where,

$$S(t-1) = diag\{s_1, s_2, , , , s_i, , s_P\},$$

$$s_i = \prod_{j=1}^{p}, j \neq i \; F_j(t), \; F_i(t) = F_i(t-1) + a_i(t),$$

Measure the strength and frequency of the particular rule that was fired.

δ is the user selected parameter,

$$\varepsilon(t) = \tilde{u}_f(t) - uf'(t)$$

$$uf'(t) = a^T(t - t_d)w(t-1)$$

The user selected parameter as in equations (7), (8) and (9) can be obtained from equivalent model of the PI controller as described in [11]

4.3 Summary

After discussing the control scheme, sequence or steps required by the controller are as follows**.**

1. Estimate the desired control action $\tilde{u}_f(t)$ using equation (5)
2. Update the parameter vector using data pair $\{x(t-t_d), \tilde{u}_f(t)\}$, as mentioned in equation (6) for NLMS and equation (7) for FLMS
3. After updating the parameter vector, Calculate the desired control action using equation (4)
4. Calculate total control action using following equation

$$u(t) = u_f(t) + k_p * e(t), \tag{11}$$

Where 'k_p' is the proportional gain.

Chapter # 5

SIMULATION RESULTS

5.1 Introduction:

This chapter first describe the responses obtained from already build in proportional controller for pitch along with proportional plus integral controller for torque.

In the second part behavior of proposed controller scheme will be discussed with two cases; one without addition of noise to sensor inputs of the controller where as other is with added noise to sensor inputs.

In the last part a comparison of proposed scheme along with traditional controller will be carried out through RMSE

5.2 MATLAB Model Parameters:

In MATLAB Simulink Model of wind turbine phaser type, six wind turbines, each of 1.5 MW has been used to generate 10 MW which is fed into the grid. The first task of our control strategy is to maintain constant power around 9 MW delivered to the grid. Why not 10MW or 1 in per unit? The answer is quiet simple as some part of the power generated is consumed as reactive power by the system.

The next task is to regulate rotor speed ‘ωr’ around 1.21 to 1.3 which is desired speed during transition period of wind profile. How the value 1.21 and 1.3 is arrived or desired set point in our case?

The answer lies in the Fig 10. In this figure power tracking curve has been shown where red line is our desired trajectory which is need to be followed. This figure demonstrates with dotted line that at wind speed 12 m/sec the output power should be greater 0.7 per unit and turbine speed is 1.21. Similarly as wind speed increase the out power also increase to 0.88 to 0.9 per unit and turbine speed is around 1.3 per unit.

Therefore the target of the control strategy is to regulate rotor speed from 1.2 to 1.3 during transition period and demonstrate it through simulation.

5.3 Proportional & PI Response in Matlab Model:

In MATLAB model of wind turbine, proportional controller has been used to generate pitch angle and PI controller has been used to generate reference rotor current which in turn responsible for controlling torque & electric power.

The proportional gain and PI gains which has been used in MATLAB model has been listed in

CONTROLLING PARAMETER	COTROLLER	GAIN
PITCH ANGLE	Proportional	500
TORQUE CONTROL	Proportional Gain	1
	Integral Gain	100

Table 1 Controller Gain detail of the controllers

E. Response of Proportional and PI Controller without noise added to 'ωr' and electric power

The proportional and proportional plus integral controller response in rated and above rated speed region has been shown in fig 14 and fig 15. The power response is ideal and ωr response shows a dip in its behaviour during transition from rated wind speed 10 to 15 m/sec to above rated wind speed 15 to 20 m/sec.

The dip in 'ωr' is due to overshoot in pitch angle response during transition period of wind speed. Now it would be task if this dip could be removed or smoothen with new proposed control strategy

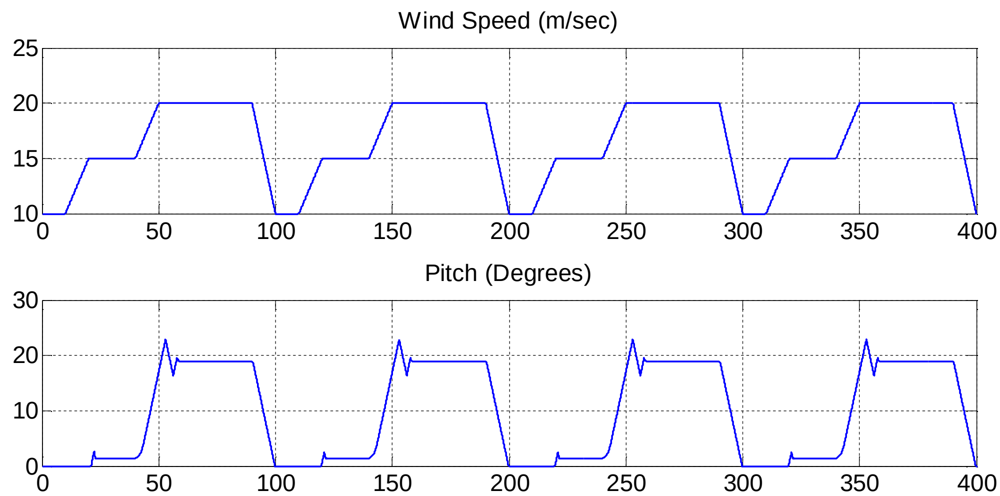


Figure 14: Wind Speed and pitch angle response of Proportional Controller

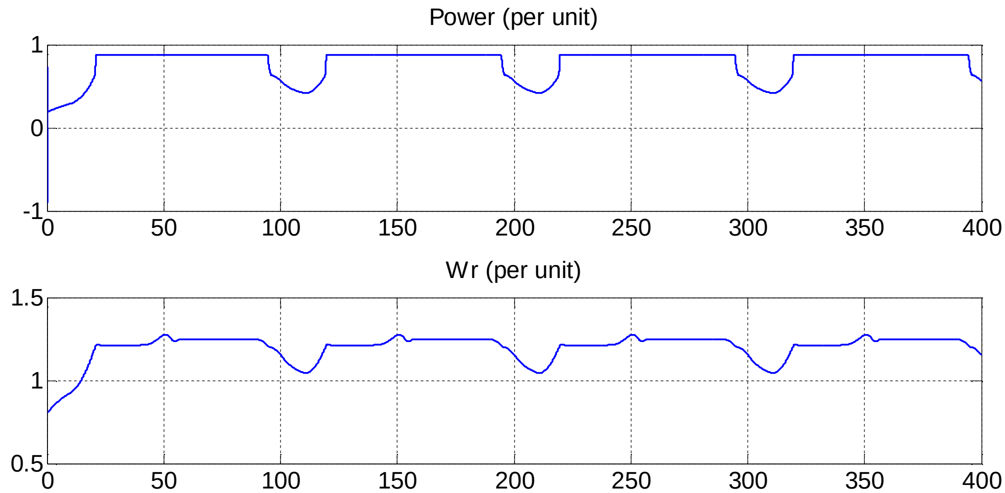


Figure 15: Power and ωr response of P & PI controller without noise added to ωr and power

F. Response of Proportional and PI Controller with noise added to 'ωr' and electric power

The behaviour of the proportional and PI controller with the addition of noise in ωr and electric power has been demonstrated in Figure 16 and Figure 17. The addition of noise in sensor inputs produces variable ωr and dips in generated power. This behaviour is unreliable for synchronization with the grid and drastic for wind turbine in respect to both mechanical and electrical

The next objective of our proposed controllers is to handle noise while removing dips in power and produce smoothness in ωr.

