CHAPTER-I

INTRODUCTION

1.1 GENERAL

Recent developments in science and technology provide a wide scope of applications of DC motor drives in areas such as, electric bicycles, robotic manipulators, and the home electric appliances[21]. It's used in speed control applications because of their low initial cost and excellent drive performance. DC motors have speed control capabilities, which means that speed, torque and even direction of rotation can be changed at any time to meet a new set of conditions. DC motors also can provide a high starting torque at low speed and it is possible to obtain speed control over a wide range. The DC motors have been popular in the industry control area for a long time, because they have enormous characteristics like, high start torque , high response performance, easier to be linear control etc.

With advancement of semiconductor technologies development of high performance motor drives is very important in industrial as well as other purpose applications such as steel rolling mills, electric trains, electric automotive, aviation and robotics . Several types of electric motors have been proposed for these types of applications . Among these types, conventional DC motors which are known with their excellent characteristics. Squirrel cage induction motor is alternative to the conventional DC motor. It offers the robustness with low cost. However, its disadvantages have poor starting torque and low power factor. for high-speed application induction motors cannot be used the alternative is the DC brushless motor, which can be considered the most dominant electric motor for these applications. Fast switching semiconductor devices has made BLDC motor dominant in small power applications for their low maintenance and can be placed in hostile environments. They are driven by dc voltage but current commutation is done by solid-state switches. The commutation instants are determined by the rotor position and the position of rotor is detected by position sensors or by sensorless techniques.

1.2 CONTROL TECHNIQUE

In many application it is required to adjust the speed of DC motor according to Loading application. DC motor speed control is a general problem but due to its non-linear nature complexity increases in case of Brushless DC motor. There are two basics classes of control schemes namely conventional and non-conventional. Conventional method includes P, PI and PID controller. The proportional integral (PI) controller is the most common form of feedback in the control systems. PI control is also an important ingredient of a distributed control system and as such these controllers come in different forms. Non-Conventional method includes Fuzzy Logic, Neural Network, Genetic Algorithm and their combination. Non-Conventional Controller offers several unique features that make it a particularly good choice for many control problems. Since the Fuzzy logic controller processes user-defined rules governing the target control system, it can be modified and implement easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules[22]. Fuzzy logic as well as neural network are not limited to a few feedback inputs and one or two control outputs, nor is it necessary to measure or compute rate-of-change parameters in order for it to be implemented. Any sensor data that provides some indication of a system's actions and reactions is sufficient. This allows the sensors to be inexpensive and imprecise thus keeping the overall system cost and complexity low.

The conventional control strategies are a fixed structure, fixed parameter design. Hence the tuning and optimization of these controllers is a challenging and difficult task, particularly, under varying load conditions, parameter changes, abnormal modes of operation, etc. Attempts to overcome such limitations using adaptive and variable structure control have had limited success due to complexity, requiring of estimation stages, model structure changes due to discontinuous drive mode of operation, parameter variations, load excursions and noisy feedback speed and current signals. In the drive field, fuzzy logic has applied to various problems, such as robust control of DC drive systems. In this study, Adaptive Neuro-Fuzzy controller is applied apart from PID controller for various loading pattern and parameter change and their responses had been compared.

The proposed controller can be implemented using a high speed DSP in order to verify the robustness of these controllers. The efficiency of Control Algorithm is presented through a simulation and compared with the quality of PID controller.

1.3 MOTIVATION

Conventional DC motors are highly efficient and their characteristic makes them suitable as servomotor. However, it needs a commutator and brushes which are subjected to wear and required maintenance. The functions of commutator and brushes were implemented by solid state switches that can realize maintenance free motors. These motors are brush-less motors and are widely used in various applications replacing conventional DC motors in their small size. Two examples of the are electric vehicle and industrial machinery [12].

Traditional motor speed controller have fixed gain like proportional-integral controller (PI) but this fixed gain controller have certain issues with load disturbances, change in parameters (which always happens due to wear and aging effect in all engineering materials) also they require exact mathematical modeling of motor but due to many reasons including temperature variation, saturation, system disturbances designing exact model of motor is not feasible, to overcome this issue Fuzzy Logic Controller(FLC) is used using certain rule base[13]. Fuzzy logic controller which was implemented by Zadeh in 1965, is a new controller. Besides that (FLC) is more efficient from the other controller such as P, PI and PID controller.

In this control scheme, DC motor is controlled using PWM inverter. The input supply to motor can be varied by varying the gate pulse to the inverter which require certain modulation technique and some reference for it. These modulation tecniques can be voltage controlled or current based controlled. The modulation techniques can be two type PWM and averaged . The PWM modulation is very common now a days and reference to this is given by error in speed and rotor position.

1.4 OBJECTIVE OF THE THESIS

The main objective of the project is, to simulate speed control of DC motor using transfer function model and MATLAB/SIMULINK model of BLDC motor. Then analyse and compare with PI and Adaptive Neuro-Fuzzy controller for generation of PWM signals in BLDC motor drive at different operating conditions such as change in load torque and change in motor parameters.

1.5 OVERVIEW OF THESIS

This thesis describe the performance, control and operation of Conventional DC motor and Brushless DC motor drive. Two control scheme has been applied for generation of gate pulse which further control speed of above motor they are PI and Adaptive Neuro-Fuzzy over the error in speed of motor. Their test results were analysed using MATLAB/Simulink environment. Further research work done in this thesis is classified below:

In **Chapter 2: Literature review,** various articles, research papers, books, tutorials are discussed which are related to the study of basic structure of DC motor (conventional and brushless), operating principles, and torque production in magnetic field created in motor air gap.

In **Chapter 3: Model development,** various articles, research papers, books, tutorials are discussed which are related to the study dynamic modeling of DC motor (conventional and brushless). Their electrical and mechanical characteristics are briefly described in terms of mathematical equations. Transfer function generation and formulation of block diagram were discussed. State space modeling and their equations were also developed in this chapter.

In **Chapter 4: Controller,** automatic control system requirements and its brief history were described under heading General, then Conventional control tecniques and their various forms were described. Non-Conventional controller and their different forms Fuzzy controller and Neural Network were described along with their learning requirements.

In **Chapter 5: Controller Tuning,** tuning of control parameters of conventional controller and stability of system were studied. Performance criterion in time and frequency domain for stable systems were described. Different controller tuning method for Conventional controller and design of Fuzzy Logic Controller for Non-Conventional Controller were described.

In **Chapter 6: Simulation Results and Discussion,** includes the proposed model of Adaptive Neuro-Fuzzy controller based on offline learning methods with motor parameters, Controller parameters is designed in MATLAB/SIMULINK environment. The dynamic performance of motors were analysed for step change of reference input and different disturbances were also applied to study their robust nature.

In **Chapter 7: Conclusion and Future Scope,** conclude the comparison between two controllers for speed regulation with their advantage and dis-advantages. The chapter also provides the required improvement to avoid these drawbacks.

1.6 CONCLUSION

The chapter provides the overview of DC motor and their control schemes. Further, objective and motivation of the project is discussed briefly. The overview of thesis is mentioned in this chapter.

CHAPTER-II

LITERATURE REVIEW

2.1 DC MOTOR

2.1.1 GENERAL

The electric motor is a machine that convert electrical energy into mechanical energy via magnetic coupling. A Motor use electricity for production of magnetic field and electric current is passed through a conductor placed in magnetic field which leads to production of torque which rotate the motor. The electrical power is provided by a voltage source, while the mechanical power is provided by a spinning rotor. A very basic dc motor is constructed of two main components: the rotor or armature and the stator. The armature rotates within the framework of the stationary stator. The stator consists of magnets which create a magnetic field. The armature consists of an electromagnet created by a coil wound around an iron core. The armature rotates due to the phenomenon of attracting and opposing forces of the two magnetic fields. A magnetic field is generated by the armature by sending an electrical current through the coil and the polarity is constantly changed by alternating the current through the coil (also known as commutation) causing the armature to rotate. The commutator is made up of two semicircular copper segments mounted on the shaft at the end of the rotor. Each terminal of the rotor coil is connected to a copper segment. Stationary brushes ride on the copper segments whereby the rotor coil is connected to a stationary dc voltage supply by a near frictionless contact.

