PITCH ANGLE CONTROL OF WIND TURBINE

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THESIS

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Summary

In case of wind turbine Induction generators which are directly connected to grid a control problem arises when the wind speed increases above the rated wind speed, some measure needs to be taken to limit the aerodynamic torque of the wind turbine in order to keep the output power at its rated value. For this purpose various controlling variables may be chosen, like generator speed and generator power and wind speed. One of the popular approach is to use PI controller because it is easy to implement and has been widely used in the industry. Problem with PI controller is that over the period of time with the variation in plant parameters, gains of the PI controller needs manual tuning. Here we have tried to implement self-learning neuro-fuzzy controller proposed by (W.W. Tan, 1999) to control the pitch angle of the wind turbine when the wind speed is above the rated speed. The self-learning neuro-fuzzy logic control strategy has the potential when the system contains strong non-linearity, such as wind turbulence is strong.

The self-learning neuro-fuzzy model will try to develop the inverse plant model of the system and will use that to generate the required control action in order to keep the output at its rated value. In order to carry out this comparison we have used WTIG (wind turbine induction generator) from Simulink distributed resources. The design of the self-learning neuro-fuzzy control and its comparison with the PI controller has been carried out in different wind profiles and overall results show that self-learning neuro-fuzzy controller can give better results in presence of strong wind disturbances.

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CHAPTER-1

INTRODUCTION

1.1 Objective

The wind turbine is an energy conversion device that takes energy from the wind and converts it into useful work (Muyeen, 2010). Almost all of the wind energy conversion systems are connected to the grid of electric power networks. Although the main objective of wind turbine operation is to optimize energy capture, other technical and environmental Objectives should also be satisfied such as mechanical loads, power quality standards, acoustic emission and obstruction. These objectives are actually a tradeoff among each other. Thus, the WECS (Wind energy conversion system) should find a well-balanced compromise among them. Due to the requirement in speed control, different wind velocities separate the operation into three operating regions as shown in Fig. 1-1, which represents a typical power curve of a wind turbine. The cut-in velocity (vcut-in) is defined as the wind speed at which the turbine starts to generate the power. Below this wind speed, it is not efficient to turn on the turbine. The rated velocity (vrated) is the wind speed at which the turbine reaches its rated turbine power. The cut-out velocity (vcut−out) is the maximum wind speed at which the wind turbine can still operate. Beyond this wind speed, the rotor has to be locked to keep the blades, the electrical generator and other components from reaching damage (Muyeen, 2010).

Region I covers a wind speed range between vcut−in and vrated and is referred as the below rated wind speed region. The control objective in region I is to extract the maximum power from the wind. Region II covers a wind speed range between vrated and vcut−out and is referred as the above-rated wind speed region. As the mechanical power generated by the rotor is limited, the main task of a controller in this region is to keep output at its rated power. Our region of interest is region II.

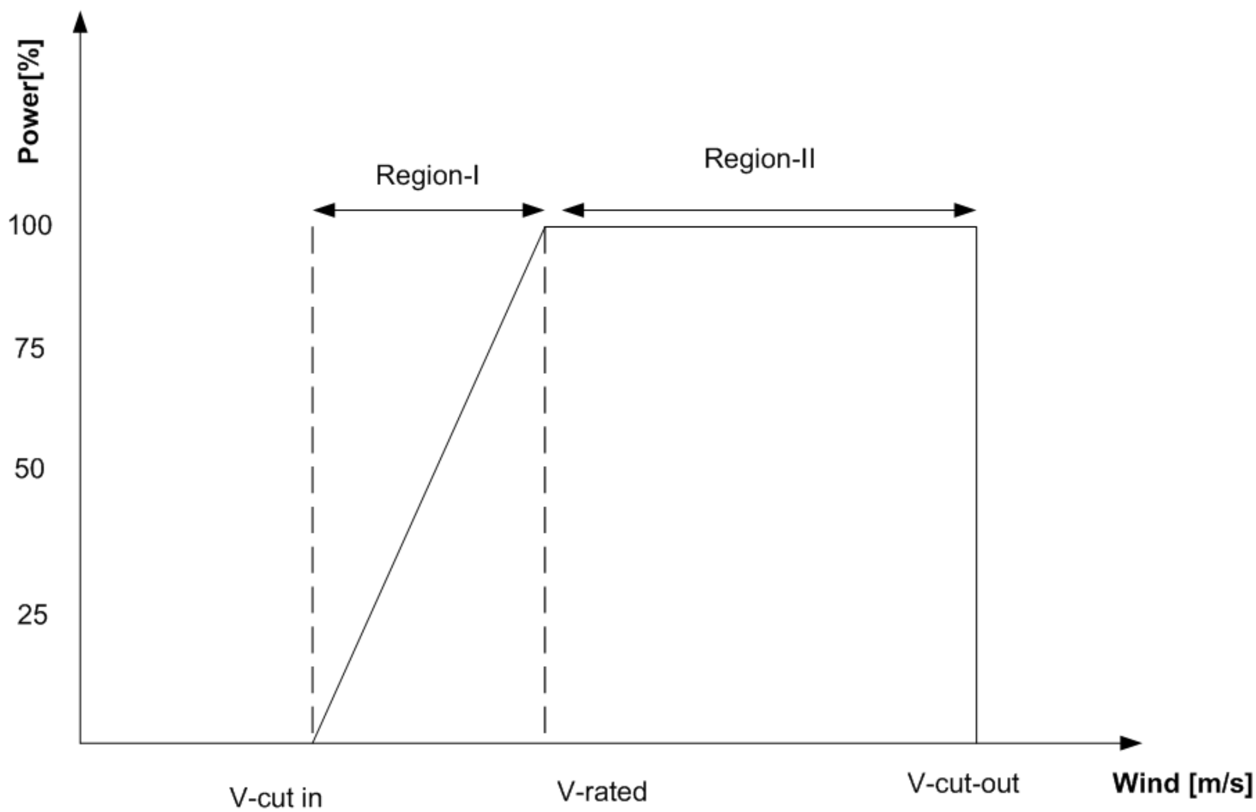


Figure 1-1 Regions Of Operation Of Wind Turbine (Muyeen, 2010).

1.2 Research motivation

About fifteen thousand billion kWh of electricity are generated each year worldwide (Ari Reeves, 2003). Out of this about sixty five percent is produced by burning fossil fuels and the remainder is obtained from other sources, including nuclear, hydropower, geothermal, biomass, solar and wind energy (Ari Reeves, 2003). About 0.3% of this power is produced by converting the kinetic energy in the wind into electrical energy (Ari Reeves, 2003). However, the use of wind for electricity generation has been expanding rapidly in recent years, due largely to technological improvements, industry maturation and an increasing concern with the emissions associated with burning fossil fuels. There is still more room to grow, as only a small portion of the useable wind resource is being tapped. Government and electrical industry regulations, as well as government incentives, play a large role in determining how quickly wind power is adopted (Ari Reeves, 2003). Effective policies will help level the playing field and ensure that wind can compete fairly with other fuel sources in the electricity market. The wind energy market has flourished because of the environmental advantages of acquiring a clean and inexhaustible energy source and because of the economic benefits supplied by several governments (Abdulsada, 2010).However; there are still many open challenges in expanding wind power. The standard controls as well as recently developed advanced controls for pitch control of wind turbine induction generator have been investigated.

1.3 Benefits of wind power

Wind power has many benefits that make it an attractive source of power for both utility-scale and small distributed power generation applications. The beneficial characteristics of wind power include (Ari Reeves, 2003).

- **Inexhaustible and Clean fuel**

  Wind power has no emissions and is not depleted over time. A single one megawatt (1 MW) wind turbine operating for one year can displace over 1,500 tons of carbon dioxide, 6.5 tons of sulfur dioxide, 3.2 tons of nitrogen oxides, and 60 pounds of mercury (based on the U.S. average utility generation fuel mix) (Ari Reeves, 2003).

- **Economic development**

  Wind plants provide a steady flow of income to owners who lease their land for wind development, while increasing property tax revenues for local communities (Ari Reeves, 2003).

- **Modular and scalable technology**

  Wind applications can take many forms, including large wind farms, distributed generation, and single end-use systems. Utilities can use wind resources strategically to help reduce load forecasting risks and stranded costs (Ari Reeves, 2003).

- **Price & Energy stability**

  By further diversifying the energy mix, wind energy reduces dependence on conventional fuels that are subject to price and supply volatility (Ari Reeves, 2003).

Reduced dependence on imported fuel wind energy expenditures are not used to obtain fuels from abroad, keeping funds closer to home, and lessening dependence on foreign governments that supply these fuels.

1.4 Emphasis on renewable energy resources in Pakistan and international market

Government of Pakistan is putting greater emphasis on Renewable Energy and has set a target of 10% renewable energy or 2700 MW in the Country's energy mix by 2015" (Power and Alternative Energy Asia). Pakistan, like other developing countries of the region, is facing a serious challenge of energy deficit. Renewable Energy resources can play an important role in bridging this deficit. More importantly, Renewable Energy can take electricity to remote rural areas, where power transmission becomes too expensive. The Government of Pakistan aims that all localities not planned to be connected with national grid in next 20 years, be earmarked for Alternative Renewable Energy resources and the solar/wind energy related technologies be indigenized in next decade through international collaboration (Power and Alternative Energy Asia).

As need for energy increase around the world, renewable energy sources that will not harm the environment are highly desirable. Some analysis indicate that the global energy demand will be almost threefold by 2050.Renewable energy resources currently supply about 15% and 20% of total world energy demand (Abdulsada, 2010). WECS is a rapidly-growing interdisciplinary field that encompasses many different branches of engineering and science. American Wind Energy Association states that the installed capacity of wind grew at an average rate of 29% per year (Abdulsada, 2010).In 2009, the installed capacity of wind energy was about 159MW. The prediction capacity for 2010 was over 203 MW (Abdulsada, 2010). The wind energy market has flourished because of the environmental advantages of acquiring a clean and inexhaustible energy source and because of the economic benefits supplied by several governments (Abdulsada, 2010). Pakistan has a considerable potential of wind energy in the coastal belt of Sindh, Baluchistan and as well as in the desert areas of Punjab and Sindh. This renewable source of energy has however, not so far been utilized significantly.