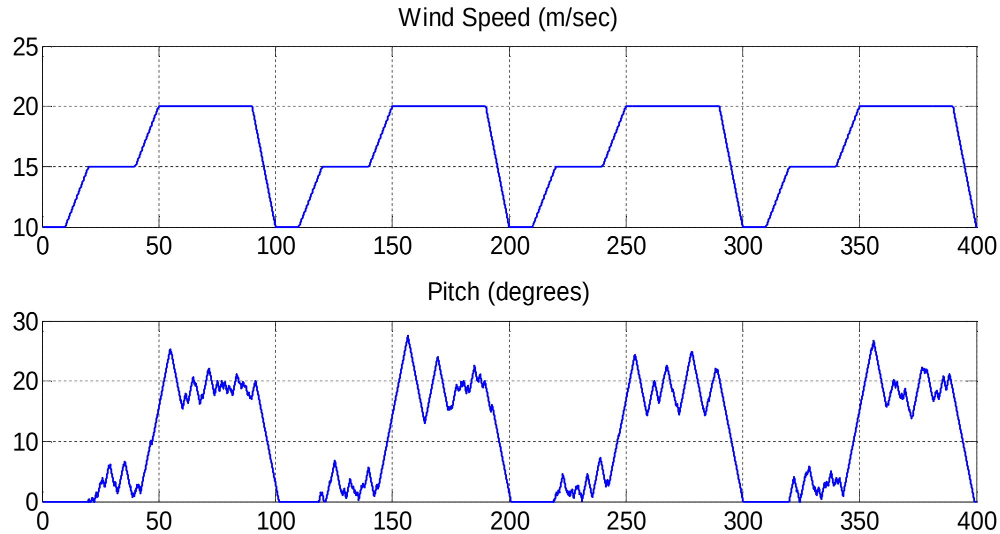


Figure 16: Wind Speed and pitch angle response of Proportional Controller

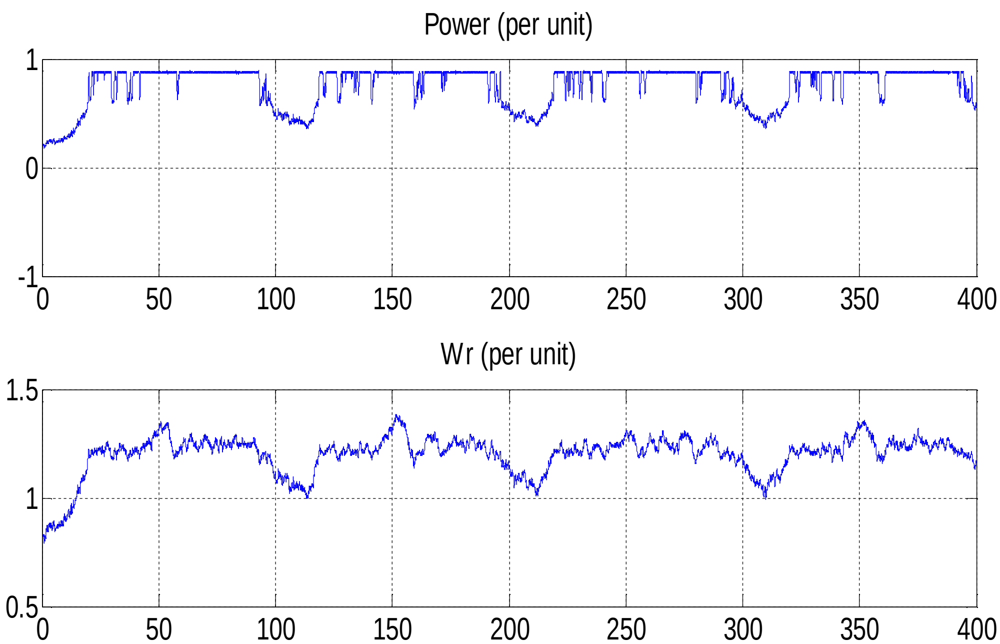


Figure 17: Power and ωr response of P & PI controller with noise added to ωr and power

The RMSE value obtained when noise added to inputs of both proportional and PI controller has been listed below.

Noise in ωr	**Controller**	**RMSE**
0.01	Proportional Controller for Pitch Angle Control	0.0729
0.02		0.07192
0.03		0.07564
0.04		0.07212
0.05		0.07416
0.06		0.07256
0.07		0.07588
0.08		0.07876
0.09		0.07872
0.1		0.07244

Table 2: RMSE values when noise added to measured ωr of proportional controller

Noise in Power	**Controller**	**RMSE**
0.01	Proportional Integral Controller for Torque Control	0.01853
0.02		0.01735
0.03		0.01672
0.04		0.01621
0.05		0.01522
0.06		0.01563
0.07		0.0148
0.08		0.01499
0.09		0.01447
0.1		0.0145

Table 3: RMSE values when noise added to measured power of PI controller

5.4 Block Diagram of Proposed Controllers

The self-learning neuro fuzzy control strategy is applied to control the pitch angle as well as the torque of a wind turbine as shown in Figure 18 & Figure 20

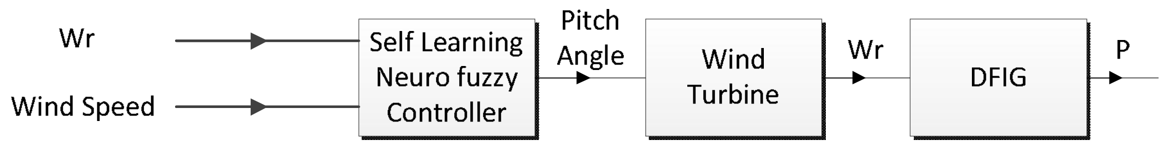


Figure 18: Control Loop of Pitch Angle Control

The pitch angle control turbine rotor speed obtained through Tacho generator, a generator whose output voltage is proportional to shaft speed, velocity of wind speed turbine is determined through anemometer, an instrument use to measure the flow of air.

The wind speed is used for two propose in the control loop; one it is used to obtain reference rotor speed and second one it serves an another input for the proposed feed forward and online learning scheme. The measured rotor speed is subtracted from the reference 'ωr', to generate error signal which is feed to Feed Back Error Learning block of the proposed controller. The Simulink block diagram of self-learning neuro fuzzy pitch controller is shown in Fig 19

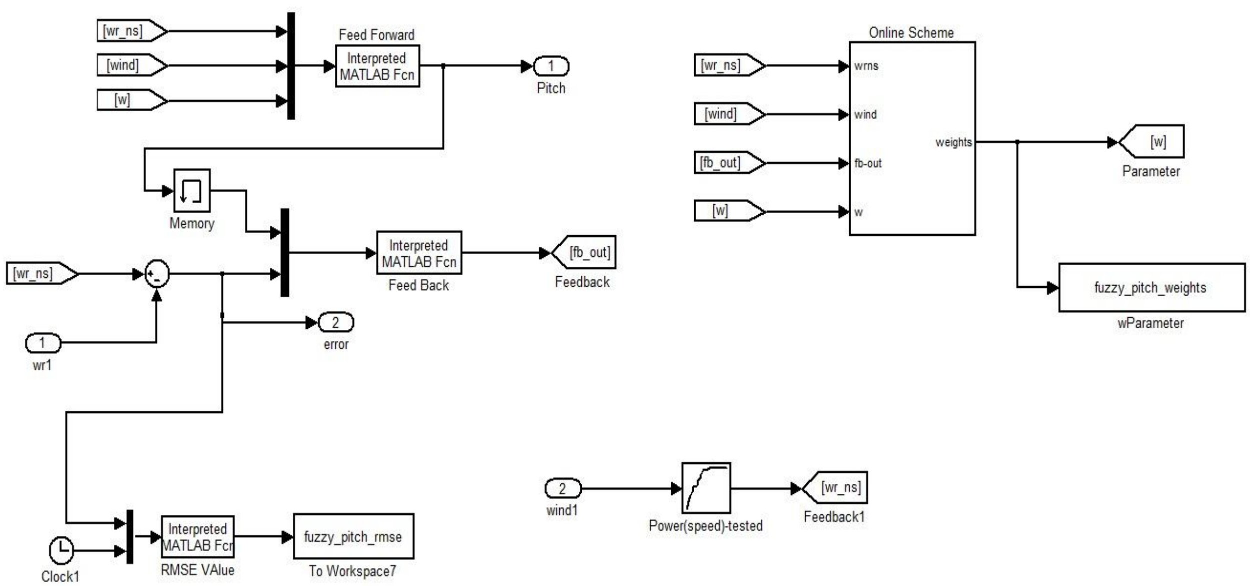


Figure 19: Simulink Block Diagram of Self Learning pitch Controller

The reference signals of ‘ωr’ and ‘wind speed’ have been used in feed forward and on line learning blocks of self-learning neuro fuzzy controller, design to generate pitch angle.

The pitch angle has to vary in MATLAB Simulink Model from 0 to 45 with the rate of 2 degree /sec and ‘ωr’ is to be regulated around 1.2 to 1.3 in per unit.