There are two types of motor as per type of electric Source which are AC and DC. DC Motors are again classified as per source of magnet into two type Permanent Magnet DC motor (PMDC) and Electro-Magnet DC Motor. Electro-Magnet DC Motor are again classified as per excitation into two type Separately Excited and Self Excited. DC Motor outperforms to AC motor because it provides better speed control on high torque loads and are used in control field. In recent trends small DC Motors are widely used for traction and transportation as it designed to use batteries and solar cells energy sources, and are portable, environment friendly thus, provide cost effective solution. DC motor used in railway engines, electric cars, elevators, robotic applications, car windows and wide verify of small appliances and complex industrial mixing process where torque cannot be compromised. DC Motors are also used in applications where precise control of motion is required. A permanent magnet direct current (DC) motor is a very common component within many dynamic systems. From this general understanding, differential equations are developed to describe the motor's dynamic behavior. Typical data for a specific motor are included within a Matlab/Simulink program to illustrate the basic time domain behavior of the system.

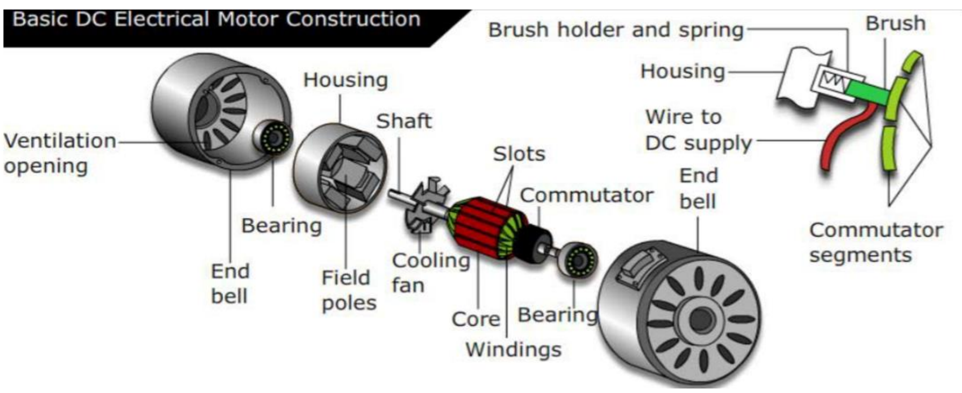

Fig 2.1 Cut-View of DC motor

2.1.2 PRINCIPLE OF OPERATION

Consider a coil in a magnetic field of flux density B (figure2.2). When the two ends of the coil are connected across a DC voltage source, current I flows through it. A force is exerted on the coil as a result of the interaction of magnetic field and electric current. The force on the two sides of the coil is such that the coil starts to move in the direction of force.

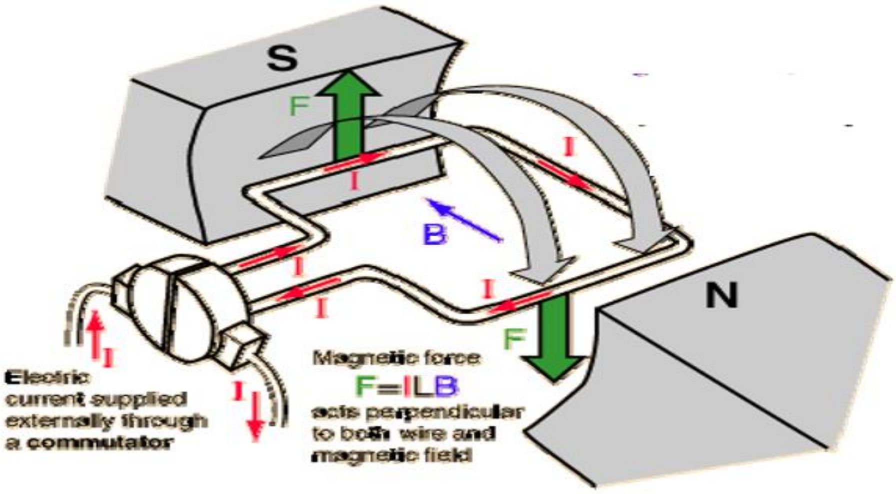

Fig 2.2 Torque production in a DC motor

In an actual DC motor, several such coils are wound on the rotor, all of which experience force, resulting in rotation. The greater the current in the wire, or the greater the magnetic field, the faster the wire moves because of the greater force created.

At the same time this torque is being produced, the conductors are moving in a magnetic field. At different positions, the flux linked with it changes, which causes an emf to be induced ($e = d\,ø/dt$) as shown in figure 2.3. This voltage is in opposition to the voltage that causes current flow through the conductor and is referred to as a counter-voltage or back emf.

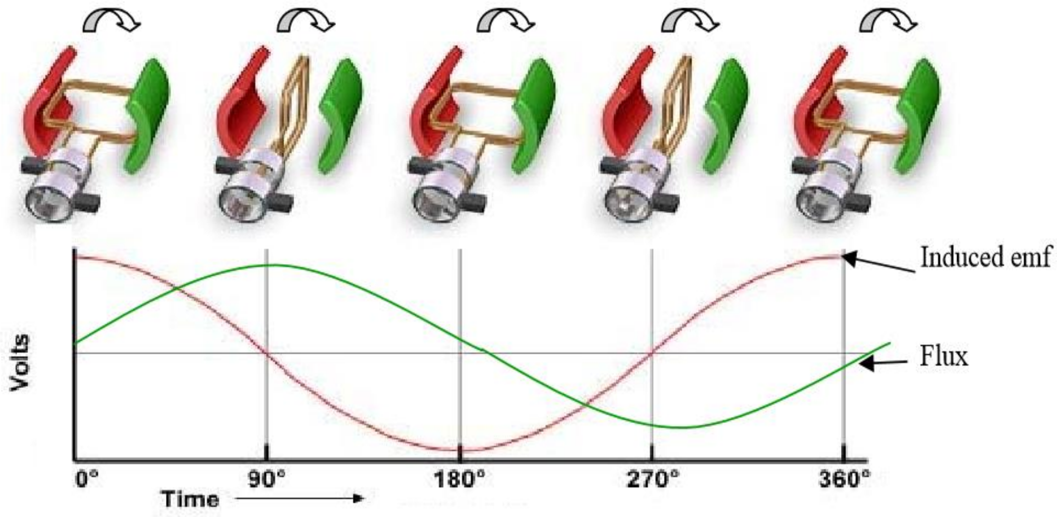

Fig 2.3 Induced voltage in the armature winding of DC motor

The value of current flowing through the armature is dependent upon the difference between the applied voltage and this counter-voltage. The current due to this counter-voltage tends to oppose the very cause for its production according to Lenz's law. It results in the rotor slowing down. Eventually, the rotor slows just enough so that the force created by the magnetic field (F = BIL) equals the load force applied on the shaft. Then the system moves at constant velocity.

2.2 BLDC MOTOR

2.2.1 GENERAL

The main difference between the BLDC and ordinary DC machine is the type of commutation applied. BLDC uses electrical commutation where as DC machine uses mechanical commutation. The construction of Brush-less DC motor is similar to those of permanent magnet synchronous motor. The rotor consists of permanent magnet, whereas poly phase winding is placed on the stator. The cross-sectional view of Brush-less DC motor is as shown below in FIG 2.4.