The Wind Data of all Pakistan has been collected from Pakistan Metrological Department and analyzed by AEDB. As per the collected data, the coastal belt of Pakistan is blessed with a God gifted wind corridor that is 60 km wide (Gharo ~ Kati Bandar) and 180 km long up to Hyderabad (Khalil, 2004-05). This corridor has the exploitable potential of 50,000 MW of electricity generation through wind energy (Khalil, 2004-05). In addition to that there have been some other wind sites have been exploited in coastal area of Balochistan and some Northern areas. Most of the remote villages in the south can be electrified through micro wind turbines. It is estimated that more than 5000 villages can be electrified through wind energy in Sindh, Balochistan and Northern areas. With the efforts of AEDB, aggressive lobbying for investment has been done with national and international investors to make them realize the potentials of renewable particularly the wind energy. Working papers with national and international companies have been signed. Till date, 34 Location of interest have been issued for 1700 MW wind power generation projects (Khalil, 2004-05).

About seven companies have already applied for the generation licenses of 50 MW each through wind energy (Khalil, 2004-05). Also, for the indigenous production of various components of wind turbines in Pakistan WTMC (Wind Turbine Manufacturing Consortium) has been formed. The Board is negotiating with international companies to start micro wind turbine manufacturing and manufacturing of parts of large wind turbines in this consortium. So far, large wind turbines for power generation have not been installed in Pakistan. However, about 30 wind mills for pumping water have been installed for experimental purposes in different parts of Sindh and Balochistan (Khalil, 2004-05). In addition to the development activities in wind energy field for on grid electricity production, the wind energy is also being used for the electrification of remote off grid villages in the southern coastal areas of Pakistan. So far more than 18 villages have been electrified using micro wind turbines. Indigenous development of micro wind turbines has also commenced in Pakistan (Khalil, 2004-05).

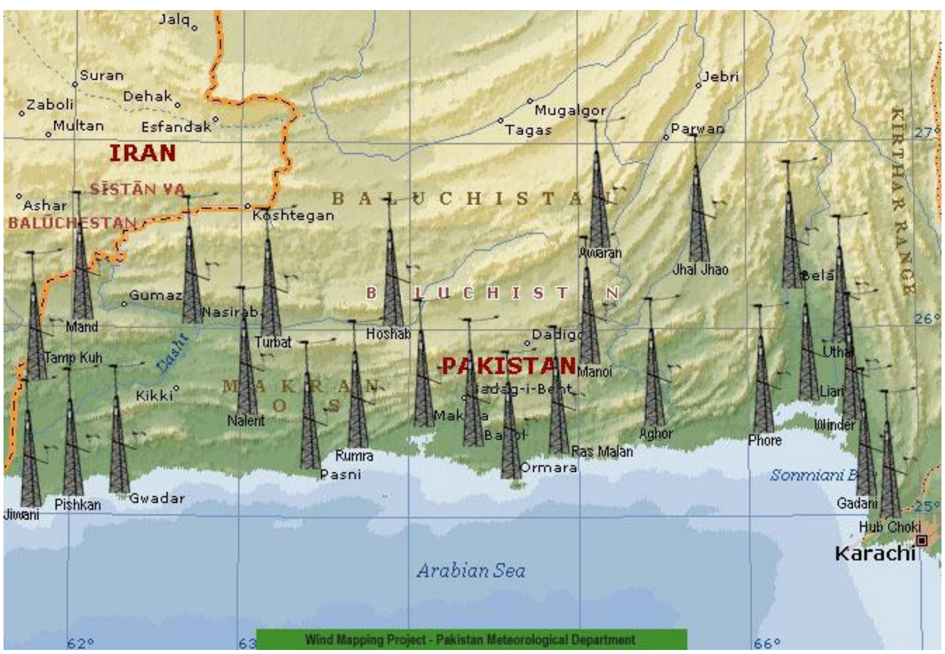


Figure 1-2 Wind stations in Balochistan

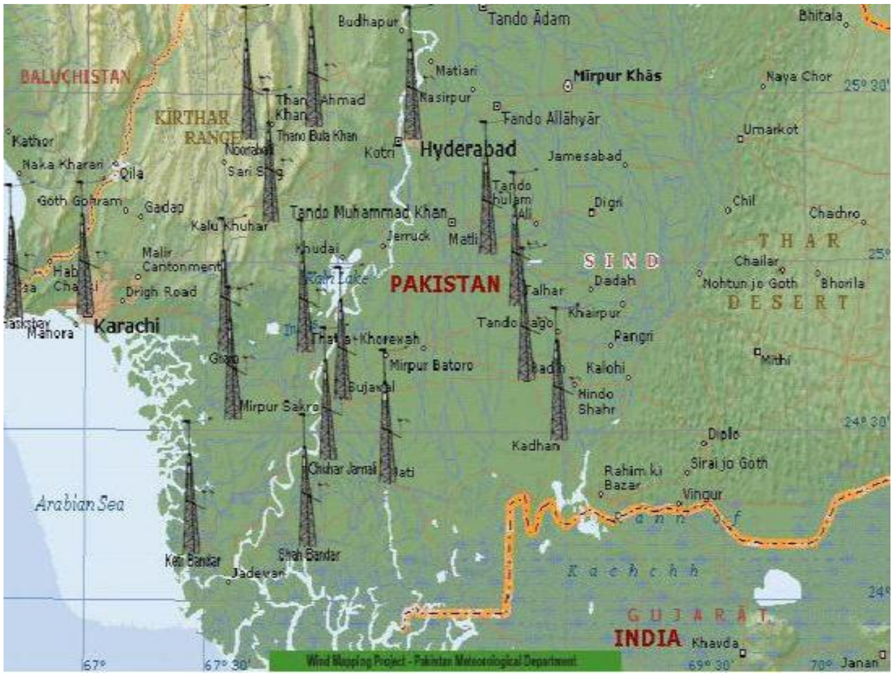


Figure 1-3 Wind Stations in Sindh

Table 1-1 Wind Power Generation Plan in Pakistan

YEAR	GENERATION PLAN	COMMULATIVE OF WIND ENERGY IN PAKISTAN
2011	200	900 MW
2012	200	1100 MW
2013	150	1250 MW
2014	200	1450 MW
2015	250	1700 MW
2016	250	1950 MW
2017	400	2350 MW
2018	400	2750 MW
2019	500	3250 MW
2020	500	3850 MW

1.5 A note from wind turbine industry

The pitch (Angle at which wind contacts the blade of the wind turbine) control of wind turbines is based today on PID controllers. Due to the non-linear behavior of the turbines, the design of these controllers is usually a very time-consuming affair. The use of fuzzy controllers in future promises a faster and more efficient procedure. Nils Johannes, who works in the Wind Turbine Application Software Department at the Beck off Wind Expertise Centre in Lübeck/Germany, presents an overview of fuzzy pitch control (BecKhoff, 2011).

Modern wind turbines control the power extracted from the wind by changing the rotor blade angle (BecKhoff, 2011). The wind generates a lift force at the rotor blades which results in a rotary movement of the rotor. However, from a wind speed of approx 12 m/s , the power taken up as a result by the rotor would be larger than the rated output of the wind turbine and must therefore be limited. To this end the inflow angle of the wind is modified by adjusting the rotor blades, thereby reducing the rotor output. This method of regulating the speed via the blade angle is usually called pitch control. The associated control loop is highly non-linear, primarily as a result of the aerodynamic behavior of the rotor blades. In modern wind turbines, therefore, the PID controller employed is supplemented by filters and further additional functions such as gain scheduling (BecKhoff, 2011).

In designing the mechanical construction of a wind turbine, the loads acting on the turbine are decisive. They form a spectrum of extreme loads and fatigue loads. The former can be reduced through intelligent operational management, the latter through careful parameterization of the speed controller (BecKhoff, 2011).

The pre-configuration of the controller parameters takes place as part of the load calculation for a wind turbine (BecKhoff, 2011). A turbine computer model is subjected to standardized wind profiles in simulation runs. Competing optimization criteria have to be taken into account in the controller design. The optimization process can, therefore, be complex and protracted, since several iteration loops are required before the optimum can be determined. The “optimum” determined in this way is still only a best possible compromise. In addition to this pre-configuration, it is usually necessary to optimize the parameters determined in the simulation during commissioning of the turbine. This process can also be rather complex, since the required wind speeds are not available 'on tap' and, moreover, only occur for a limited period of time, depending on the site (BecKhoff, 2011).

Unlike the PID controllers that are predominantly used today, fuzzy controllers are non-linear state controllers with a reputation for great robustness. It is known from other applications with similar boundary conditions that the use of fuzzy controllers in highly non-linear systems leads to better control characteristics (BecKhoff, 2011).

The difficult stability check and the lack of a systematic design procedure are often mentioned as disadvantages of fuzzy controllers. In order to check the stability, a model would be required, which could in turn be used for the adjustment of a PID controller. However, the fuzzy controller needs only an indistinct mathematical model and not a detailed one. In the case of wind turbines the model is always only a reproduction, since the real conditions of the wind, turbulence and aerodynamics can only ever be approximated. Changes in the air density, the rotor blades and the inertia in the drivetrain are already enough to cause great changes in the aerodynamic behavior of the rotor (BecKhoff, 2011).

PID controllers are based on the model of the turbine, to which the parameters are oriented. If the model changes, the control quality is automatically reduced. Fuzzy controllers, conversely, are based on rules. Even if the model were to change strongly, the fundamental process would still be the same and the rules would still be fully valid. The control value is calculated on the basis of these rules, for which reason no exact information about the system needs to be available. The controller reflects the human behavior of the expert who designed these rules and enables an individual reaction to each state. As a result, fuzzy controllers are considerably more robust in relation to changes of the turbine, the set point or faults. In addition, parameterization is considerably simplified, because cognitive, not mathematical knowledge is required (BecKhoff, 2011).

1.6 An introduction to fuzzy logic

Fuzzy Logic was initiated in 1965 (ZADEH, 1965), by Lotfi A.Zadeh, Professor for computer science at the University of California in Berkeley. Basically, Fuzzy Logic (FL) is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers (Hellmann).
A block diagram of a fuzzy control system is shown in Figure 1-4. The fuzzy controller is composed of the following four elements

1. **A rule-base**

   A set of If Then rules, which contains a fuzzy logic quantification of the expert's linguistic description of how to achieve good control (Kevin M. Passino, 1998).

2. **An inference mechanism**

   Also called an "inference engine" or "fuzzy inference" module, which emulates the expert's decision making in interpreting and applying knowledge about how best to control the plant (Kevin M. Passino, 1998).

3. **A fuzzification interface**

   It converts controller inputs into information that the inference mechanism can easily use to activate and apply rules (Kevin M. Passino, 1998).