In chapter 3, it has been discussed that feed forward controller and online learning mechanism is to be designed according fuzzy relational model. Keeping in mind this, zero order Takage Sugeno fuzzy system is selected as weights are associated with each rule in this system which will be updated till error becomes zero. Membership functions with partition of unity between the two functions have been defined for both reference signals i.e. ‘ωr’ and wind speed already shown in Fig 12 & Fig13

The Gaussian type membership function has been defined of reference Wind Speed signal and triangular type membership is defined for rotor speed ‘ωr’. The wind speed varies from 0 to 30 m/sec with 12 membership functions while reference ‘ωr’ input has been defined from 0 to 1.4 with 14 membership functions. The total no of rules which has been used in proposed control scheme of pitch angle is 168. The task of control strategy is to find the weights associated with each rule which results in desired results of our pitch angle and rotor speed.

The self - learning neuro torque controller’s inputs are measured power, rotor speed (ωr) and reference electric power.

In torque angle control loop, the reference power obtained from the tracking power characteristics curve as shown in Fig 10. This reference power and measured power at the grid side compared and the resultant is used in feedback error learning scheme for torque controller as shown in Fig 20

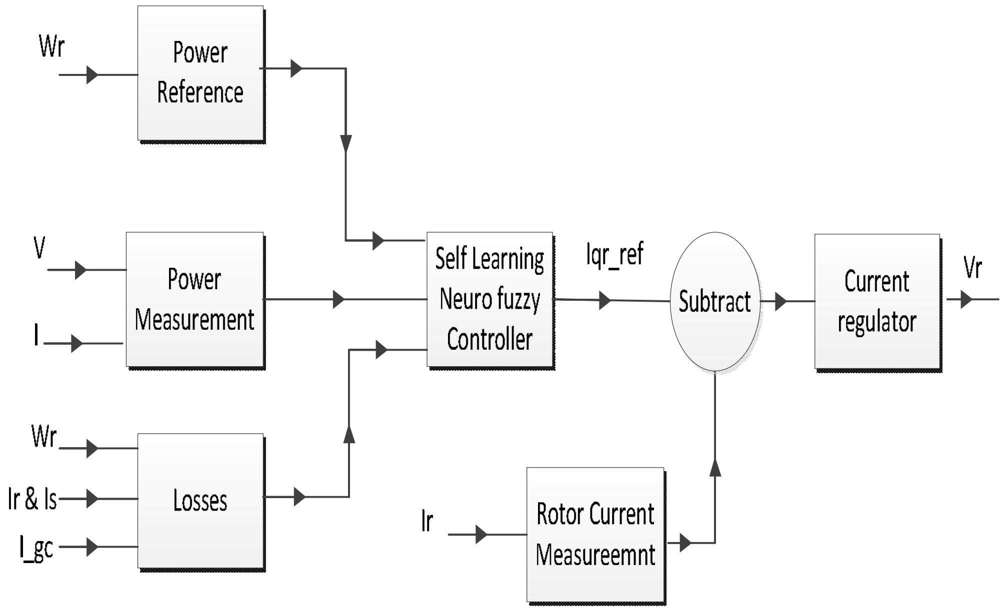


Figure 20: Control Loop of Electromagnetic Torque Control

The rotor speed and reference power used in same way as discussed above in feed forward and on line learning scheme of self -learning neuro fuzzy control. The complete Simulink Block of electromagnetic torque control has been shown in Fig 21 and detail Simulink block of self –learning neuro fuzzy torque control has been shown in Fig 22

In self-learning neuro torque controller 14 memberships functions are defined in the range 0 to 1.3 for ‘ωr’ and 10 memberships functions from 0 to 0.9 in per unit are defined for reference power. The total 140 rules are used in self-learning torque Neuro fuzzy controller. Similar as pitch angle controller, each rule of neuro fuzzy controller has associated weights as shown in Fig 22 which have been updated in such a way to obtained constant power in the rated and above rated wind speed regions.