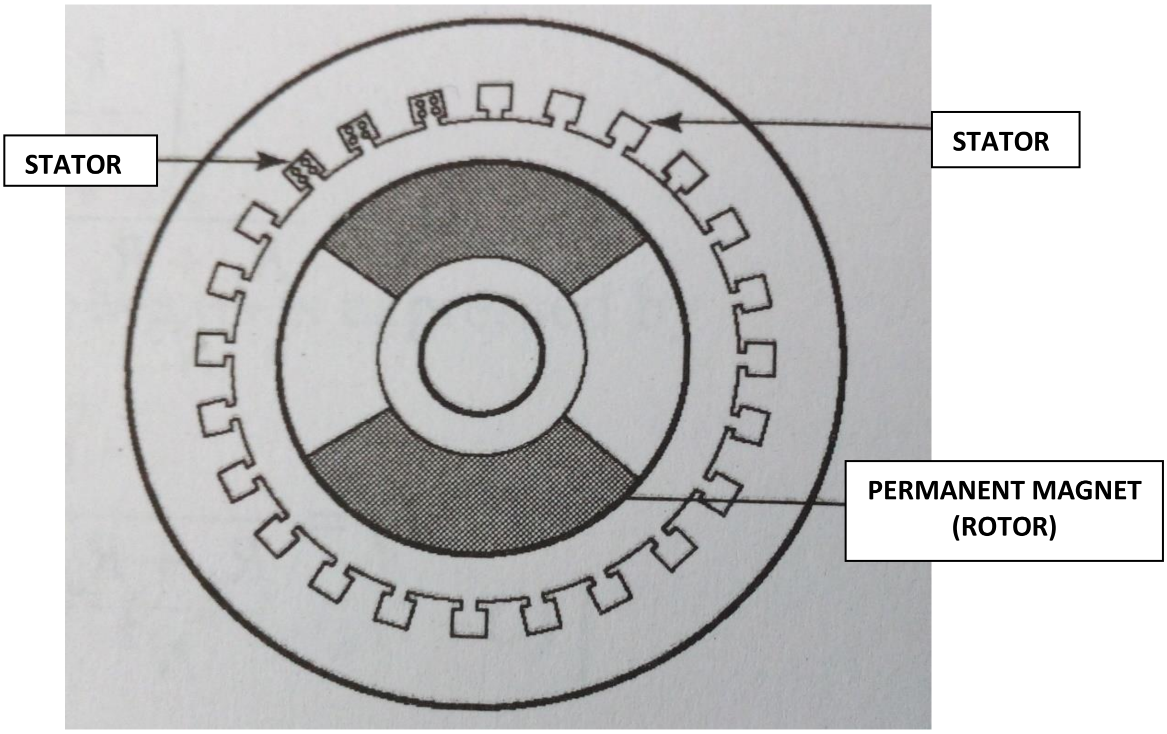

Fig 2.4 Cross-sectional view of Brush-less DC motor

2.2.2 PRINCIPLE OF OPERATION

Due to the combination of drive, its electronic drive circuit and rotor position sensor the word “brushless dc motor” is used. The electronic drive circuit in the Brush-less DC motor is an inverter consists of transistor, and it feeds stator winding, where the transistor is controlled by the pulse generated by rotor position sensors ensuring that the rotor revolves at an angular speed. This speed is the average speed of field produced by stator.

The driver circuit is fed by DC supply like DC motor where the field of stator and rotor remains stationary w.r.t. each other at all speed. The torque speed characteristic is similar to that of DC motor. The speed can be controlled by varying DC supply voltage. This is similarity with permanent magnet DC motor but it is without brush. A simple circuitry of Brush-less DC motor is as shown in Fig2.5.

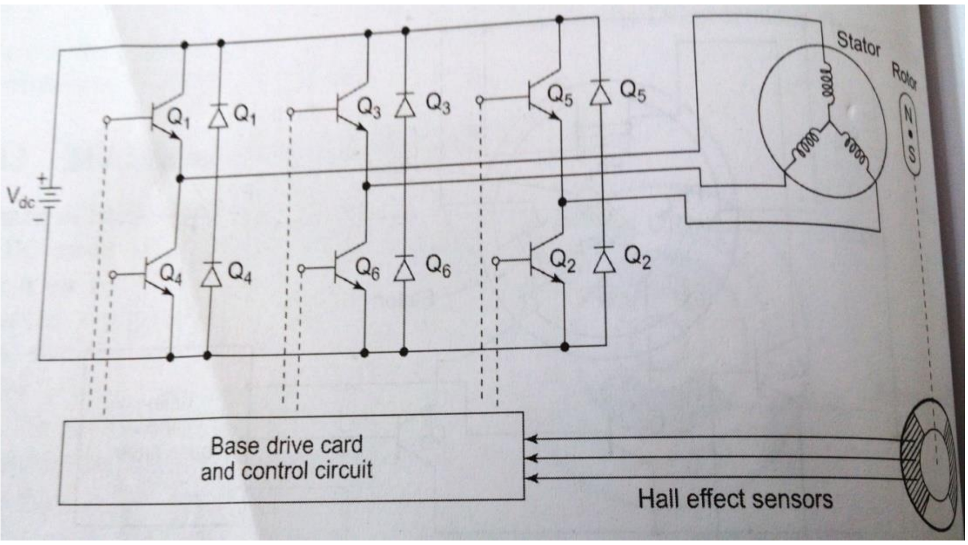

Fig 2.5 Driving circuitry of Brush-less DC motor

To control a speed of Brush-less DC motor, Atmel Corporation have produced using ATmega32M1 which apply a classic control. It is PID control. A quality control of Brush-less DC motor depends on the PID constant that is Kp, Ki, Kd. Tune Kp, Ki, Kd is done trial and error method. This method is dangerous applied for the large capacity of Brush-less DC motor and difficult to achieve an accurate value.

CHAPTER III

MODEL DEVELOPMENT

The goal in the development of the mathematical model is to relate the voltage applied to the armature to the velocity of the motor. The transfer function is one of the most important concepts of control theory, and the transfer-function-based mathematical models are widely used in automatic control fields. Some control design and analysis methods, such as the root-locus method and the frequency-response method, are also developed based on the system transfer function. Two balance equations were developed by considering the electrical and mechanical characteristics of the system.

3.1 PMDC MOTOR

3.1.1 ELECTRICAL CHARACTERISTICS

The equivalent electrical circuit of a dc motor is illustrated in Fig 3.1. It can be represented by a voltage source (Va) across the coil of the armature. The electrical equivalent of the armature coil can be described by an inductance (La) in series with a resistance (Ra) in series with an induced voltage (Vc) which opposes the voltage source. The induced voltage is generated by the rotation of the electrical coil through the fixed flux lines of the permanent magnets. This voltage is often referred to as the back emf (electromotive force).

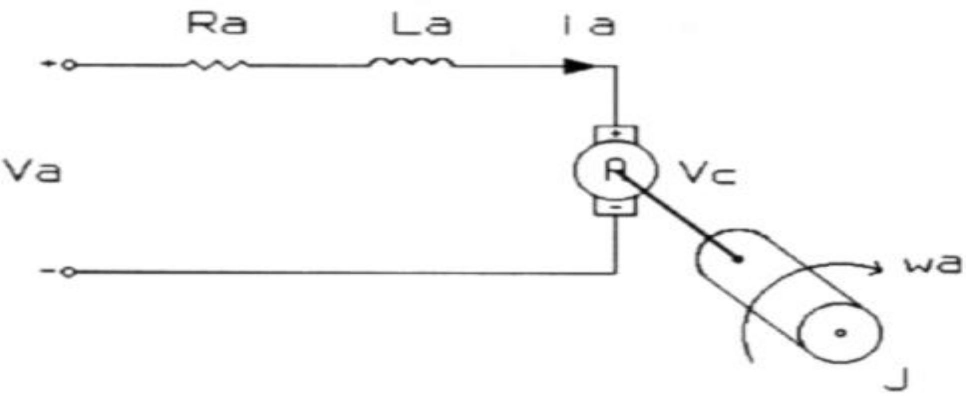

Fig 3.1 Electrical Representation of PMDC motor

A differential equation for the equivalent circuit can be derived by using Kirchoff's voltage law around the electrical loop. Kirchoff's voltage law states that the sum of all voltages around aloop must be equal to zero,or