4. **A defuzzification interface**

   It converts the conclusions of the inference mechanism into actual inputs for the process. (Kevin M. Passino, 1998)

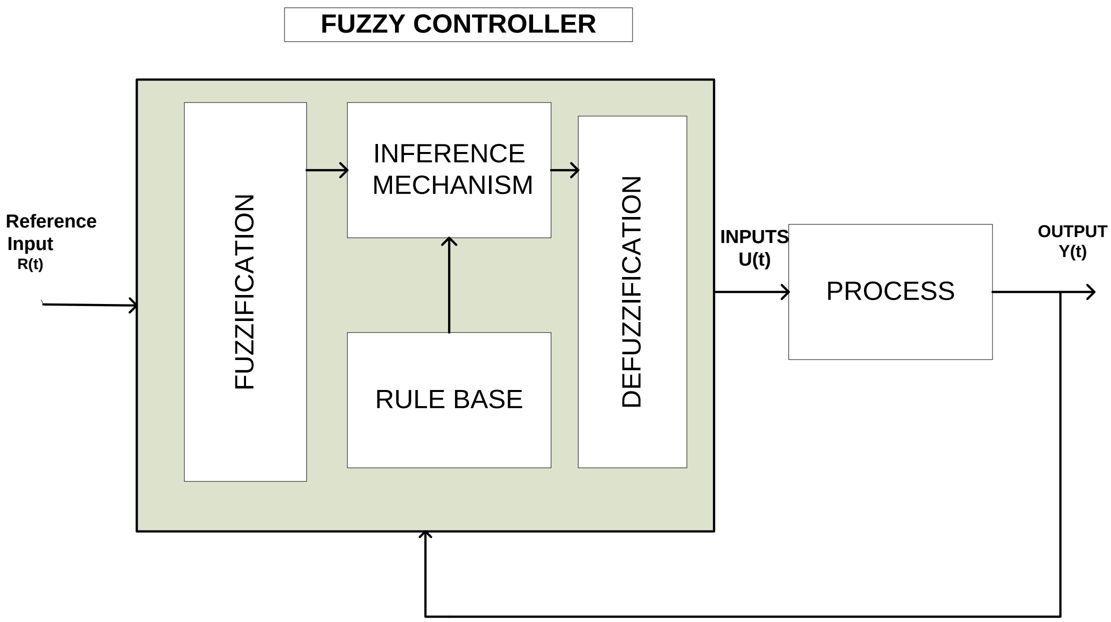


Figure 1-4   Fuzzy Logic controllers

1.7 Types Of fuzzy controllers

Fuzzy Models can be broadly classified into Linguistic fuzzy models, Rule Based fuzzy models and the Fuzzy Relational models (R.Babuska and H. B. Verbruggen).In our thesis we will be emphasizing on rule based controllers.

1) **Mamdani Controllers**

   In case of Mamdani models inputs are associated with the rule antecedents and the outputs with the rule consequents. Both the antecedent and the consequent are fuzzy propositions. The affine form of Mamdani Fuzzy model can be represented by

$$\text{if } X \text{ is } A_i \text{ then } Y_i \text{ is } B_i \quad i = 1,2,3,\ldots k \tag{1.1}$$

Where $X = [x_1, x_2, x_3, \ldots\ldots, x_p]$ is a vector whose elements are the antecedents variable A_i is a multi-dimensional fuzzy set, B_i is a one-dimensional fuzzy set, and Y_i is the consequent variable of the i^{th} rule.

2) Takagi Sugeno Models (Takagi and Sugeno 1985)

Takagi Sugeno Fuzzy model is a special case of a functional fuzzy system (Kevin M. Passino, 1998) . In this type of system the rule consequents are defined as functions. Therefore the rule consequent does not have associated membership functions and is a crisp value. The affine form of the T-S Fuzzy model consists of rules R_i with the following structure.

$$\text{if } X \text{ is } A_i \text{ then } Y_i = a_i^T X + b_i \quad i = 1,2,3, \dots k \tag{1.2}$$

where, X is a crisp input, A_i is a multidimensional fuzzy set, Yi is the scalar output of the ith rule, a_i is a parameter vector, b_i is a scalar constant and k is the number of rules in the rule base. The output of multi input single output (MISO) TS Model can be described by

$$Y(x) = \frac{\sum_{i=1}^{p} a_i(x) b_i}{\sum_{i=1}^{p} a_i(x)} \tag{1.3}$$

Where b_i is the weight vector, $a_i(x)$ is the degree of membership of x in the multi-dimensional fuzzy set A_i, Y(x) is the crisp output.

1.8 Thesis Outline

This thesis report is divided into five distinct chapters. A brief description of each chapter is as follows.

Chapter 1 – This chapter provides objective of our control scheme, overview and benefits of wind power and emphasis of renewable energy in Pakistan.

Chapter 2 – This chapter describes the adaptive fuzzy control approach proposed by (W.W. Tan, 1999) which we have used to control the pitch angle of the wind turbine.

Chapter 3 – This chapter describes the wind turbine plant from Simulink distributed resources which we will be using for testing our controller.

Chapter 4 – This chapter describes the simulation results of the adaptive fuzzy control in comparison to PI controller.

Chapter 5 – This chapter describes the conclusion and future additions which we plan to do on the basis of our current work.

CHAPTER-2

STRUCTURE OF SELF LEARNING NEURO-FUZZY CONTROLLER

2.1 Inverse plant modeling

The simplest way to control a process, when an inverse model is available, is to use this inverse model in an open loop configuration. Considering the model M mapping the control actions u to the systems outputs y, the control actions are simply given by $u=M^{-1}r$, where r are the references to be followed.

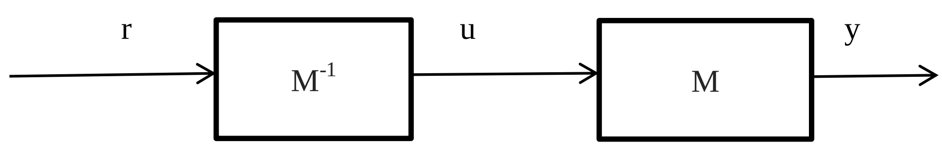


Figure 2-1 Mapping and perfect Inversion of the system.

If an Ideal model of the process is available, i.e. the model is equal to the process and both model and controller (Inverse model) are input-output stable, the control is perfect, and input output stable (Economou, et al . 1986).This situation of perfect control is impossible to achieve because an exact inverse of the process can only be found in some special situation, and the model is never equal to the process. Resulting in model plant mismatches. Moreover, the variables of the process can be subjected to level and rate constraint, and disturbances acting on the process are present and not taking into account in the controller. Further when the system has a delay of d steps inverse must be done d steps ahead. All these problems must be overcome, in order to apply inverse model control in practice. Fuzzy modeling is often used to model complex and nonlinear control processes, giving good approximations of nonlinear systems. More over special type of fuzzy models can be analytically inverted and used for control processes.

Two of the control processes for which the exact inversion of the process is possible are

1. Singleton fuzzy models. This type of model belong to general class of function approximations (Friedman, 1991), which is at least as accurate as a linguistic fuzzy model.
2. Takagi-Sugeno fuzzy models with affine input u(k) .

Several methods can be applied to obtain the inverse model of a given process (Boullart,et al.1992;Hunt,et al . 1992),but the following two are the most utilized.

1. Identification of the inverse model from input-output data.
2. Inversion of the original model.

The first method may seem an intuitive approach to inverse modeling, and it tries to fit the data in an inverse function. There are two methods used under this approach direct inverse learning and specialized inverse learning (Fischer and Isermann, 1996). In case of direct inverse learning the process is excited with a training signal and the fuzzy system reconstructs the input signal of the process from the given output signal. Two major drawbacks were found in this approach. First, the dynamics of the system can be a many-to-one mapping, and several values for u are possible for the same output of the process. If a least squares approach is used, the identification algorithm maps *y* to the mean value of all the u which can lead to meaningless inverse model .Secondly, it is difficult to obtain an appropriate training signal for direct inverse signal, because the inverse model is supposed to work over a wide range of input amplitudes on y and for a large bandwidth.

Both the drawbacks of the direct inverse modeling can be overcome by using specialized inverse learning, see e.g. Jordan and Rumlhart(1992). The inverse model is cascaded with the process or with forward plant model. The parameters of the inverse model M^{-1} are adapted in order to minimize the deviation between the reference r and the output y. Thus, the adaptation is a goal oriented scheme.

Although specialized inverse learning overcomes the problems of excitation and possible non-inevitability, it is still difficult to use this inverse model in a control scheme due to model plant mismatches and the influence of disturbances. A scheme proposed by (Fischer and Isermann, 1996) can be implemented, but this scheme needs some parameter tuning and uses the linearization of inverse model at certain point. Therefore exact inversion of the nonlinear fuzzy model is not obtained.

Another possibility is to invert a feed forward fuzzy model numerically when it is invertible, i.e. when a unique mapping from the output to the inputs of process is possible to obtain. The inverted model can be obtained with desired accuracy, depending on the chosen number of discretized points. However, even for a small number of points, the computational costs are too high, and this solution cannot be considered as a feasible one. Therefore, the best solution seems to invert a fuzzy model exactly, by using some analytical technique. If this inversion is possible, the computational operations can be done by using standard matrix operations and linear interpolations, apart from computation of degree of fulfillment. Thus, the inversion is computationally very fast, making it suitable for applications in real-time control.

2.2 Inversion of the singleton fuzzy model

The inversion of the singleton fuzzy models was introduced by (Babuska, 1995). It is developed in (Babuska, 1997), a special structure of the singleton fuzzy model, which is presented in this section, is necessary to perform this inversion.

Assume that a SISO singleton model of the process is available. Such a model can be constructed directly from process measurements. A general rule R_i has the following form.

$$R_i : \mathrm{y(k)\ is\ A_{i1}\ \ and\ \ y(k-p+1) is\ A_{ip}\ \ and}$$
$$\mathrm{u(k)\ is\ B_{i1}\ and\ \ldots\ldots\ldots.and\ u(k-m+1) is\ B_{im}\ \ then\ \hat{y}(k+1) is\ c}\ .$$

Let a state vector x(k) containing the m-1 past inputs , the p-1 past outputs and the current output i.e. all the antecedents variables except u(k), be defined as.

$$\mathrm{x(k) = [y(k), y(k-p+1), u(k-1), \ldots.. u(k-m+1)]^T} \qquad (2.1)$$

The fuzzy sets of $x(k)$ are aggregated into multidimensional fuzzy set x, by applying the Cartesian product .

$$x = A_1 * \ldots\ldots * A_p * B_2 * \ldots\ldots * B_m \tag{2.2}$$

By introducing the formal substitution of B1 by U in order to simplify the notation,

The fuzzy rule can be written as .

$$\text{If } x(k) \text{is } x \text{ and } u(k) \text{is } U \text{ then } \hat{y}(k+1) \text{ is } c$$

Let N denote the number of different fuzzy sets X_i defined for the state x(k) and M the number of different fuzzy sets U_J defined for the input u(k). If the rule base consists of all possible combination of X_i and U_J (the rule base is complete). The total number of rules is K=N.M. The entire rule base can be represented as a table.