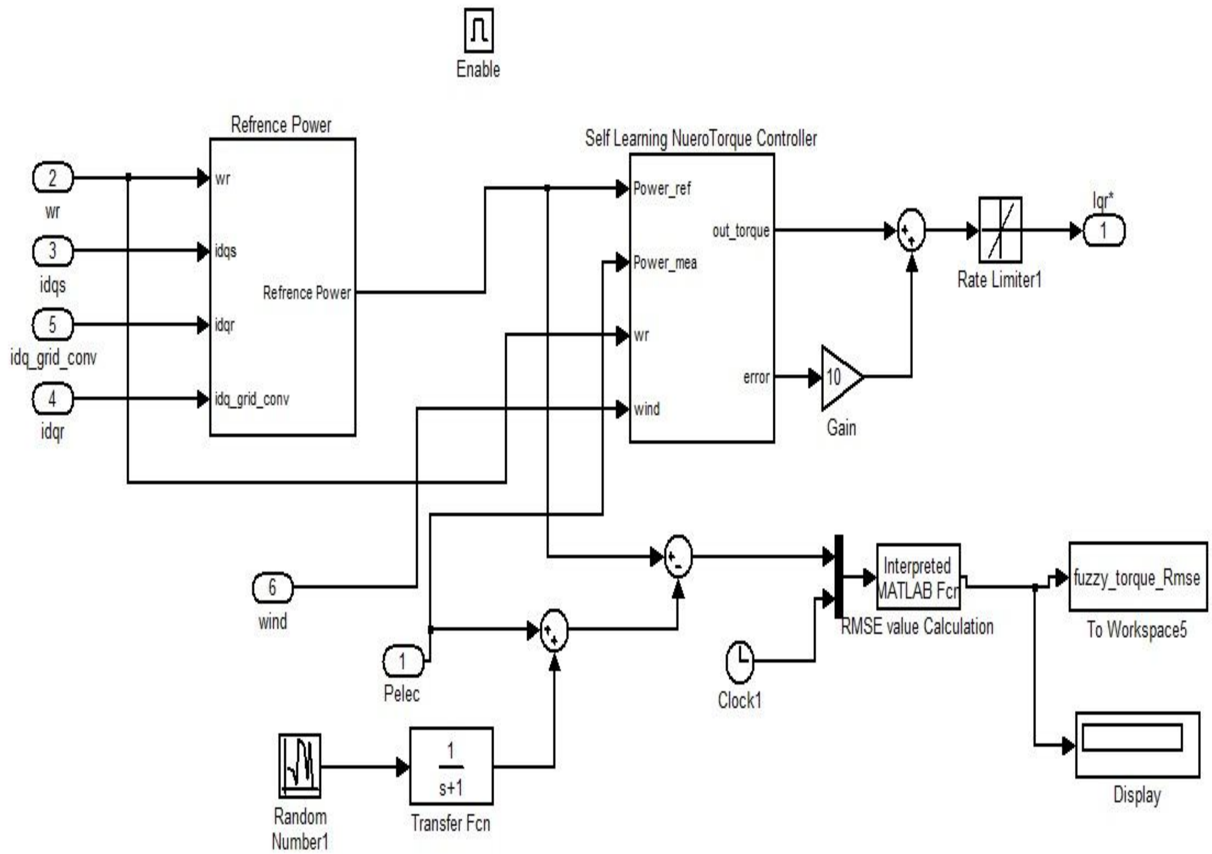


Figure 21: Simulink Block Diagram of Electromagnetic Torque Control

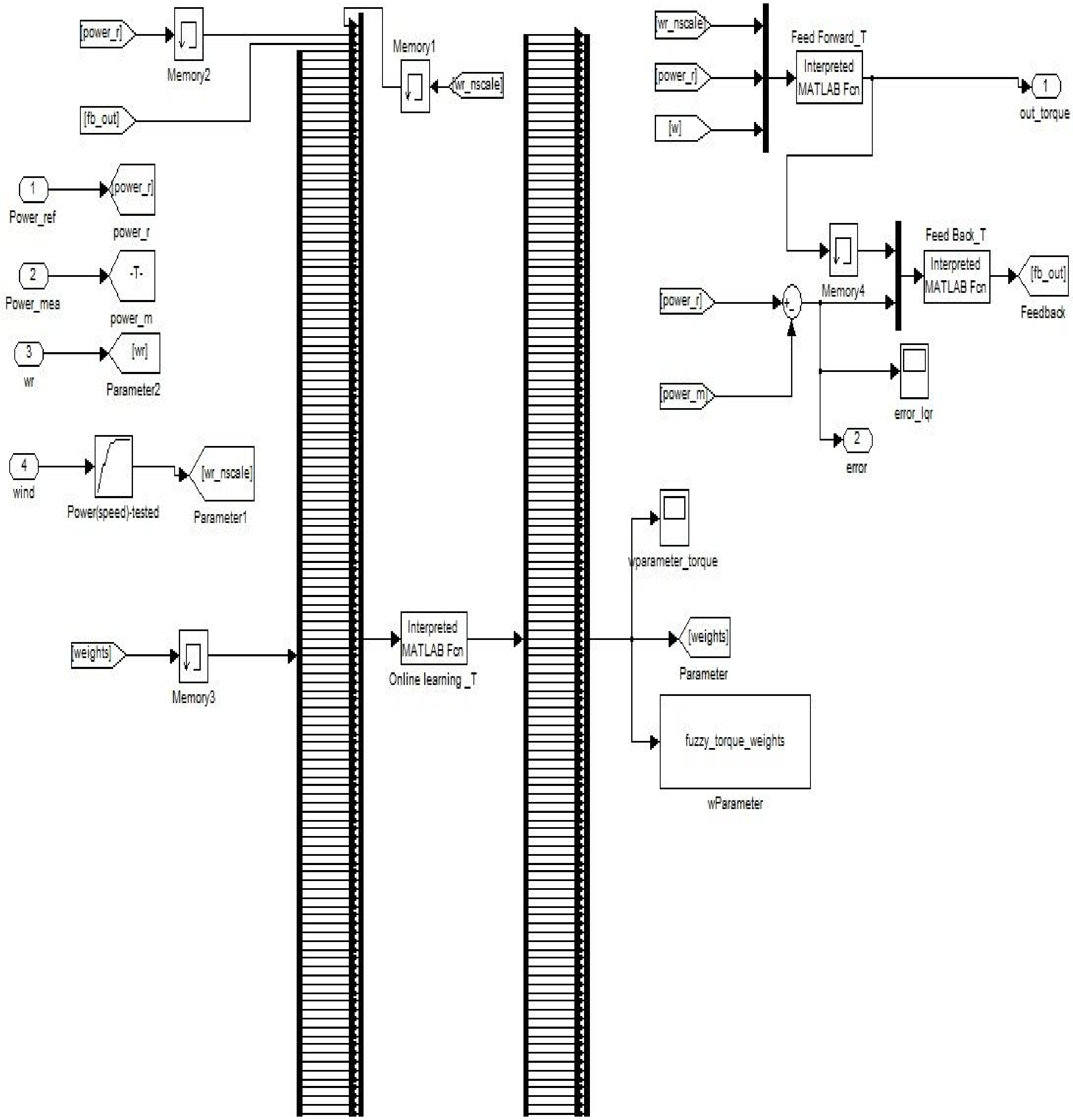


Figure 22: Simulink Block Diagram of Self Learning Neuro Torque Controller

To check the above mentioned approach and find the weight convergences of the controller, we will take two cases. In first case wind speed profile is varied from 10 m/sec to 20 m/sec without any disturbance such as noise added to any input of the controller coming from sensor i.e. ‘ωr’ and electric power. In Second Case wind speed profile variation is remain same as in first one but random noise is inserted in controller inputs of ‘ωr’ and electric power.

5.5 Simulation Results of the Proposed Controller

G. CASE 1: without noise added to Measured 'ωr' and Electric Power:

Wind Profile under consideration i.e. from 10 to 20 m/sec is being repeated four times to study the learning or adaptation behaviour of both proposed self-learning neuro fuzzy controllers.

Wind speed variation from 10 to 20 m/sec along with proposed controller responses to generate pitch angle has been depicted in Fig.23 whereas pitch angle variation effect on 'ωr' has been shown in Fig 24 along with resulted power response of self-learning torque controller.

During rated speed region of wind (10 to 15m/sec) the pitch angle varies from 0 to 4 degree/sec which is desired to obtain optimum value of 'Cp' already discussed in above chapters and to maintain constant 'ωr' up to 1.2 per unit.

When wind speed switches from rated to above rated speed region (15 to 20 m/sec), the pitch angle varies from 4 degree /sec to 19 m/sec in two steps as shown in Fig 23 for smooth transition of 'ωr' from 1.2 to 1.3 depicted in Figure 24

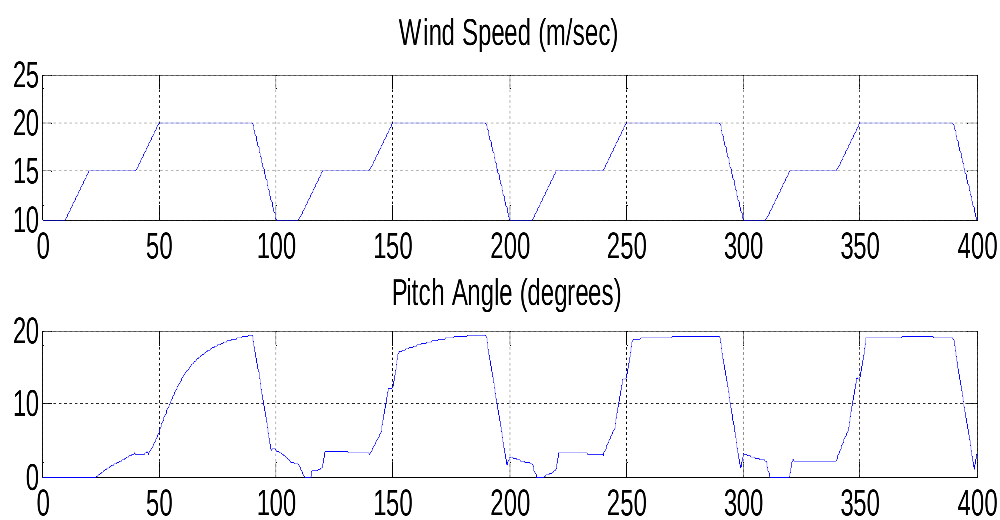


Figure 23: Wind Speed and pitch angle response without noise added to ωr and power

The self-learning neuro fuzzy torque controller has to maintain constant power around 0.88 to 0.9 in per unit during rated and above rated speed regions of wind profile. The power response has been shown in Fig 24 along with 'ωr'. In the learning phase the power remain below 0.88 and converges to 0.88 in above rated speed region. The power response, after the end of three iterations of wind profile gets better and after end of learning phase the power get converges to 0.88.

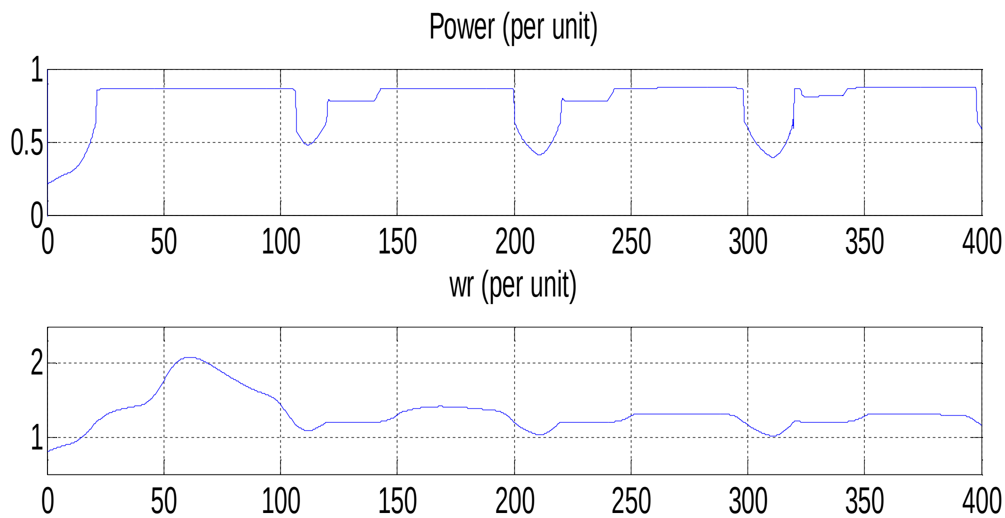


Figure 24: Power and ωr response without noise added to ωr and power

The obtained simulation results and controller responses for Case one show the adaptation or learning behaviour of the proposed controllers as shown in Fig 23 and Fig 24. During the three iterations of wind profile out of four iterations, both pitch angle and torque self –learning neuro fuzzy controllers were learning and tuning their weights parameters associated with each rule. That is why we see dip in power and overshoots in 'ωr' which settle down to their desired values in last two wind profile iteration value once the parameters of the controller tuned.