$$V_a - V_{Ra} - V_{La} - V_c = 0 \tag{3.1}$$

According to Ohm's law, the voltage across the resistance can be represented as

$$V_{Ra} = i_a R_a \tag{3.2}$$

Where $i_a$is the armature current. The voltage across the inductor is proportional to the change of current through the coil with respect to time and can be written as

$$V_{La} = L_a \frac{di_a}{dt} \tag{3.3}$$

Where, La is the inductance of the armature coil. Finally, the back emf can be written as

$$V_c = K_V \, \omega_a \tag{3.4}$$

Where, K_V is the velocity constant determined by the flux density of the permanent magnets, the reluctance of the iron core of the armature, and the number of turns of the armature winding. ω_A is the rotational velocity of the armature. Substituting eqns. (3.2), (3.3), and (3.4) into eqn. (3.1) gives the following differential equation:

$$V_a - i_a R_a - L_a \frac{di_a}{dt} - K_V\, \omega_a = 0 \qquad (3.5)$$

3.1.2 MECHANICAL CHARACTERISTICS

Performing an energy balance on the system, the sum of the torques of the motor must equal zero. Therefore,

$$T_e - T_{\omega'} - T_{\omega} - T_L = 0 \qquad (3.6)$$

Where $\boldsymbol{T_e}$ is the electromagnetic torque, $\boldsymbol{T_{\omega'}}$ is the torque due to rotational acceleration of the rotor, $\boldsymbol{T_{\omega}}$ is the torque produced from the velocity of the rotor, and $\boldsymbol{T_L}$ is the torque of the mechanical load. The electromagnetic torque is proportional to the current through the armature winding and can be written as:

$$T_e = K_t i_a \qquad (3.7)$$

Where $\boldsymbol{K_t}$ is the torque constant and like the velocity constant is dependent on the flux density of the fixed magnets, the reluctance of the iron core, and the number of turns in the armature winding. $T_{\omega'}$ can be written as:

$$T_{\omega'} = J\, \frac{d\omega_a}{dt} \qquad (3.8)$$

Where J is the inertia of the rotor and the equivalent mechanical load. The torque associated with the velocity is written as:

$$T_{\omega} = B\, \omega_a \qquad (3.9)$$

Where, B is the damping coefficient associated with the mechanical rotational system of the machine. Substituting eqns. (3.7), (3.8), and (3.9) into eqn. (3.6) gives the following differential equation:

$$K_t i_a - J\,\frac{d\omega_a}{dt} - B\,\omega_a - T_L = 0 \qquad (3.10)$$

3.1.3 STATE SPACE REPRESENTATION

The differential equations given in eqns. (3.5) and (3.10) for the armature current and the angular velocity can be written as:

$$\frac{d}{dt} i_a = -\frac{R_a}{L_a} i_a - \frac{K_V}{L_a}\omega_a + \frac{V_a}{L_a} \qquad (3.11)$$

$$\frac{d}{dt}\omega_a = \frac{K_t}{J} i_a - \frac{B}{J}\omega_a - \frac{T_L}{J} \qquad (3.12)$$

Which describe the dc motor system. Putting the differential equations into state space form gives

$$\frac{d}{dt}\begin{bmatrix} i_a \\ \omega_a \end{bmatrix} = \begin{bmatrix} -\frac{R_a}{L_a} & -\frac{K_V}{L_a} \\ \frac{K_t}{J} & -\frac{B}{J} \end{bmatrix}\begin{bmatrix} i_a \\ \omega_a \end{bmatrix} + \begin{bmatrix} \frac{1}{L_a} & 0 \\ 0 & -\frac{1}{J} \end{bmatrix}\begin{bmatrix} V_a \\ T_L \end{bmatrix} \qquad (3.13)$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} i_a \\ \omega_a \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} V_a \\ T_L \end{bmatrix} \qquad (3.14)$$

Which is expressed symbolically as

$$\frac{d}{dt}\hat{X} = \hat{A}\hat{X} + \hat{B}\hat{u} \qquad (3.15)$$

$$\hat{y} = \hat{C}\hat{X} + \hat{D}\hat{u} \qquad (3.16)$$

Where $\hat{X}$ is the state vector, $\hat{u}$ is the input vector, and $\hat{y}$ is the output vector.

3.1.4 TRANSFER FUNCTION BLOCK DIAGRAM

A block diagram for the system can be developed from the differential equations given in eqns. (3.11) and (3.12). Taking the Laplace transform of each equation gives

$$Si_a(S) = -\frac{R_a}{L_a} i_a(S) - \frac{K_V}{L_a} \omega_a(S) + \frac{1}{L_a} V_a(S) \quad (3.17)$$

$$S\omega_a(S) = \frac{K_t}{J} i_a(S) - \frac{B}{J} \omega_a(S) - \frac{1}{J} T_L(S) \quad (3.18)$$

If perturbations around some steady state value are considered, the initial conditions go to zero and all the variables become some change around a reference state, and the equations can be expressed as follows:

$$I_a(S) = \frac{[-K_V \omega_a(S) + V_a(S)\ ]}{SL_a + R_a} \quad (3.19)$$

$$\omega_a(S) = \frac{[-K_t I_a(S) - T_L(S)\ \ ]}{SJ + B} \quad (3.20)$$

The above equations can then easily be put into block diagram form. The block diagram obtained from these equations for a permanent magnet dc motor is shown in Fig 3.2.

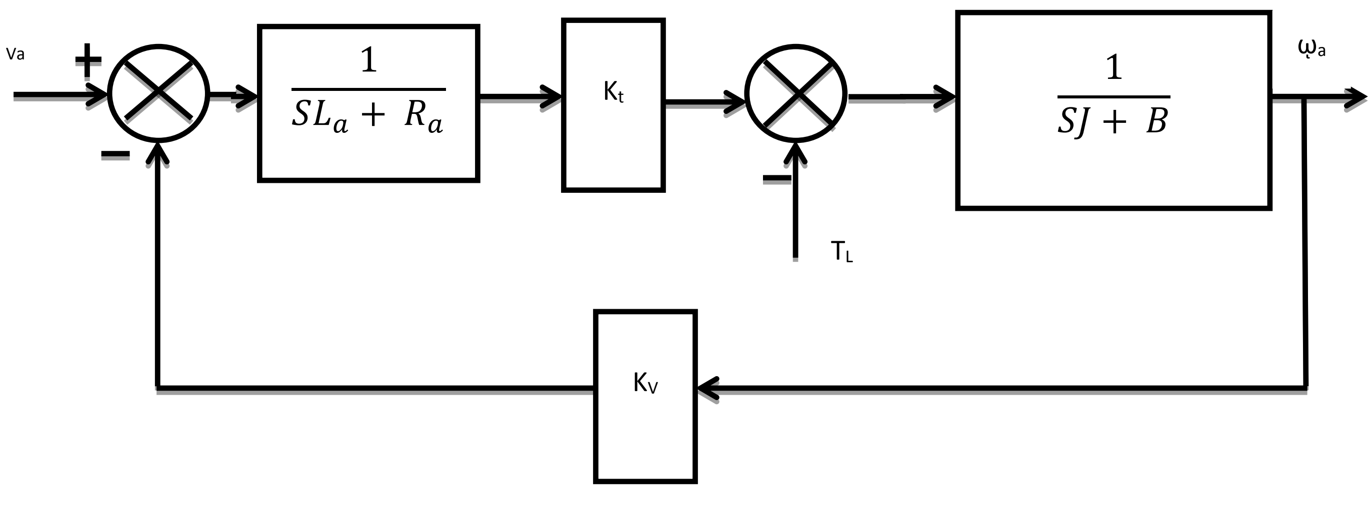

Fig.3.2 Block diagram representation of eqns. (3.19) and (3.20)

The block diagram in Fig 3.2 can be simplified by making the assumption that the load torque is constant. Since the change in T_L is zero, it does not need to appear in the block diagram. Also, if one only focuses on the angular velocity as the response of interest, the block diagram becomes as shown in Fig 3.2. This block diagram is then easily reduced by block diagram algebra to an overall transfer function.