Table 2.1 Rule Base

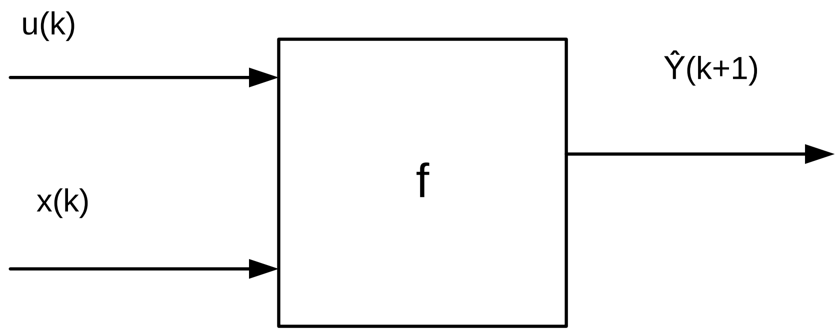
X(k)	**U(k)** U_1 U_2 ……………..U_M
X_1	C_{11} C_{12} ……………………..C_{1M}
X_2	C_{21} C_{22}……………………..C_{2M}
X_N	C_{N1} C_{N2} …………………….. C_{NM}

The degree of fulfillment of the rule antecedent $\beta_{ij}(k)=\mu_{xi}(x(k)).\ \mu_{uj}\ (u(k))$,

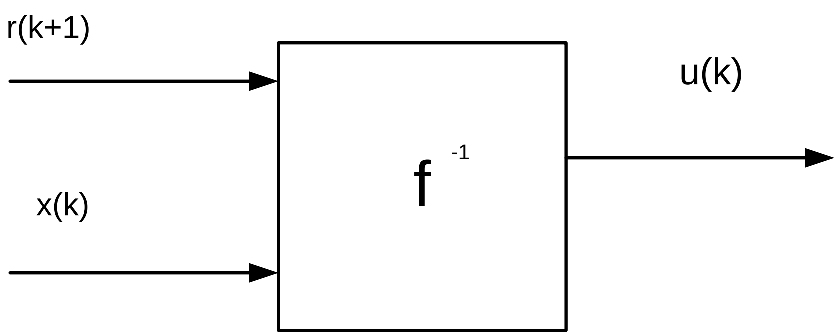
Where $\mu_{xi}(x(k))$ is the membership degree of an input u(k) in the fuzzy set U_J. The predicted output of the model is computed by fuzzy mean defuzzification. The rule based model shown in table 2.1 corresponds to a nonlinear regression model

$$\widehat{y}(k+1) = f(x(k), u(k)). \tag{2.3}$$

shown schematically in Fig 2.2a. The model inputs are the current state x and the current input $u(k)$ and the output is the system predicted output at the next sampling instant $\hat{y}(k+1)$



(a) Model of the system.



(b) Derived controller.

Figure 2-2 Fuzzy model and controller based on the model inverse

Given the current system state x(k) and the reference at the next sampling time r(k+1) .The objective of the control algorithm is to find u(k) such that the system output $y(k+1)$ Is as close as possible to the reference $r(k+1)$.This can be achieved by inverting the plant model as indicated in Fig 2.2(b), substituting the reference substituting the reference $r(k+1)$ for $\hat{y}(k+1)$ in the static function .

$$u(k) = f^{-1}(x(k), r(k+1)) \tag{2.4}$$

2.3 General structure of the control scheme.

In this section we will describe the structure of the controller proposed by (W.W. Tan, 1999).Broadly the controller is composed of the feed forward controller and Reference model as shown in Fig 2-3. As for as the structure of the controller is concerned it contains the fuzzy system defined according to the structure of the neural network, that merges the linguistic reasoning framework of fuzzy models with the learning ability of neural network. Feed forward controller basically approximates the inverse plant model and uses that to generate the appropriate control signal to minimize the error.

For instance assume that each input universe of discourse is characterized by p_j fuzzy sets (triangular membership functions with a partition of unity are used) and the fuzzy system contains the following 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_{11}, X_2 IS A_{21},……….. And X_n IS A_{n2}, then u_f is W_2

RULE i : IF X_1 IS A_{1i_1}, X_2 IS A_{2i_2} ,……….. And X_n IS A_{ni_n}, then u_f is W_i

For P no of rules.

RULE p : IF X_1 IS A_{1p_1}, X_2 IS A_{2p_2},……….. And X_n IS A_{np_n} then u_f is W_p

The output of neuro-fuzzy feed forward controller is given by

$$u_f\,(t) = \sum_{i=1}^{p} a_i(x(t))\omega_i$$

$$= a^T(t)\hat{w}\,(t) \tag{2.5}$$

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

$x(t) = [x_1(t)\ x_2(t) \ldots\ldots\ldots x_n(t)]^T$is input vector at time t

$a_i\ (x(t)) = \mu_{A_{1i_1}}(x(t)) \times \mu_{A_{1i_2}}(x(t)) \times \ldots\ldots\ldots.. \mu_{A_{ni_n}}(x(t))$ Is the product of membership grades in the fuzzy sets of the antecedents of the ith rule $a(t) = [a_1\ a_2 \ldots\ldots\ldots a_p]$ is the transformed input vector at time t, $w(t) = [w_1\ w_2 \ldots\ldots\ldots w_p]$ Is the parameter vector at time t.

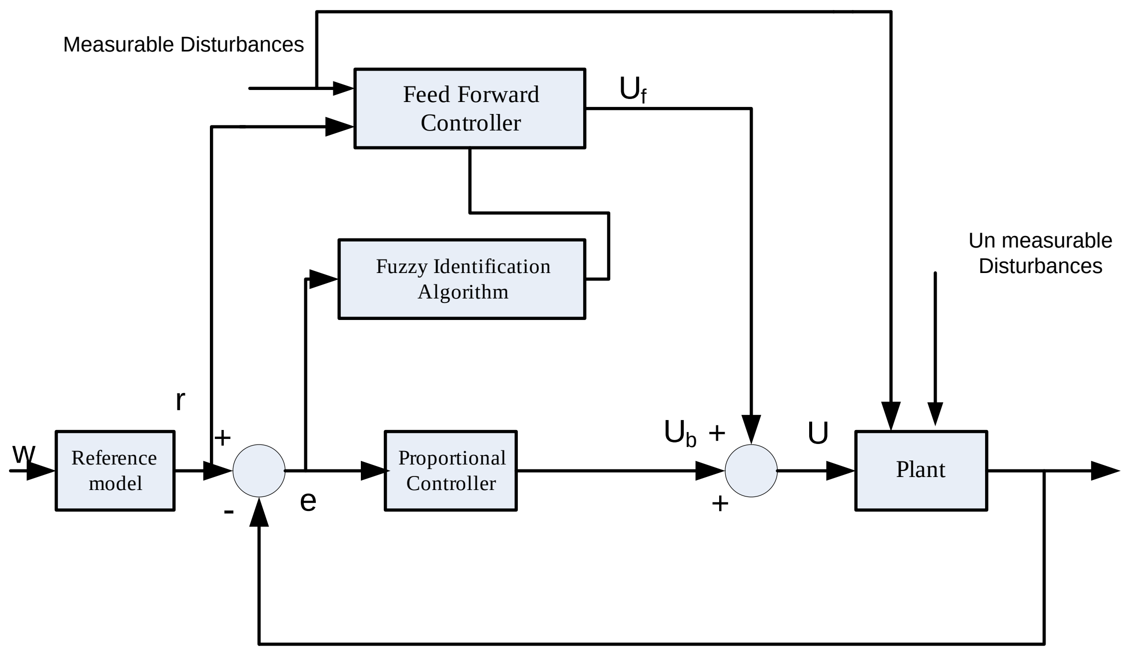


Figure 2-3 General structure of the adaptive fuzzy control scheme.

Following goals are to be achieved

1) To identify entries in the parameter vector w(t) so that the neuro-fuzzy model represents the mapping between the input vector, containing the filtered set point and measurable disturbances, and the control signal that is required to drive the output of the plant to the desired value.

2)When properly trained, the feed forward controller should approximate the inverse plant model. Since an exact inverse mapping is difficult, if not impossible, to obtain practically, the neuro-fuzzy feed forward controller will exhibit finite modeling errors. A simple feedback strategy should suffice since the on-line training algorithm should ensure accurate set point tracking. The total control action applied to the system at the sampling instant t is, therefore, defined by

$$u(t) = u_f(t) + k_p e(t) \tag{2.6}$$

Another essential component of the self-learning controller is the reference model. It is used to filter the desired changes in the plant output, *w*, in order to provide a set point trajectory, *r*, which can be followed by the plant, given the physical constraints and the plant dynamics.

2.4 Online learning mechanism

(W.W. Tan, 1999) proposed that Identification of neuro-fuzzy model can be done by feeding a recursive identification algorithm with input output data. Here the input to the neuro-fuzzy model , **x**(t) is a vector containing the time history of the set point trajectory and the measureable disturbances , while output is the pitch angle control signal. Practically control signal is unknown initially. The online learning mechanism must , therefore , estimate the desired control action before presenting the data to the identification algorithm which updates the parameters of the neuro-fuzzy model. First the strategy for computing the required control signal is described .

Suppose the control action $u_f(t)$ is applied to the plant at time t, because of the inherent system delay, the plant will respond to the control action t_d sampling intervals later. Since a nonzero feedback error is caused by an incorrect feed forward control action, the system error reflects the control error at $t - t_d$.

Hence a new estimate of the control action needed to derive the output along the reference trajectory, $\tilde{u}_f(t)$, may be derived by adding a fraction of the feedback error to the control signal , $u_f(t - t_d)$ i.e .

$$\tilde{u}_f(t) = u_f(t - t_d) + \gamma e(t) \tag{2.7}$$

Where γ is the on-line learning rate. The strategy of using the feedback signal as a modeling error is known as the feedback error learning scheme (Kawato, 1998), (Tan, 1997) and is essentially an iterative search for the control action that will derive the output to the set point.

Since the output of the neuro-fuzzy model is linear-in-the parameters, identification techniques which minimize the sum of error squared may be used to update the parameter vector.