The tuning and saturation of associated parameters of both self-learning neuro fuzzy controllers have been shown in Fig 25 and Fig 26, as 168 and 120 weights are associated with both self – learning neuro fuzzy pitch and torque controllers respectively, out of them few parameters have been selected which describe the saturating effects.

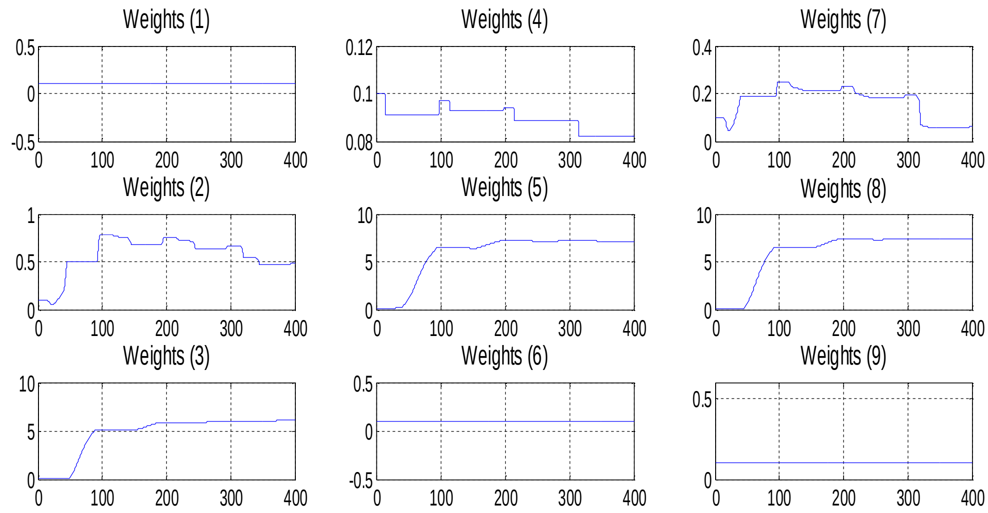


Figure 25: Weights of Self–Learning Pitch Controller, when no noise added to ωr and power

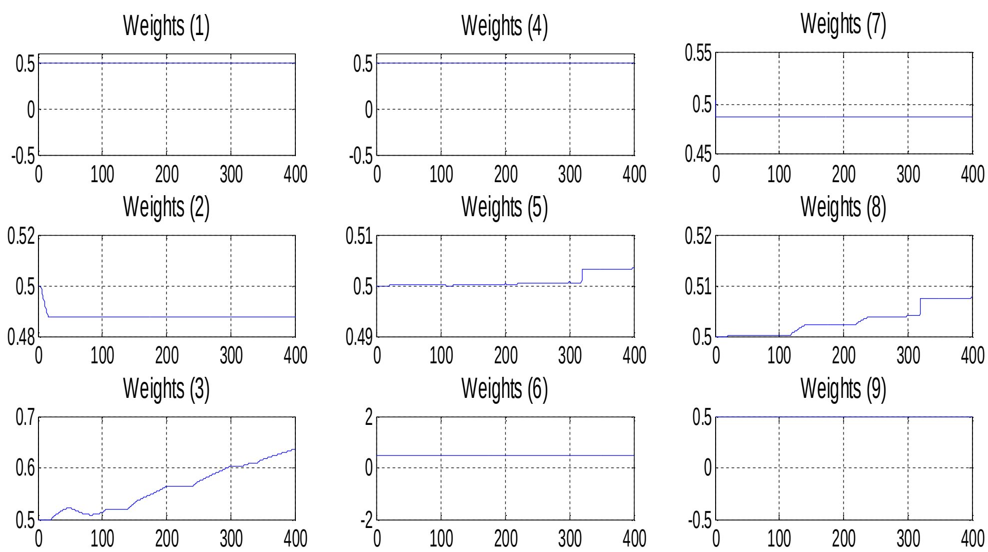


Figure 26: Weights of Self–Learning Torque Controller, when no noise added to ωr and power

The Learning or adaptation ability of the proposed controllers can also be verified from Fig 27 and Fig 28 in which reference signal is compared with the generated output of the controller.

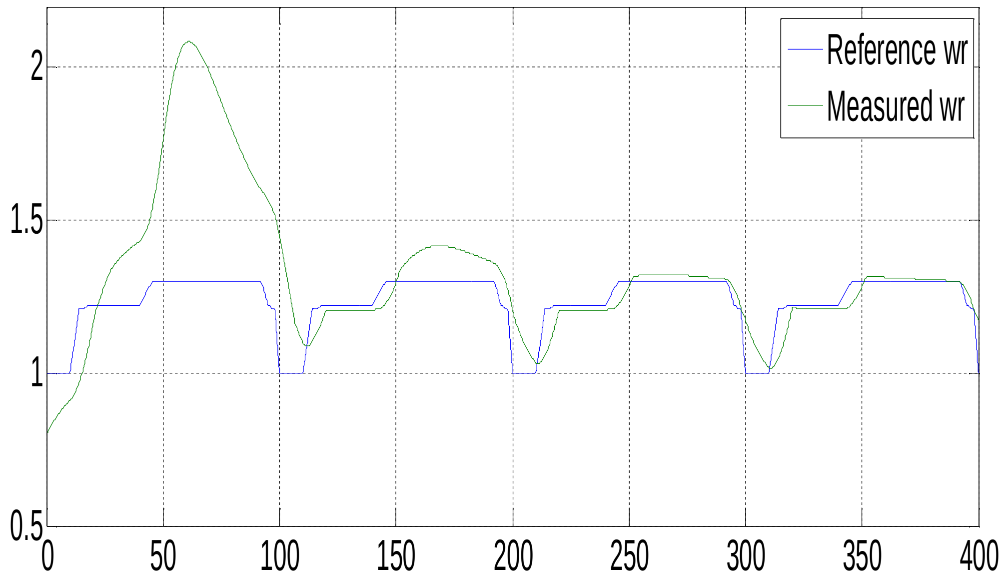


Figure 27: Comparison of Reference ωr and Generated ωr

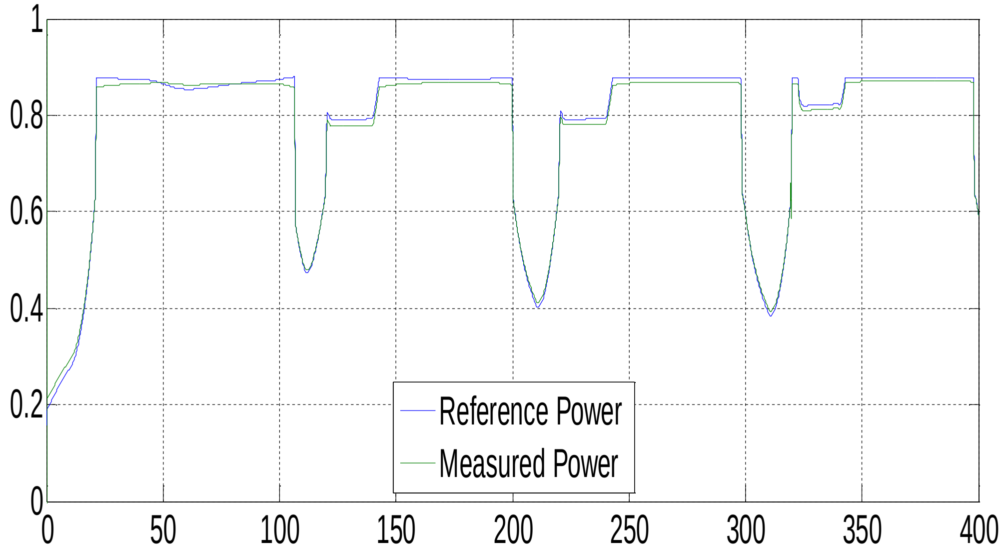


Figure 28: Comparison of Reference Power and Generated Power

H. CASE II: With Noise Added to Measured ‘ωr’ and Electric Power:

In this scenario, to check response of both proposed controllers, random noise is added to their inputs i.e. both ‘ωr’ and electric power

The pitch angle variation as shown in Fig 29 is found same as describe in Case I despite of noise addition in ‘ωr’. The continuously adjustment in pitch by the self –learning Neuro controller is due to the adaptation behaviour so that desire results obtained in ‘ωr’. During the first three iteration of wind speed, the pitch angle continuously adjusted until the fourth iteration. After the end of the third iteration of wind speed, most of associated weights associated with each rule are tuned to get desired ‘ωr’ response as shown in Fig 30.