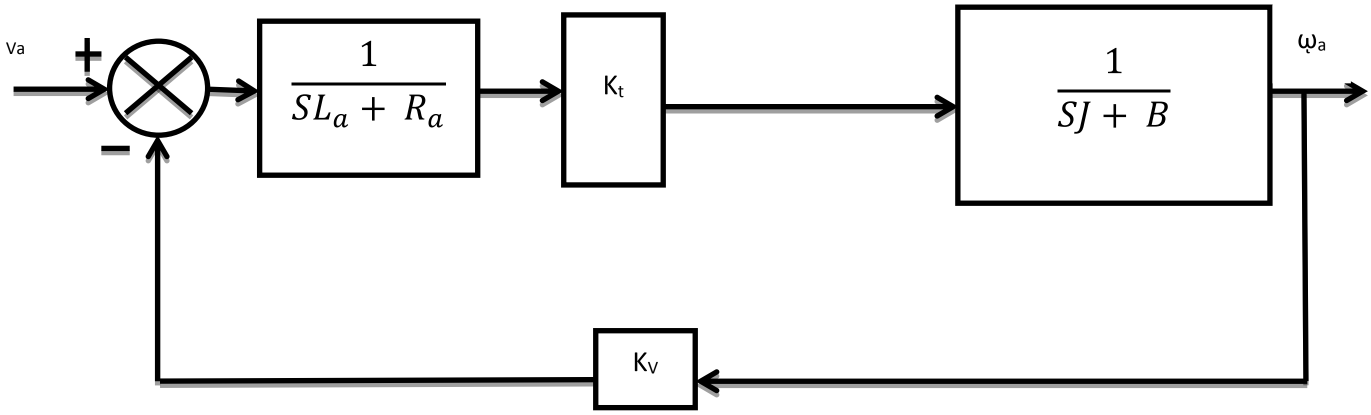

Fig 3.3 Block diagram representation of PMDC motor driving fixed load.

3.2 BLDC MOTOR

3.2.1 ELECTRICAL CHARACTERISTICS

Suppose that the three phase BLDC motor is controlled by full bridge driving in the two phase conduction mode. The mechanisms of back-EMF and electromagnetic torque are all the same with those of the traditional brushed DC motor, thus similar analysis methods can be adopted.

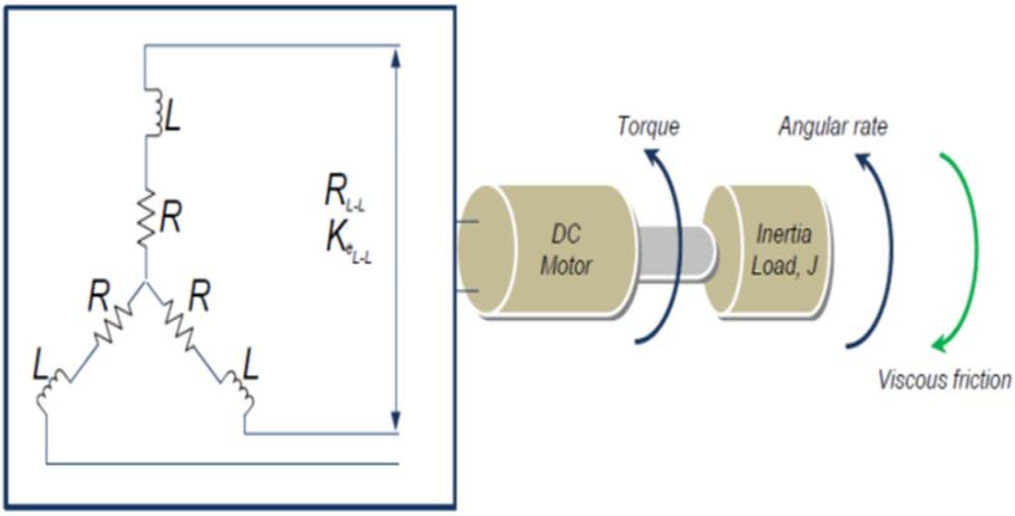

Fig 3.4 Brushless DC Motor Schematic Diagram

At any time the two phases are excited either AB or BC or CA. the simplified equivalent circuit will be as Fig. 3.5.

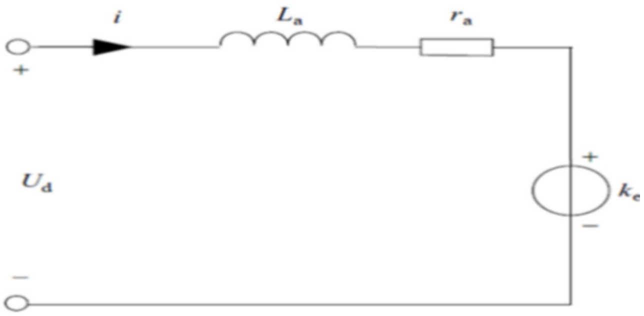

Fig 3.5 Simplified equivalent circuit of BLDC motor

$$i_A = -i_B = i \tag{3.21}$$

$$\frac{di_A}{dt} = -\frac{di_B}{dt} = \frac{di}{dt} \tag{3.22}$$

$$u_{AB} = 2Ri + 2(L-M)\frac{di}{dt} + (e_A - e_B) \tag{3.23}$$

$$\therefore\ e_A = -e_B \tag{3.24}$$

$$u_{AB} = U_d = 2Ri + 2(L-M)\frac{di}{dt} + 2e_A = r_a i + L_a\frac{di}{dt} + K_e \tag{3.25}$$

3.2.2 MECHANICAL CHARACTERISTICS

$$K_T i - T_L = J\frac{d\omega}{dt} + B_v\omega \qquad (3.26)$$

Assume Torque Load $T_L = 0$.

$$i = \frac{J}{K_T}\frac{d\omega}{dt} + \frac{B_v}{K_T} \qquad (3.27)$$

Substitute (3.27) in (3.25)

$$U_d = r_a(\frac{J}{K_T}\frac{d\omega}{dt} + \frac{B_v}{K_T}\omega) + L_a\frac{d(\frac{J}{K_T}\frac{d\omega}{dt} + \frac{B_v}{K_T}\omega)}{dt} + K_e\omega$$

Or,

$$U_d = \frac{L_aJ}{K_T}\frac{d^2\omega}{dt^2} + \frac{r_aJ + L_aB_v}{K_T}\frac{d\omega}{dt} + \frac{r_aB_v + K_eK_T}{K_T} \qquad (3.28)$$

3.2.3 TRANSFER FUNCTION BLOCK DIAGRAM

$$G_u(S) = \frac{\omega(S)}{U_d(S)} = \frac{K_T}{L_aJS^2 + (r_aJ + L_aB_v)S + (r_aB_v + K_TK_e)} \qquad (3.29)$$

By the same method

$$G_L(S) = \frac{\omega(S)}{T_L(S)} = -\frac{r_a + L_aS}{L_aJS^2 + (r_aJ + L_aB_v)S + (r_aB_v + K_TK_e)} \qquad (3.30)$$

The speed response of Brush-less DC motor motor affected together by applied voltage and load torque.

$$\omega(S) = G_u(S)U_d(S) + G_L(S)T_L(S)$$

Or,

$$= \frac{K_TU_d(S)}{L_aJS^2 + (r_aJ + L_aB_v)S + (r_aB_v + K_TK_e)} - \frac{r_a + L_aS}{L_aJS^2 + (r_aJ + L_aB_v)S + (r_aB_v + K_TK_e)} \qquad (3.31)$$

3.2.4 STATE SPACE MODEL

State space equation method is one of the most important analysis method in modern control theory. The state space method is becoming more and more popular in designing control systems with the fast development of computer techniques.