The approach which we are using was basically proposed by Tan and Dexter which utilizes an algorithm which combines aspects of a recursive fuzzy identification scheme with the well-known Normalized Least-Mean-Square (NLMS) update rule. The NLMS algorithm is attractive because it is computationally undemanding. However, the NLMS learning rule uses only the current input output data to reduce the instantaneous modeling error and it may corrupt values of the parameters that have previously been correctly estimated, destroying the knowledge stored in the neuro-fuzzy model. A fuzzy least-mean-square (FLMS) update rule has been developed (Tan, 1997)that alleviates this learning interference problem by taking account of the strength and frequency of particular combinations of the input values that have occurred in the training data.

At each sampling instant, the new estimate of the parameter vector is given by

$$\hat{w}\,(t) = \hat{w}\,(t\text{-}1) + \delta \frac{s(t-1)a(t-t_d)}{a^t(t-t_d)s(t-1)a(t-t_d)}\varepsilon(t) \tag{2.8}$$

Where $s(t) = \mathrm{diag}\{s_1, s_2 \ldots s_i, \ldots \ldots .. s_p\}$, $s_i = \prod_{j=1}^{p} F_j(t)$ and $F_i(t) = F_i(t-1) + a_i(t)$.

Measures the strength and frequency at which the *i*th rule is fired by data that have been presented to the algorithm (Fi has an upper bound of 5000 and is initialized to unity) δ is a user-selected constant that determines the update rate , $\varepsilon(t) = \tilde{u}_f(t) - \hat{u}_f(t)$, $\hat{u}_f(t) = a^t(t-t_d)\,\hat{w}(t-1)$ is the feed forward control action estimated from the current weight vector.

2.5 Sequence of Task's performed by the Controllers

In summary, the sequence of tasks performed by the self-learning control scheme at the sampling instant t is

(i) Estimate the desired control action $\tilde{u}_f(t)$ using the feedback error learning scheme given by Eq. (2.7).

(ii) Update the parameters of the feed-forward controller by presenting the data $\{x(t), \tilde{u}_f(t)\}$ to the FLMS update rule given by Eq. (2.8) .

(iii) Calculate the feed forward control action, u_f (t) by substituting the input vector and the modified parameter vector $\hat{w}$ (t) into Eq. (2.5).

(iv) Determine the total control action applied to the plant using Eq. (2.6).

CHAPTER – 3

SYSTEM MODEL AND EXPERIMENTAL SETUP

3.1 Wind Distribution

The most commonly used probability density function to describe the wind speed is the Weibull functions (PETERSSON, 2005). The Weibull distribution is described by the following probability density function.

$$f(w) = \frac{k}{c}(w/c)^{k-1}e^{-(w/c)^{k}} \tag{3.1}$$

Where k is a shape parameter, *c* is a scale parameter and w is a wind speed. If the shape parameter equals 2, the Weibull distribution is known as the Rayleigh distribution. the wind speed probability density function of the Rayleigh distribution is shown in Fig 3-1

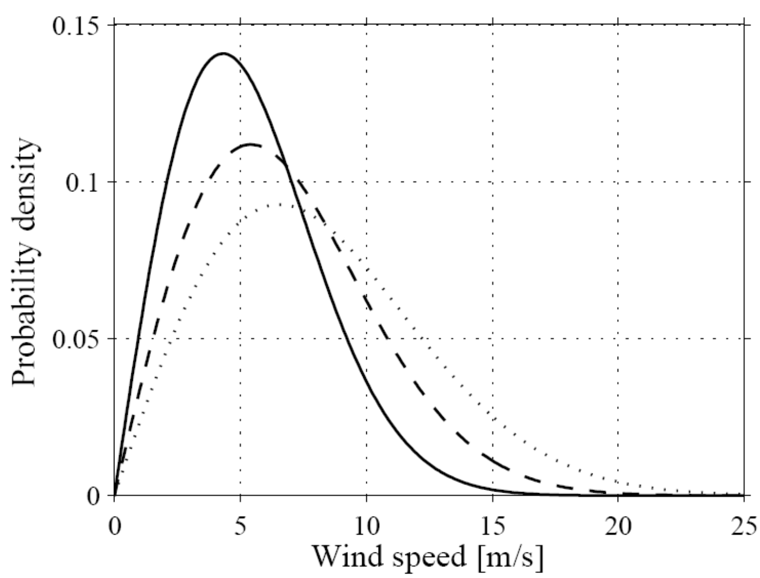


Figure 3-1 Probability density of Rayleigh distribution

Nominal wind speed or rated wind speed refers to the wind speed at which the nominal power of the turbine is reached. When the wind speed becomes very high, the energy contained in the airflow and the structural loads on the turbine become too high and the turbine is taken out of operation. Depending on whether the wind turbine is optimized for low or high wind speeds. In case of stall control Design the rotor blades in such a way that their efficiency inherently decreases when the wind speed increases to values above nominal. In case of Pitch control, the control objective is to reduce the aerodynamic efficiency of the rotor by turning the blades out of the wind using hydraulic mechanisms or electric motors. In our case the nominal wind speed is 8 m/s, at which the wind turbine generates 2 MW, in this scenario pitch angle is kept at zero. However when the wind speed exceeds the nominal value, output power exceeds the reference value of 2 MW and fuzzy controller increases the pitch angle in order to decrease the C_p. The fact that C_p decreases with the increase in pitch angle β is evident from Fig. 4-1 and Fig. 4-2.

3.2. Wind Turbine Induction Generator (WTIG)

Fig. 3-2 illustrates WTIG (wind turbine induction generator) . The stator winding is connected directly to the 60 HZ grid and the rotor is driven by a variable pitch wind turbine. The power captured by the wind turbine is converted into electrical power by the induction generator and is transmitted to the grid by the stator winding. The pitch angle is controlled in order to limit the generator output power to its nominal value for high wind speeds. The pitch angle controller regulates the wind turbine blade pitch angle β, according to the wind speed variations. Hence, the power output of WTIG depends on the characteristics of the pitch controller in addition to the turbine and generator characteristics. This control guarantees that, irrespective of the voltage, the power output of the WTIG for any wind speed will be equal to the designed value for that speed. This designed power output of the WTIG with wind speed is provided by the manufacturer in the form of a power curve. Since the parameters of the turbine and generators varies for different wind turbines. For obtaining simulation results for different power settings, GUI provides user with the flexibility to enter different parameters of turbine and generator like stator and rotor resistances, nominal output power, pith angle , base wind speed and PI controller gains as shown in Fig.3-6 and 3-7.

The pitch angle β is controlled in order to limit the generator output power at its nominal value for winds exceeding the nominal speed. β is controlled by a Fuzzy controller in order to limit the electric output power to the nominal mechanical power. When the measured electric output power is under its nominal value, β is kept constant at zero degree. When it increases above its nominal value the fuzzy controller increases β to bring back the measured power to its nominal value. The pitch angle control system is shown in Fig. 3-2.

3-3 Simulink Wind Turbine Block

The wind turbine model employed in the present study is based on the steady-state power characteristics of the turbine. The stiffness of the drive train is infinite and the friction factor and the inertia of the turbine are combined with those of the generator coupled to the turbine. The wind turbine mechanical power output is a function of rotor speed as well as the wind speed and is expressed as:

$$P_m = C_p(\lambda,\beta)\,\frac{\rho A}{2}\,v^3{}_{wind} \qquad (3.2)$$

P_m Mechanical output power of the turbine

Cp Performance Coefficient of the turbine

ρ Air density (kg/m^3)

A Turbine swept area

V Wind speed in m/s .

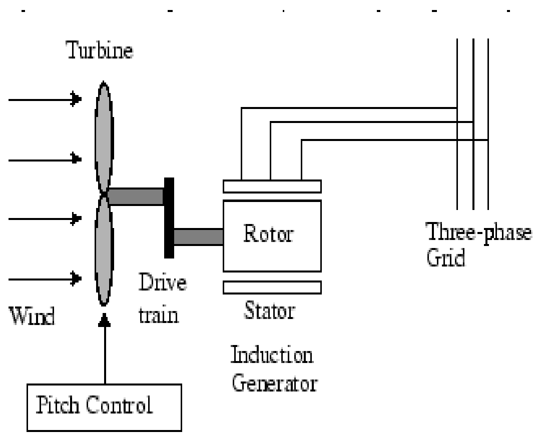


Figure 3-2 Wind Turbine Induction generator

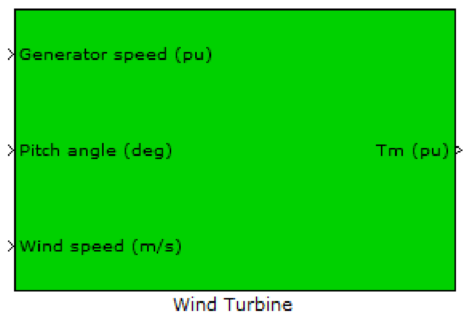


Figure 3-3 Simulink Wind Turbine block

The Simulink wind turbine block shown in Fig.3-3 requires pitch angle, wind speed and generator speed for the producing the mechanical power at its output as specified in Eq.(3.2). All the values are in per unit system.

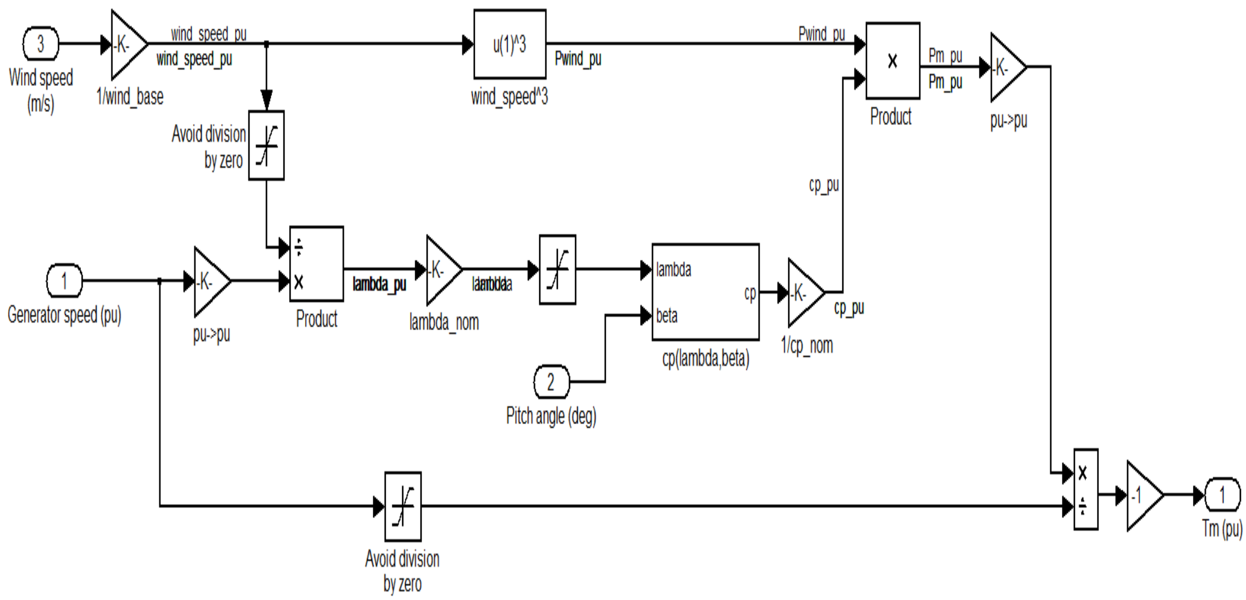


Figure 3-4 Internal Dynamics of Simulink wind Turbine Block

A generic equation is used to model Cp(λ,β). This equation, based on the modeling turbine characteristics is (Description of Wind turbine Induction generator from Simulink distributed resources)

$$C_p(\lambda,\beta) = C_1\left(\frac{C_2}{\lambda_i} - C_3\beta - C_4\right)e^{\frac{C_5}{\lambda_i}} + C_6\,\lambda \tag{3.3}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda_i + 0.08\beta} - \frac{0.035}{\beta^3+1} \tag{3.4}$$

3.4 Asynchronous Machine

Model the dynamics of three-phase asynchronous machine, also known as induction machine. Electrical power is produced when mechanical power output from the Simulink wind turbine block is applied at the three-phase asynchronous machine Tm terminal.