The during rated speed region ‘ωr’ remains to 1.2 per unit and smooth transition occur in ‘ωr’ from 1.2 to 1.3 when wind speed varies from 15 m/sec to 20 m/sec.

The electric power response generated by self- learning neuro fuzzy controller is shown in Fig 30. In the first two iteration of wind speed, a dip from 0.88 to 0.7 in electric power observed at rated wind speed region i.e.10 to 15m/sec which converges to 0.88 in above rated wind speed region i.e. 15 to 20 m/sec. This behavior is due to learning and adaption ability of the proposed controller. This dip is completely removed in the fourth iteration of wind speed after the tuning of the associated weights with each rule by the proposed controller.

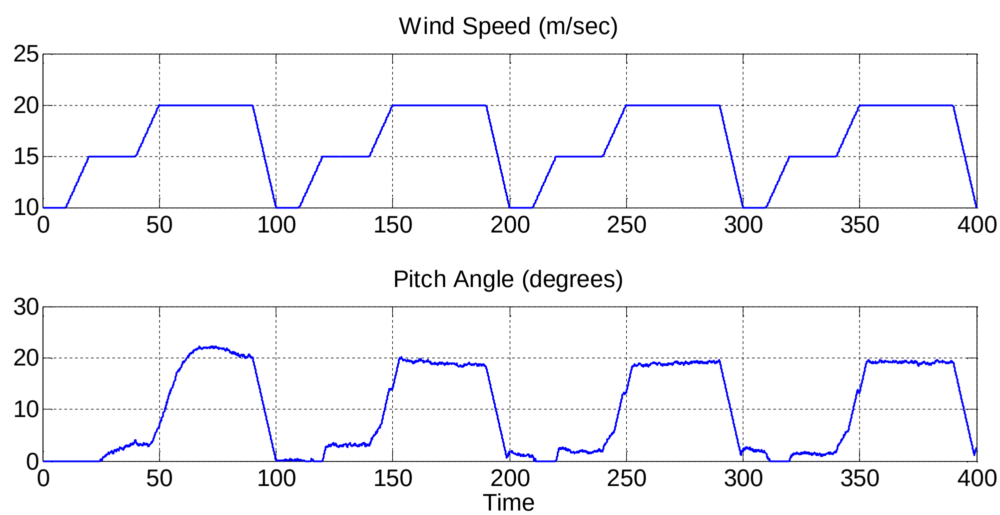


Figure 29: Wind Speed and pitch angle response with noise added to ωr and power

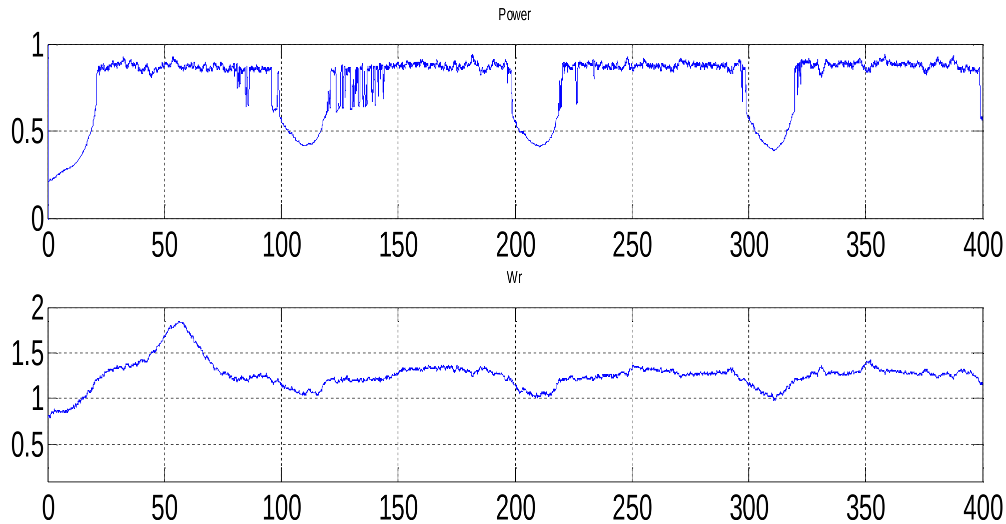


Figure 30: Power and ωr response with noise added to ωr and power

The behavior of the associated weights with each rule of both self –learning neuro fuzzy controllers have been shown in Fig 31 and 32.

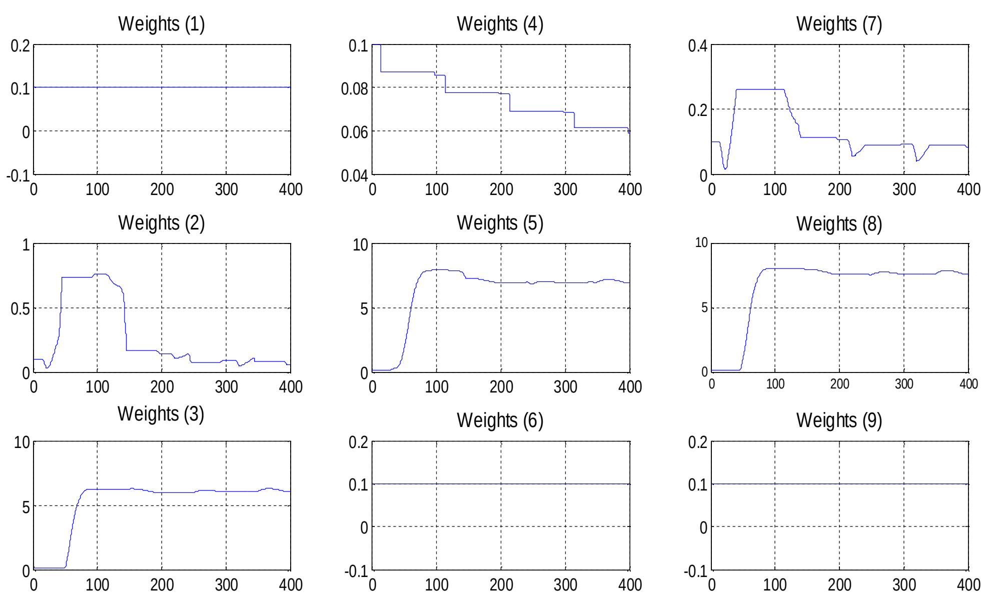


Figure 31: Weights of Self–Learning Pitch Controller, when noise added to ωr and power

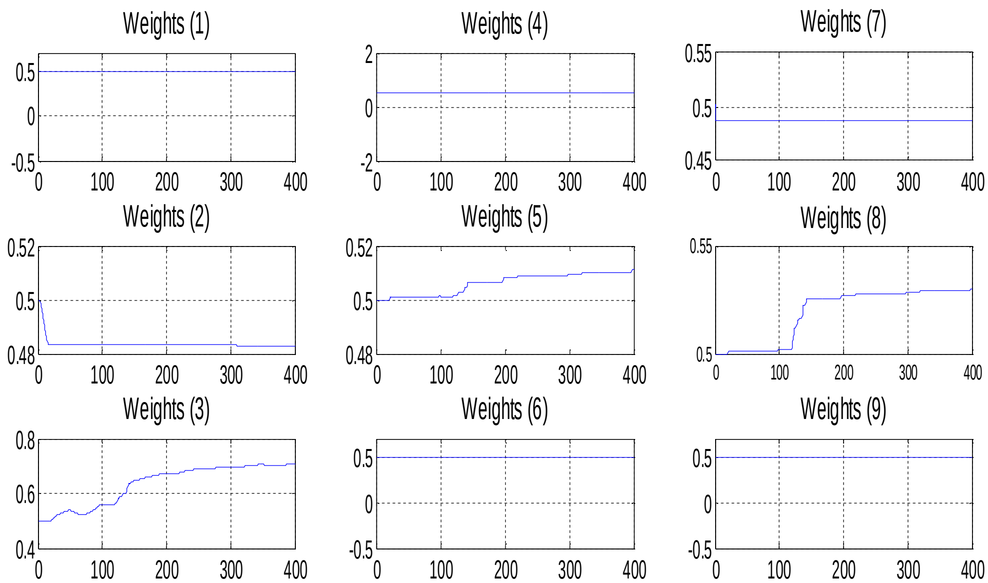


Figure 32: Weights of Self–Learning Torque Controller, when noise added to ωr and power

The combine response of reference and generated ωr and power are shown in Fig 33 & Fig 34.