$$i_A + i_B + i_C = 0 \tag{3.32}$$

$$u_{AB} = r_a(i_A - i_B) + L_a \frac{d(i_A - i_B)}{dt} + e_{AB} \tag{3.33}$$

$$u_{BC} = r_a(i_A + 2i_B) + L_a \frac{d(i_A + 2i_B)}{dt} + e_{BC} \tag{3.34}$$

Substract equation (3.33) from equation (3.34)

$$u_{AB} - u_{BC} = -3r_a - 3L_a \frac{di_B}{dt} + e_{AB} - e_{BC} \tag{3.35}$$

$$i_B = -\frac{r_a}{L_a} i_B - \frac{1}{3L_a}(u_{AB} - e_{AB}) + \frac{1}{3L_a}(u_{BC} - e_{BC}) \tag{3.36}$$

By the same method,

$$u_{AB} = r_a(2i_A + i_B) + L_a \frac{d(2i_A + i_B)}{dt} + e_{AB} \tag{3.37}$$

$$u_{CA} = r_a(i_C - i_A) + L_a \frac{d(i_C - i_A)}{dt} + e_{CA} \tag{3.38}$$

Substract equation (3.37) from equation (3.38)

$$(u_{AB} - e_{AB}) - (u_{CA} - e_{CA}) = 3r_a i_A + 3L_a \frac{di_A}{dt} \tag{3.39}$$

$$i_A = -\frac{r_a}{L_a} i_A + \frac{1}{3L_a}(u_{AB} - e_{AB}) - \frac{1}{3L_a}(u_{CA} - e_{CA}) \tag{3.40}$$

$$u_{AB} = u_{BC} \tag{3.41}$$

$$e_{AB} = e_{BC} \tag{3.42}$$

$$u_{CA} = -(u_{AB} + u_{BC}) = -2u_{AB} \tag{3.43}$$

$$e_{CA} = -(e_{AB} + e_{BC}) = -2e_{AB} \tag{3.44}$$

By substituting (3.41), (3.42), (3.43),(3.44) in (3.40) will become.

$$i_A = -\frac{r_a}{L_a} i_A + \frac{1}{3L_a}(u_{BC} - e_{BC}) + \frac{2}{3L_a}(u_{AB} - e_{AB}) \tag{3.45}$$

From equation (3.26),

$$\omega = -\frac{B_v}{j}\omega + \frac{1}{J}(T_e - T_L) \tag{3.46}$$

Where, $T_e = K_T i$ (3.47)

$$\begin{bmatrix} \dot{i_A} \\ \dot{i_B} \\ \dot{\omega} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} -\frac{r_a}{L_a} & 0 & 0 & 0 \\ 0 & -\frac{r_a}{L_a} & 0 & 0 \\ 0 & 0 & -\frac{B_v}{J} & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} i_A \\ i_B \\ \omega \\ \theta \end{bmatrix} + \begin{bmatrix} \frac{2}{3L_a} & \frac{2}{3L_a} & 0 \\ \frac{-1}{3L_a} & \frac{1}{3L_a} & 0 \\ 0 & 0 & \frac{1}{J} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u_{AB} - e_{AB} \\ u_{BC} - e_{BC} \\ T_e - T_L \end{bmatrix} \tag{3.48}$$

CHAPTER IV

CONTROLLER

4.1 GENERAL

It is instructive to trace brief historical development of automatic control. Automatic control systems did not appear until the middle of eighteen century. The first automatic control system, the fly-ball governer, to control the speed of steam engines, was invented by James Watt in 1770. The importance of positioning heavy masses like ships and guns quickly and precisely was realized during the World War-I. In early 1920, Minorsky performed the classic work on the automatic steering of ships and positioning of guns on the shipboards. Hazen's work in 1934 may possibly be considered as the first struggling attempt to develop some general theory for servomechanism. The word 'Servo' has originated with him. Prior to 1940 automatic control theory was not much developed and for most cases the design of control system was indeed an art. During the decade of 1940's, mathematical and analytic methods were developed and practiced and control engineering was established as an engineering discipline in its own rights.

During World War-II it became necessary to design and construct automatic aeroplane pilots, gun positioning systems, radar tracking systems and other military equipments based on feedback control principle. This gave great impetus to automatic control theory. The industrial use of automatic control has tremendously increased since World War-II. Modern industrial processes such as manufacture and treatment of chemicals and metals are now automatically controlled. Control engineering has enjoyed tremendous growth during the years since 1955. Particularly with the advent of analog and digital computers and with perfection achieved in computer field, a highly sophisticated control schemes have been devised and implemented. Furthermore, computers have opened up vast vistas for applying control system concepts to non-engineering fields like business and management. On technology front fully automated control schemes have been introduced for electric utilities and many complex industrial process with several interacting variables particularly in chemical and metallurgical processes.

4.2 CONVENTIONAL CONTROLLER

4.2.1 PROPORTIONAL CONTROLLER

This is the most simple and oldest form of control in which the control output is simply proportional to the input to the controller.

$U = K_p \varepsilon$,

Where, U is controller output

K_p is the proportionate constant, and

E is the error or controller input.

This controller is still in use in mostly mechanical systems as it is simple and easy to implement hence cheap also. But, this method gives steady state error and not suitable for higher order systems or complex systems.

4.2.2 PI CONTROLLER

The “Proportional plus Integral” (PI) controller is development to Proportional controller in which steady state error is reduced. The controller output is sum of two terms that is Proportional and Integral as the name states. This type of controller are used mostly in industry as a reliable controller. Mathematical expression to input output relations are as,

$$U = K_p\varepsilon + K_i \int_0^t \varepsilon dt$$

Here in this output of the controller is sum of history of errors overtime and then multiplied by K_i. This controller gives no steady state error but suffer from a serious effect called integral windup that is in long term a small error causes very high control action which may saturate the final control elements and may damage electronic amplifiers used in between path. Thus, to overcome this effect further derivative action has been utilized to stabilize the system from integral windup hence, PID controller.

4.2.3 PID CONTROLLER

PID control is by far the most common way of using feedback in natural and man-made systems. PID controllers are commonly used in industry and a large factory may have thousands of them, in instruments and laboratory equipment. In engineering applications the controllers appear in many different forms: as a stand alone controller, as part of hierarchical, distributed control systems, or built into embedded components. Most controllers do not use derivative action. In this chapter we discuss the basic ideas of PID control and the methods for choosing the parameters of the controllers. Many aspects of control can be understood based on linear analysis. However, there is one nonlinear effect, that has to be considered in most control systems namely that actuators saturate. In combinations with controllers having integral actions saturations give rise to an effect called **integral windup**. This phenomenon that occurs in practically all control systems will be discussed in depth for PID controllers. Methods to avoid windup will also be presented. Finally we will also discuss implementation of PID controllers, similar methods can be used to implement many other controllers.

A proportional-integral-derivative controller (PID controller) is a generic control loop feedback mechanism (controller) widely used in industrial control systems. A PID controller calculates an "error" value as the difference between a measured process variable and a desired set point. The controller attempts to minimize the error by adjusting the process control outputs.

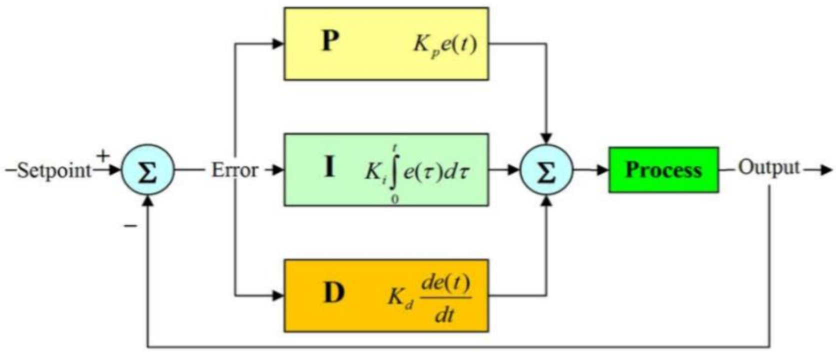

Fig 4.1 Block diagram of a PID Controller

The PID controller algorithm involves three separate constant parameters, and is accordingly sometimes called **three-term control**: the proportional, the integral and derivative values, denoted *P*, *I*, and *D*. Simply put, these values can be interpreted in terms of time: *P* depends on the *present* error, *I* on the accumulation of *past* errors, and *D* is a prediction of *future* errors, based on current rate of change. The weighted sum of these three actions is used to adjust the process via a control element such as the position of a control valve, a damper, or the power supplied to a heating element. In the absence of knowledge of the underlying process, a PID controller has historically been considered to be the best controller. By tuning the three parameters in the PID controller algorithm, the controller can provide control action designed for specific process requirements. The response of the controller can be described in terms of the responsiveness of the controller to an error, the degree to which the controller overshoots the set point, and the degree of system oscillation.