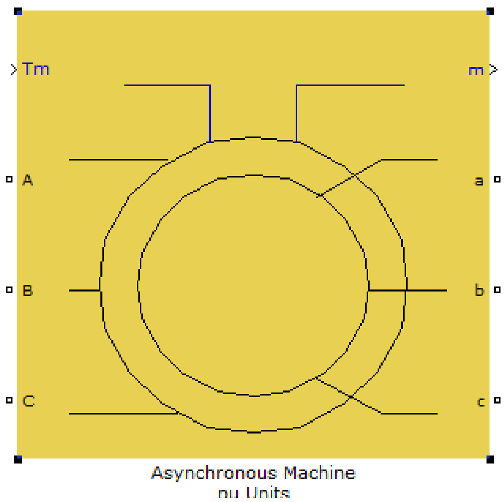


Figure 3-5 Asynchronous Machines

GUI For Generator Data.

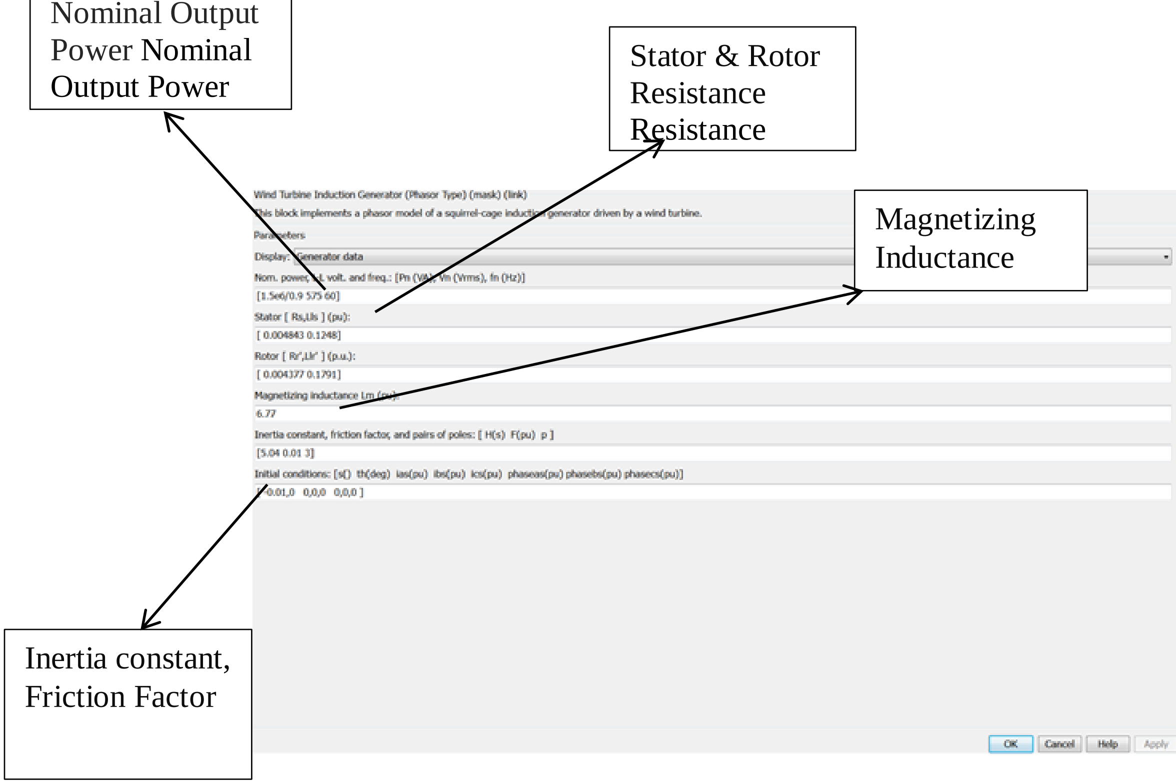


Figure 3-6 GUI for generator data

GUI For Turbine Data

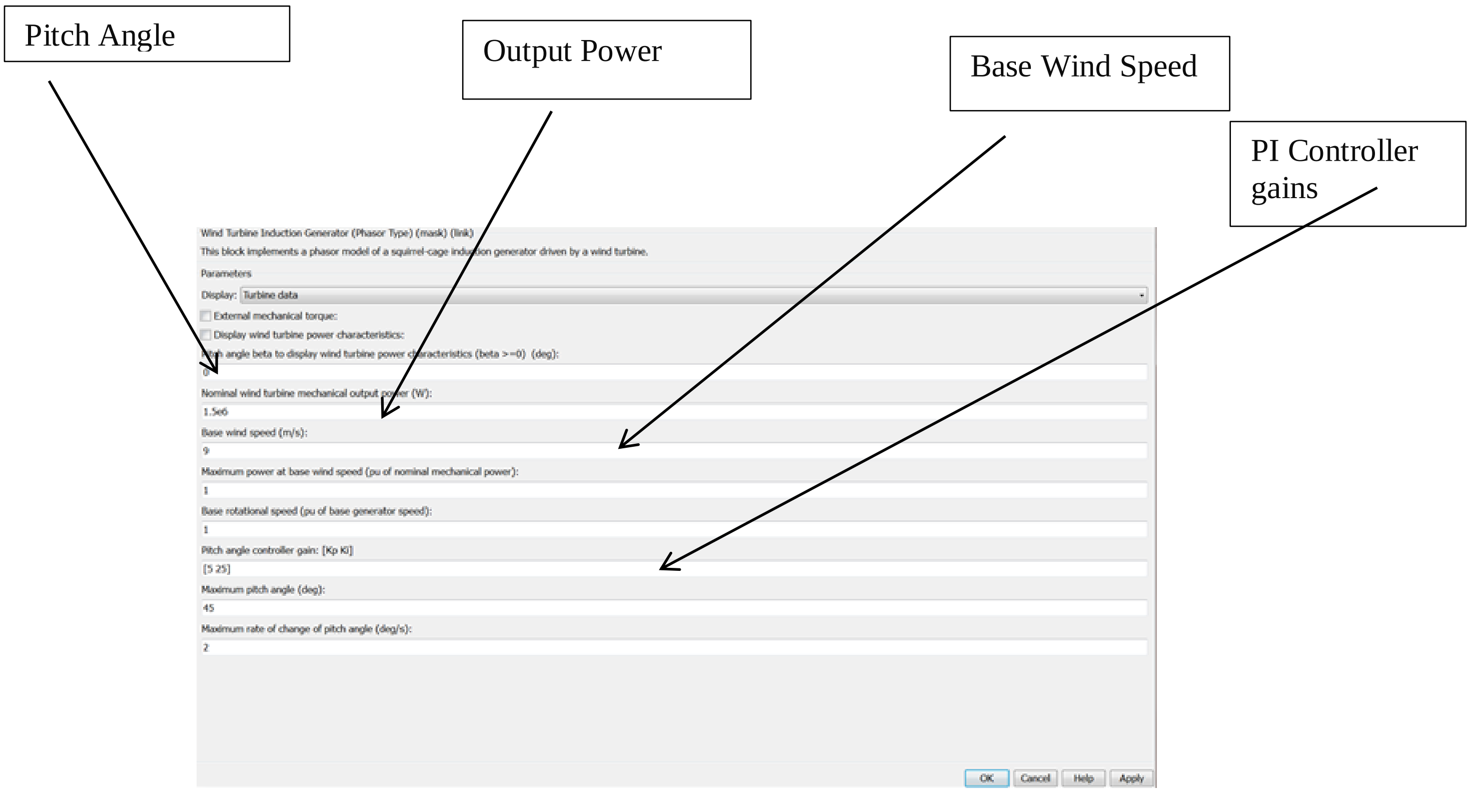


Figure 3-7 GUI for turbine data

3.5 Model Description

Fig.3-8 shows 3MW 575 V 60 Hz wind turbine is connected to a step up transformer(575V/25KV) which is connected to a 25 km transmission line which is then connected to a distribution system which exports 120KV.