The dip in reference signal of power is due to ωr as reference power is generated by turbine characteristics curve in which 'ωr' is used as input.

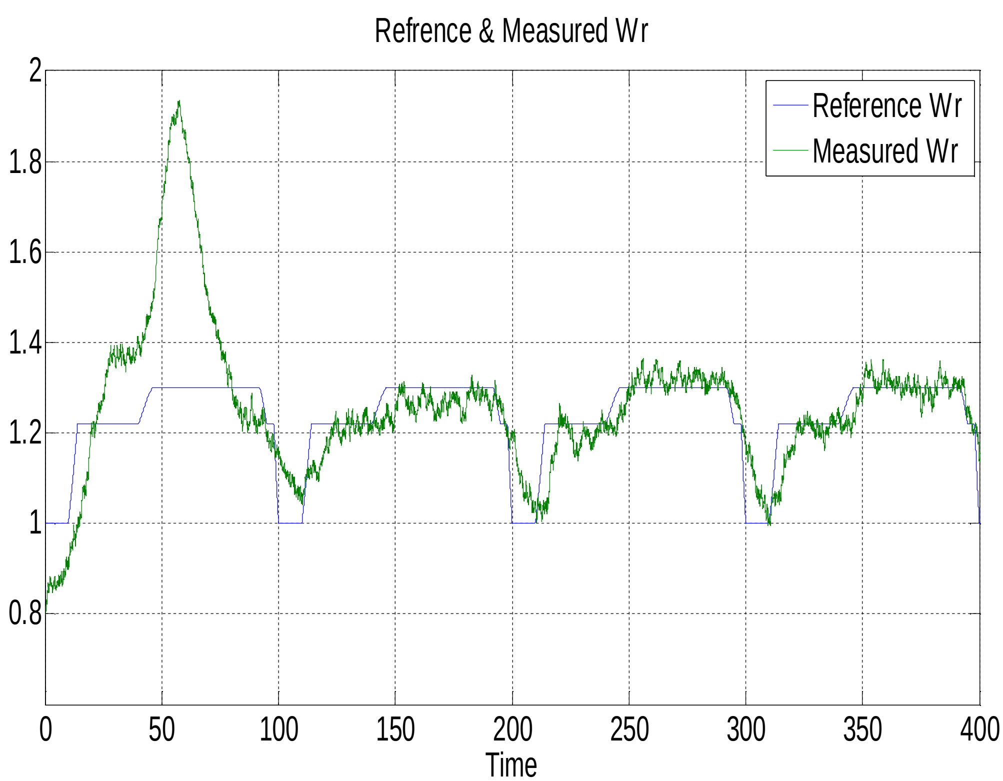


Figure 33: Comparison of reference ωr and measure ωr

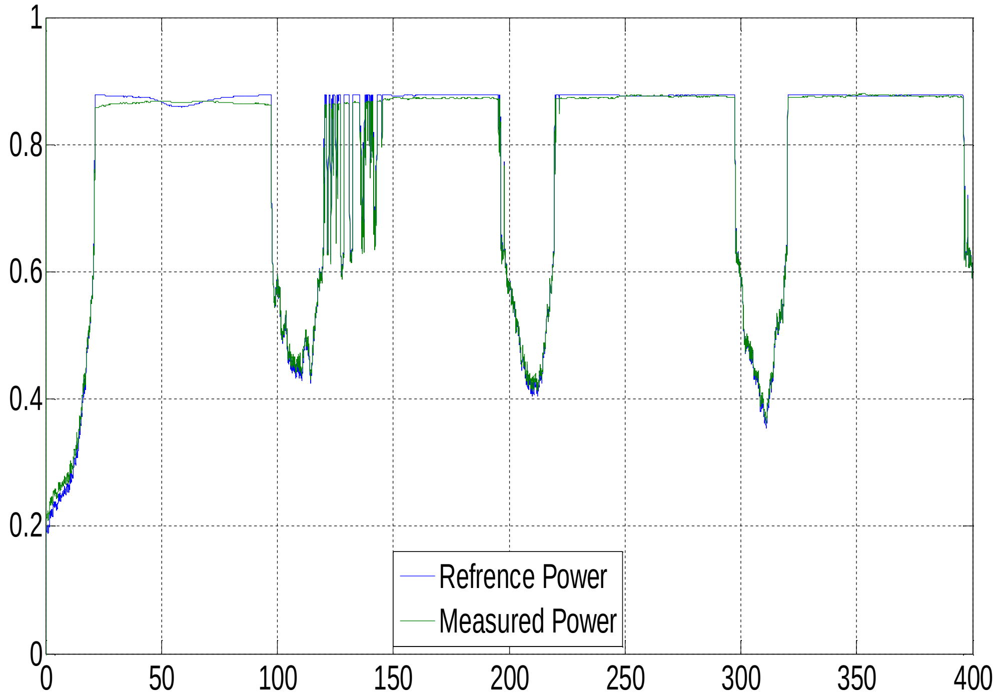


Figure 34: Comparison of reference power and measure power

The RMSE values of both self-learning neuro fuzzy controller for the comparison with proportional & PI controller have been tabulated below.

Noise in ωr	Controller	RMSE
0.01	Self –Learning Neuro Fuzzy Pitch	0.05803
0.02		0.04699
0.03		0.04359
0.04		0.04881
0.05		0.05341
0.06		0.0506
0.07		0.04549
0.08		0.04981
0.09		0.05344
0.1		0.05029

Table 4: RMSE values when noise added to measured ωr of Self Learning Pitch controller

Noise in Power	Controller	RMSE
0.01	**Self –Learning Neuro Fuzzy Torque**	0.007398
0.02		0.007339
0.03		0.006255
0.04		0.005486
0.05		0.005247
0.06		0.005463
0.07		0.004807
0.08		0.004595
0.09		0.004731
0.1		0.00541

Table 5: RMSE values when noise added to measured power of Self Learning Torque controller

5.6 Quantitative Analysis of Controllers through RMSE:

Quantitative Comparison of classical controllers with proposed self-learning fuzzy controllers have been shown in Figures 35 and 36, which shows superiority of self –learning neuro fuzzy control scheme.

Noise in ωr	RMSE Comparison	
	Proportional Controller	**Self –Learning Neuro Fuzzy Pitch**
0.01	0.0729	0.04517
0.02	0.07192	0.04094
0.03	0.07564	0.04137
0.04	0.07212	0.04297
0.05	0.07416	0.0439
0.06	0.07256	0.04511
0.07	0.07588	0.04696
0.08	0.07876	0.04228
0.09	0.07872	0.05344
0.1	0.07244	0.04854