4.3 NON-CONVENTIONAL CONTROLLER

4.3.1 FUZZY CONTROLLER

Fuzzy logic is a type of multi valued logic. It deals with approximate reasoning rather than precise. Fuzzy logic derived from fuzzy set theory. Fuzzy logic was first proposed by Lotfi Zadeh in 1965. Fuzzy controller is an innovative technology that modifies the design of systems with engineering expertise. Fuzzy logic use human knowledge to implement a system. It is mostly use in system where there are no mathematical equations for handling system. Common sense, human thinking and judgement are fuzzy rules. It helps engineers to solve non linear control problems. It mathematically emulates human knowledge for intelligent control system and complex application. Fuzzy Logic Controller (FLC) has some advantages compared to other classical controller such as simplicity of control, low cost, and the possibility to design without knowing the exact mathematical model of the process. Fuzzy logic incorporates an alternative way of thinking which allows modelling complex systems using higher level of abstraction originating from the knowledge and experience. Fuzzy logic can be described simply as “computing words rather than numbers” or “control with sentence rather than equations”. There are two famous type of system currently used in fuzzy logic which are Mamdani fuzzy inference, and Sugeno fuzzy inference.

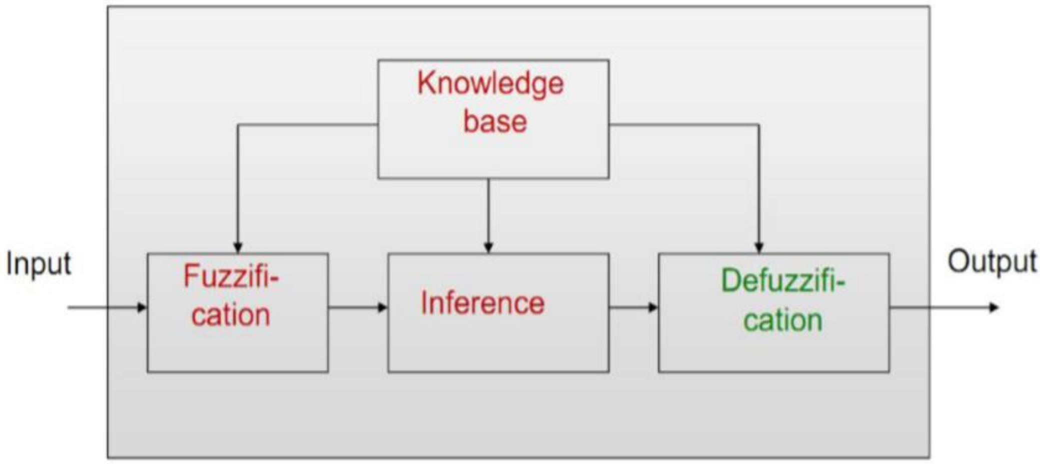

Fig 4.2 Block diagram of a Fuzzy Controller

4.3.1.1 Fuzzification

The first step of fuzzy inference system is Fuzzification in which crisp inputs are transformed into corresponding fuzzy inputs using different membership functions. The crisp input are the exact inputs measured by sensors and feed to control unit for further processing. Each crisp inputs are processed by fuzzy inference unit having own membership functions within the universe of discouse. The following terms are used in fuzzy inference system:

1. Crisp input : It is exact measured input from system fed to controller.
2. Membership grade: It describes the trueness having range between 1 and 0.
3. Membership Function : It is defined by mapping crisp input into fuzzy set according to the membership grade.

The various type of membership function available are:

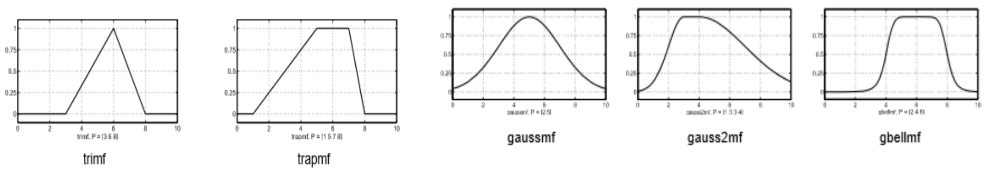

Fig 4.3 Different membership functions available

The number of inputs may be single or multiple as required and number and type of membership function selected is based on expert experience. Some of the points is that lesser number of membership function gives instability as their membership function are less likely to overlap each other at the same time higher number of membership function may cause the system sluggish due very high computing data and sometimes may go sort fall in data source.

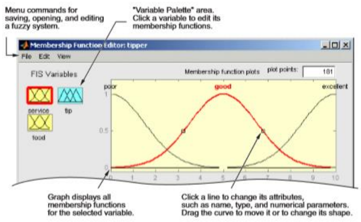

Fig 4.4 Membership function in Simulink Environment

4.3.1.2 Rule Base:

It consists of an IF-THEN table relating inputs and output. In general it is described by Zadeh in the syntax form for two input and one output as,
"IF (antecedent1) Zadeh operator (antecedent 2) THEN (Consequent1)"
Here, zadeh operator is like a logical operator and are of three type namely "max & OR", "min & AND" and "NOT".

It can be better understood by considering an e.g. that

"If *service* is **good** then *tip* is **average**"

The concept "**good**" is represented as a number between 0 and 1, and so the antecedent is an interpretation that returns a single number between 0 and 1. Conversely, **average** is represented as a fuzzy set, and so the consequent is an assignment that assigns the entire fuzzy set B to the output variable y. In the if-then rule, the word is gets used in two entirely different ways depending on whether it appears in the antecedent or the consequent. In MATLAB terms, this usage is the distinction between a relational test using "==" and a variable assignment using the "=" symbol. A less confusing way of writing the rule would be If service == good then tip = average In general, the input to an if-then rule is the current value for the input variable (in this case, service) and the output is an entire fuzzy set (in this case, average).

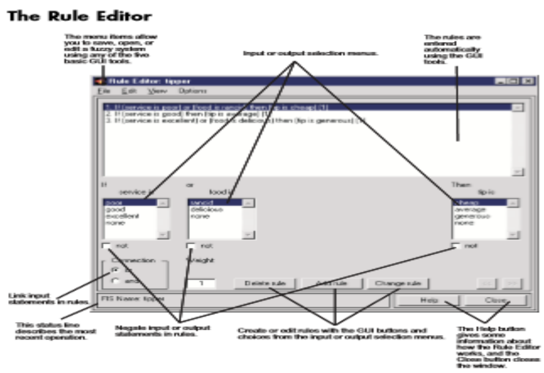

Fig 4.5 Rule base formulation in Simulink environment

4.3.1.3 Defuzzification:

It is a method of transforming the fuzzy output into a crisp output so that the further this can be utilized as a control signal for controlling the relevant plant. There are many mathematical rules or algorithm to carry out Defuzzification as:

LOM : last of maximum

COA : center of area

COG : center of gravity

BOA : bisector of area

MOM : middle of maximum

MeOM: mean of maximum

FOM : first of maximum

4.3.2 NEURAL NETWORK

Neural networks consist of a large class of different architectures. In many cases, the issue is approximating a static nonlinear, mapping $f(x)$ with a neural network$f_{NN}(x)$, where,$\in \; R^K$. The most useful neural networks in function approximation are Multilayer Layer Perceptron (MLP) and Radial Basis Function (RBF) networks. Here we concentrate on MLP networks. A MLP consists of an input layer, several hidden layers, and an output layer. Node i, also called a neuron, in a MLP network is shown in Fig.4.6. It includes a summer and a nonlinear activation function g.