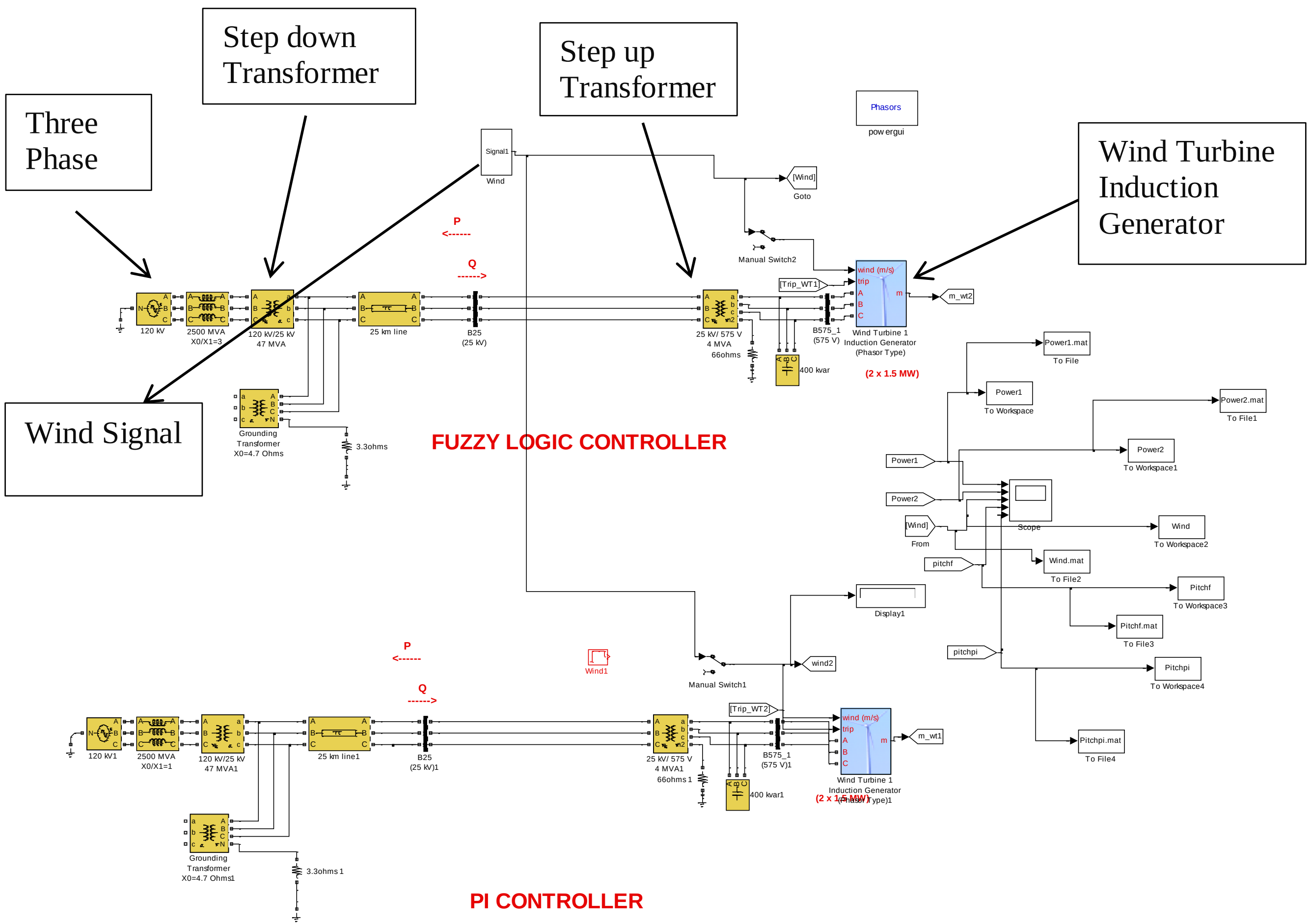


Figure 3-8 Experimental Setup in Simulink

Fig.3-9 shows that the wind turbine induction generator is composed of the wind turbine, output Mechanical power from wind turbine is fed into induction generator, which in turn give us 3-Phase electrical power. This 3-phase electrical Power has been normalized.Fig.3-9 also shows a self-learning neuro fuzzy pitch angle controller. The inputs to self-learning neuro fuzzy controller are normalized feedback signal, the reference signal and the error signal.

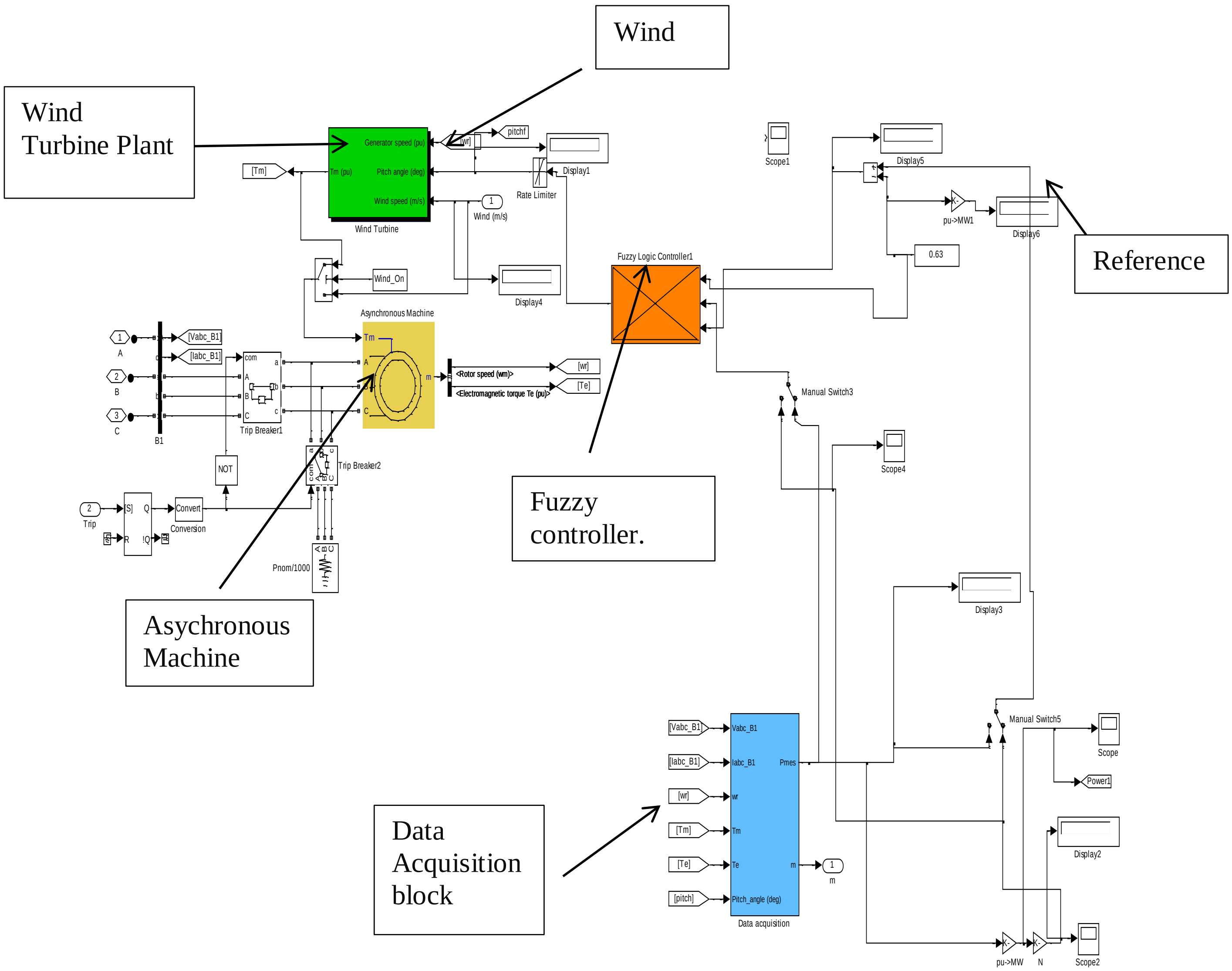


Figure 3-9 Subsystem of wind turbine in Simulink

Basically wind Turbine Generator Block is Composed of several subsystems. One Of the subsystem is a block which simulates the dynamics of the wind turbine. Output mechanical power from the shaft of the wind turbine is transferred to the generator through drive trains. Three phase electrical power generated from the generator is fed to the output, also it has been normalized so that it can be fed into the neuro fuzzy controller for the purpose of pitch angle controlling. Inputs to the neuro-fuzzy controller are normalized output power, reference output power. Based on these inputs neuro-fuzzy controller controls the parameter β which is the pitch angle of the wind turbine in order to keep the output power at its rated value.

3.6 How Self Learning Neuro Fuzzy Controller Works

As discussed before in section 2.5, the sequence of task's performed by the controller are achieved by using Simulink user defined functions in the following manner.

i. Desired control action $\tilde{u}_f(t)$ is acquired through feedback error learning scheme as specified by Eq. (2.7).
ii. Updating the parameters of the feed-forward controller by presenting the data $\{x(t), \tilde{u}_f(t)\}$ to the FLMS update rule given by Eq. (2.8) . Where $x(t)$ is composed of normalized reference signal and normalized output power.
iii. Calculate the feed forward control action, u_f (t) by substituting the input vector and the modified parameter vector $\widehat{w}$ (t) into Eq. (2.5).
iv. Determine the total control action applied to the plant using Eq. (2.6).

CHAPTER- 4

SIMULATION RESULTS

In order to compare the performance of the Fuzzy and PI controller we applied an identical wind signal on both fuzzy and PI based wind turbines as shown in Fig 3-8.

Case 1 : In in Fig-4-3 we can see that at the time when 0<=time <=50 sec magnitude of wind speed is 10 m/s, initially Power has exceeded to 3.7 MW it is also evident from the power characteristics(at pitch angle 0^0 Fig.4-1) that at a wind speed of 9.6 m/s the value of generated power is above the rated value of the wind turbine as well as it is above the reference value of 2 MW or 0.63 pu. Now in order to bring it back to the reference value the pitch angle of 10^0 is required as is evident from the power characteristics of wind turbine Fig.4.2 Pitch angle is 10^0. At this pitch angle of 10^0 we can see that if the wind speed is approx. 9.6 m/s than output power will be 0.6 pu or 2 MW. Than at Time=50 Sec there is wind gust and wind speed has suddenly jumped to 12 m/s again power has exceeded the reference value so both the controllers has jumped to 15 Deg. At time=70 secs we can see there is wind gust at time=70 sec and at time=80 sec wind is again back to normal. During this wind gust we can see that fuzzy has performed well both in terms of bringing output power back to reference in less time as compared to PI and also there are fewer ripples in case of fuzzy controller.

Case 2 : In Fig-4-4 we can see that at time 0 <= time <= 30 wind speed is blowing at rated wind speed of 8 m/s at this speed we are getting rated output power of 2 MW. At time t=30 a wind gust hits the wind turbine and we can observe from Fig-4-4 that output power has suddenly exceeded the rated output power. During this phase we observed that fuzzy controller has managed to increase the pitch timely and has successfully brought the output power to its reference value in next 10 sec. However during this phase we observed that PI controller has not been able to control the pitch angle and the system has got destabilized.