Table 6: RMSE Comparison when noise added to measured ωr

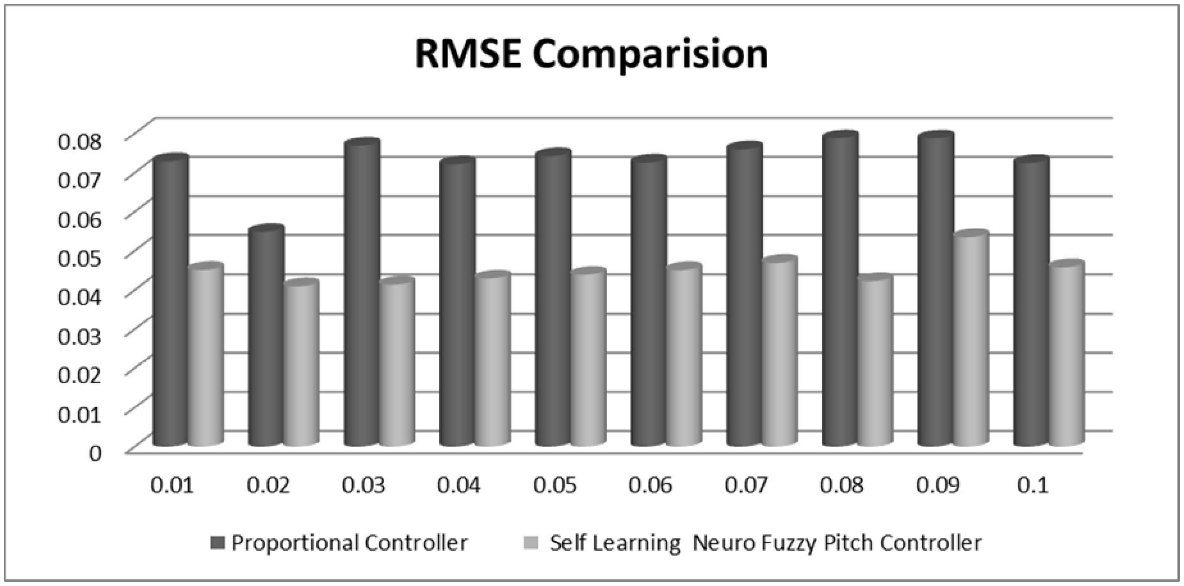


Figure 35: Bar Graph showing RMSE Comparison of Pitch Controller

Noise in Power	RMSE Comparison	
	Proportional Integral Controller	Self –Learning Neuro Fuzzy Torque
0.01	0.01853	0.00775
0.02	0.01735	0.006757
0.03	0.01672	0.009371
0.04	0.01621	0.007282
0.05	0.01522	0.006057
0.06	0.01563	0.005413
0.07	0.0148	0.005676
0.08	0.01499	0.005554
0.09	0.01447	0.004731
0.1	0.0145	0.006009

Table 7: Comparison of RMSE when noise added to measured power

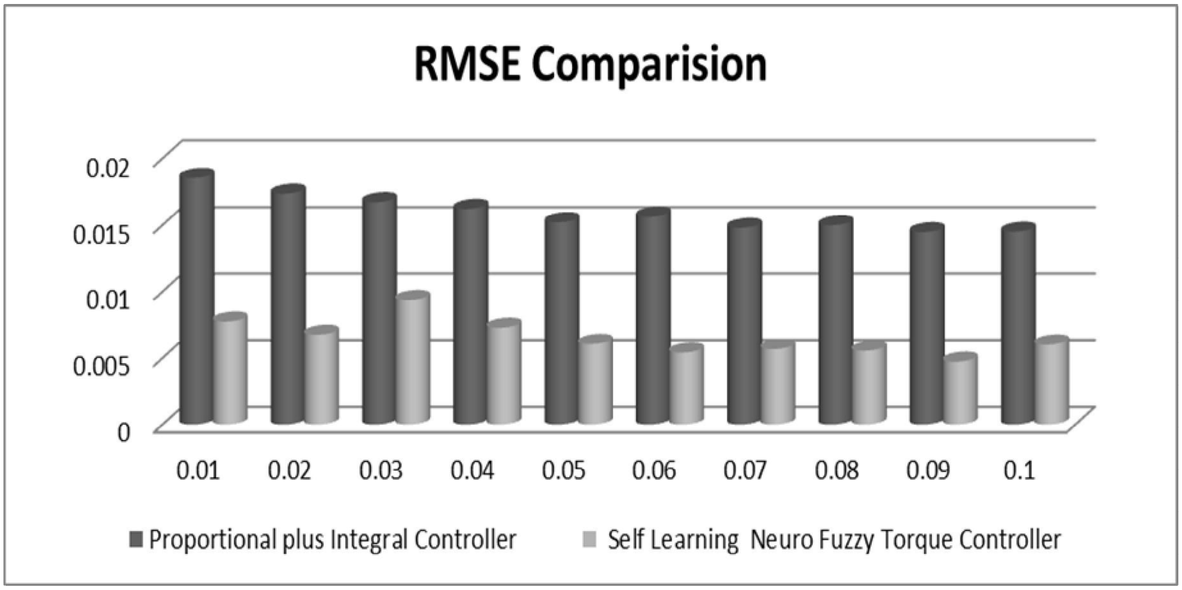


Figure 36: Bar Graph showing RMSE Comparison of Torque Controller

Chapter # 5

CONCLUSION & FUTURE RECOMMENDATIONS

6.1 Conclusion:

The objective of this thesis was to develop an online self-earning neuro fuzzy controller so that it can handle the non-linearity of the wind turbine without knowing much about the plant as well as disturbances caused by the noise added by the sensor installed in the field. The convergence of the weighting parameter vector of both self –learning neuro fuzzy pitch controllers shows the satisfactory performance over classical proportional & PI controllers. The results are further supported by quantitative analysis of RMSE values obtained when random noise is added to both ωr and power.

The development of the self –learning neuro fuzzy controller is step towards development of single MIMO self–learning neuro controller which can handle both pitch and torque. The other helpful references which help in writing this thesis are [13-20]

6.2 Future Recommendations:

In this research work we have replaced the classical controller with the self-learning neuro fuzzy controller and their results are quite satisfactory.

These results have been obtained by using NLMS in the online learning scheme which can be improved if research carried out in using FLMS in the online learning scheme.

So far the work has been carried out in this research is on SISO controller, now other aspect or improvement or advancement can be made if both self -learning neuro fuzzy controllers are being replaced with the single MIMO neuro fuzzy controller.

The one part of designing of MIMO control action is the SISO controller which has already been done , but now two coupling controllers are to be designed whose output are added to the control action of the SISO which further smoothness the responses of the controller. A one of the proposed MIMO structure has been shown below in Fig 37[21]

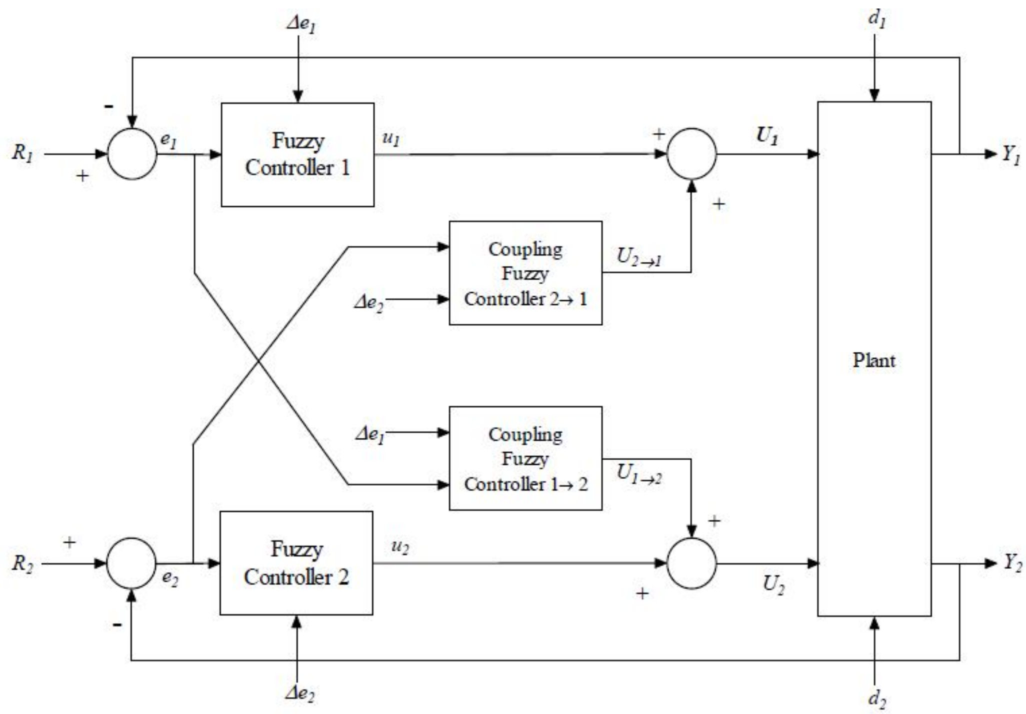


Figure 37: MIMO Fuzzy Controller Scheme

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