4.1 Power Characteristics of wind turbine at pitch angle β =0°

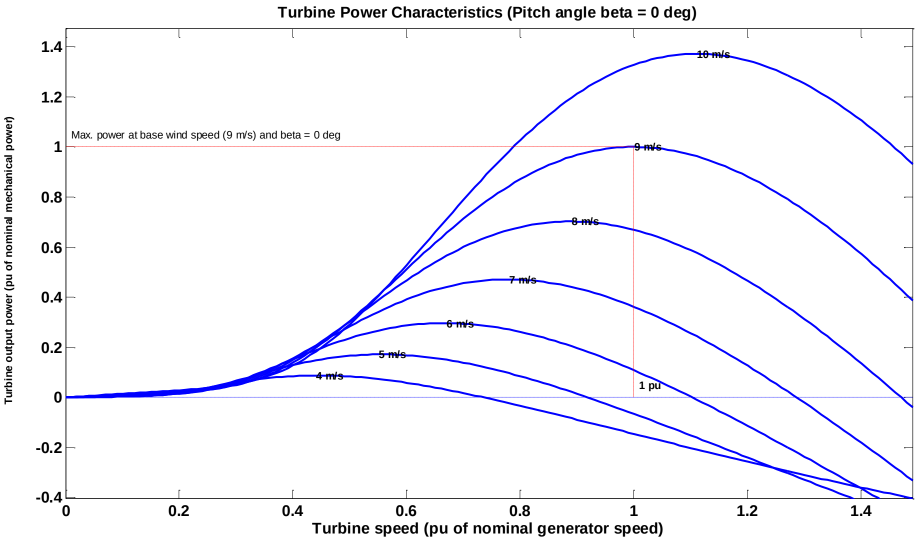


Figure 4-1 Turbine Power characteristics

4.2 Power Characteristics of wind Turbine at pitch angle β =10°

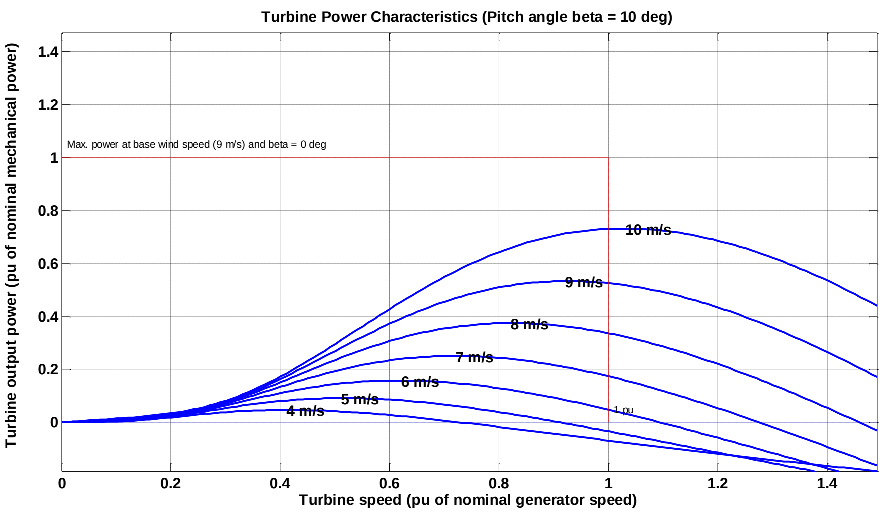


Figure 4-2 Turbine Power characteristics at 10^{o} Pitch angle.

4.3 Results for Case-1

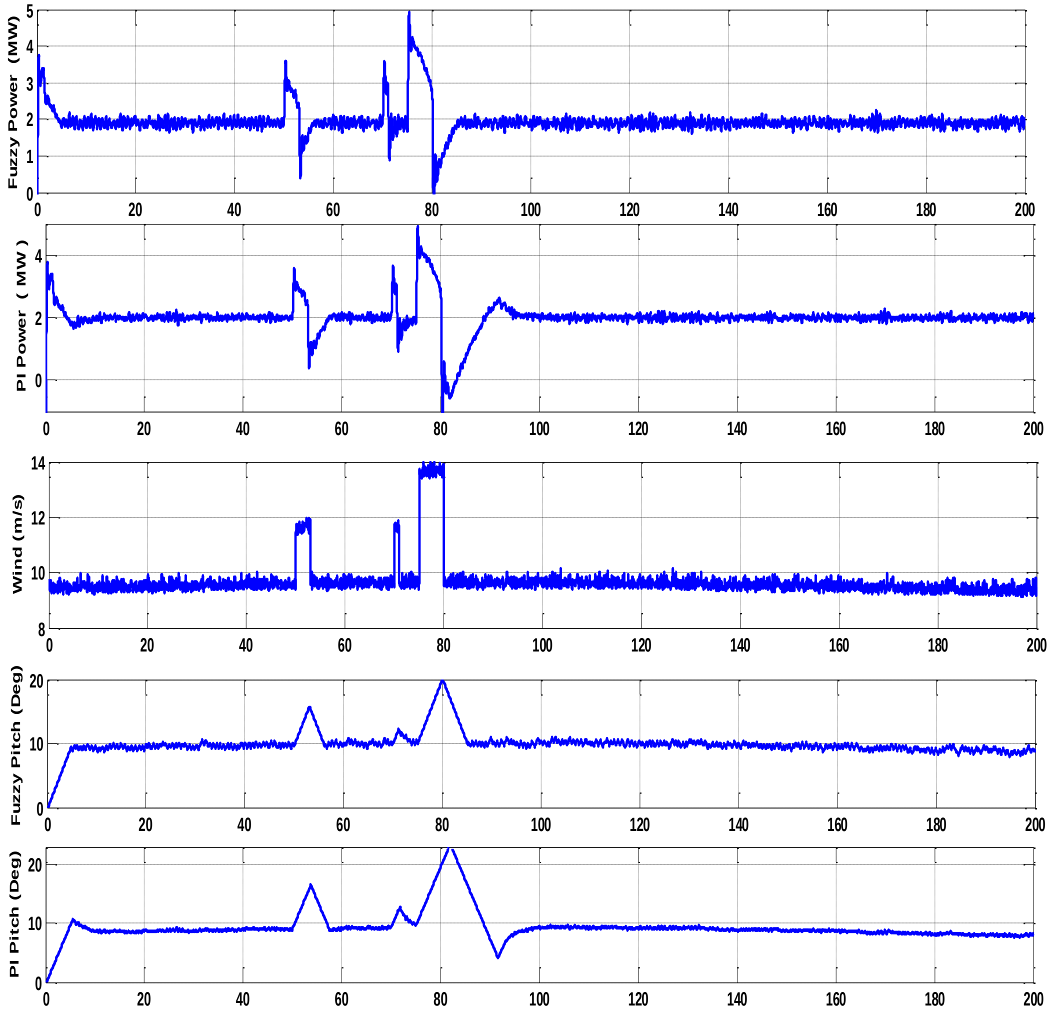


Figure 4-3 Results and comparison of fuzzy and PI controller for case 1

4.4 Results for Case- 2

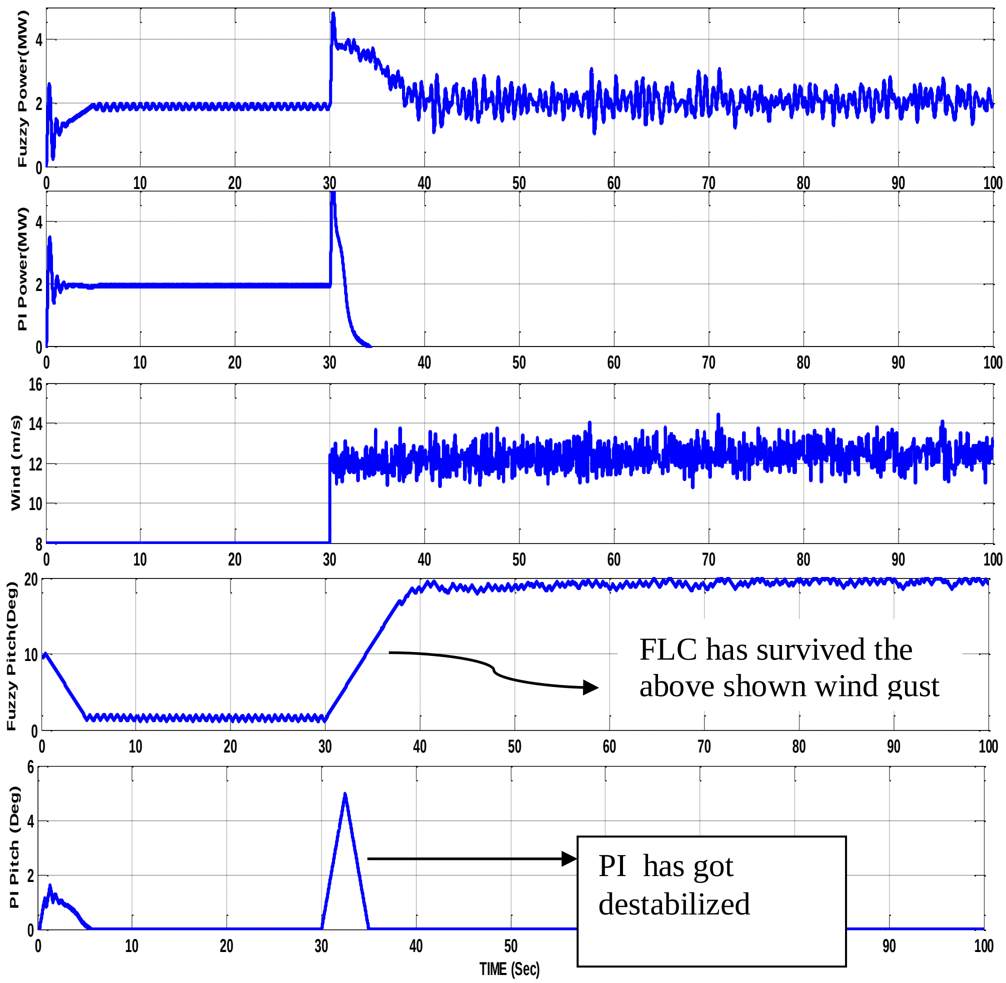


Figure 4-4 Results and comparison of fuzzy and PI controller for case 2

CHAPTER 5

FUTURE WORK & CONCLUSION

The on-line learning mechanism is able to train the neuro fuzzy controller to provide good quality control using a set of parameters. Moreover, unlike the algorithms for automatically tuning a PI controller, learning and output regulation can be achieved simultaneously. From the simulation results presented in this thesis, we observed that in areas where abrupt increase occurred in the wind speed, as compared to PI controller, fuzzy controller efficiently controlled the pitch angle in order to minimize the error.

In this thesis we have focused on the pitch angle control of wind turbine induction generator which is directly connected to the grid using fuzzy logic. In future we would like to extend this approach to Doubly fed Induction generator wind turbines. Also we will try to implement the self learning fuzzy controller on embedded system and will try to control a real wind turbine.

Glossary

Abbreviations

WTIG Wind Turbine Induction Generator.

WECS Wind Energy Conversion System.

NLMS Normalized Least Mean Square.

FLMS Fuzzy Least Mean Square.

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