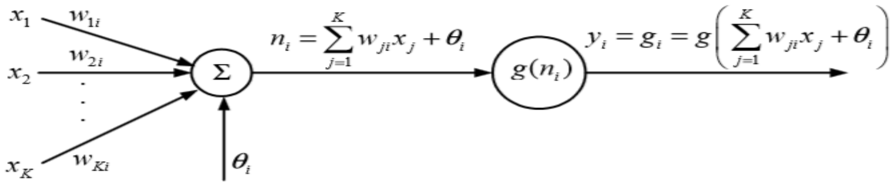

Fig 4.6 Single node In a MLP Network

The inputs $x(k)$, K = 1,2….K; to the neuron are multiplied by weights w_{ki} and summed up together with the constant bias term θ_i . The resulting n_i is the input to the activation function g. The activation function was originally chosen to be a relay function, but for mathematical convenience a hyperbolic tangent (tanh) or a sigmoid function are most commonly used. Hyperbolic tangent is defined as

$$\tanh(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{49}$$

The output of node i becomes

$$y_i = g_i = g\left(\sum_{j=1}^{k} w_{ji} x_j + \theta_i\right) \tag{50}$$

Connecting several nodes in parallel and series, a MLP network is formed. A typical network is shown in Fig 4.7.

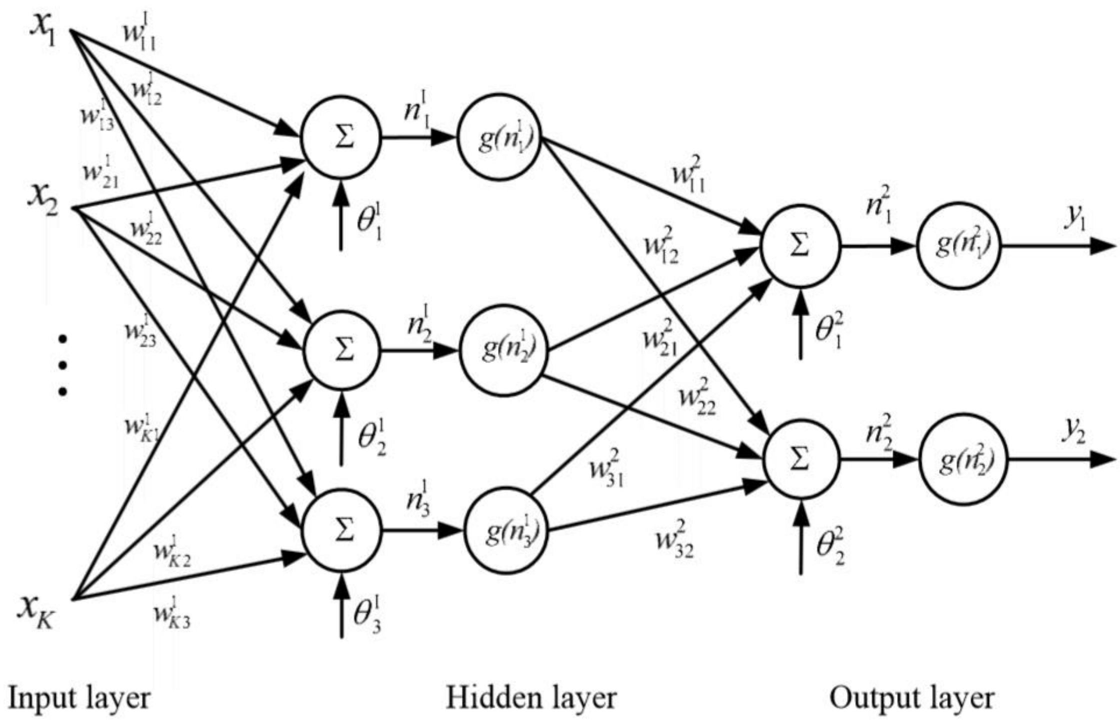

Fig 4.7 A MLP Network with single hidden layer

Here the same activation function g is used in both layers. The superscript of n,θ , and $w$refers to the layer, first or second.

The output ,y_i , $i = 1{,}2$ of the MLP network becomes

$$y_i = g\left(\sum_{j=1}^{3} w_{ji}^2 g\left(n_j^1\right) + \theta_j^2\right)$$

Or,

$$= g\left(\sum_{j=1}^{3} w_{ji}^2 g\left(\sum_{k=1}^{k} w_{kj}^1 x_k + \theta_j^1\right) + \theta_j^2\right) \qquad (51)$$

From eq^n (51) we can conclude that a MLP network is a nonlinear parameterized map from input space $x \in R^K$ to output space $y \in R^m$ (here m = 3). The parameters are the weights $w_{ji}^k$and the biases θ_j^k . Activation functions g are usually assumed to be the same in each layer and known in advance. In the figure the same activation function g is used in all layers. Given input-output data $(x_i, y_i), i = 1 \dots \dots N$, finding the best MLP network is formulated as a data fitting problem. The parameters to be determined are $\left(w_{ji}^k, \theta_j^k\right)$.

4.3.2.1 DESIGN OF NEURAL NETWORK

The procedure goes as follows: First the designer has to fix the structure of the MLP network architecture: the number of hidden layers and neurons (nodes) in each layer. The activation functions for each layer are also chosen at this stage, that is, they are assumed to be known. The unknown parameters to be estimated are the weights and biases, $\left(w_{ji}^{k}, \theta_{j}^{k}\right)$.

Many algorithms exist for determining the network parameters. In neural network literature the algorithms are called learning or teaching algorithms, in system identification they belong to parameter estimation algorithms. The most well-known are back-propagation and Levenberg-Marquardt algorithms. Back-propagation is a gradient based algorithm, which has many variants. Levenberg-Marquardt is usually more efficient, but needs more computer memory.

Summarizing the procedure of teaching algorithms for multilayer perceptron networks:

a. The structure of the network is first defined. In the network, activation functions are chosen and the network parameters, weights and biases, are initialized.

b. The parameters associated with the training algorithm like error goal, maximum number of epochs (iterations), etc, are defined.

c. The training algorithm is called.

d. After the neural network has been determined, the result is first tested by simulating the output of the neural network with the measured input data. This is compared with the measured outputs. Final validation must be carried out with independent data.

CHAPTER V

CONTROLLER TUNING

5.1 GENERAL

Control system operation is dictated by its components, and the disturbances to which it is subjected. The disturbances are controlled by external events and can't be predicted in advance. The controller is the only component in control loop whose behaviour can be modified by changing its operating parameters, such as Kp , Ki, Kd . The modification of controller parameters is known as 'controller tuning' and it affects the operation of the entire control loop. Controller tuning is carried out to obtain a desired performance from the control loop. Controller tuning is necessitated by one of the following situations:

Case 1 New Plant

Case 2 Old Plant (new requirement)

Case 3 Old Plant (component aging)

5.2 PERFORMANCE CRITERION

5.2.1 TIME DOMAIN

- Steady state error (Ess): The difference between system output from desired output as time progresses.
- Settling (Tss) : Time required to settle system output within specified range generally 2% and 5% of output.
- Peak Over-shoot (Mp): It is the ratio of peak deviation in output to desired out in percentage.
- Relative stability : It gives the degree of stability or how close to instability, measured by the relative real part of each root or pair of roots.
- Speed of response : It is the gradient or slope of system response.
- Damping ratio : It is the dimensionless measure describing how oscillations in a system decay after a disturbance.

5.2.2 FREQUENCY DOMAIN

- Gain Margin : The amount of gain increase or decrease required to make loop gain unity at frequency W_{gm} where phase angle is -180^0.
- Phase Margin : The difference between phase of response and -180^0 when the loop gain is unity.
- System Band Width : The range of frequencies, where absolute gain falls to -3db.

Once performance criterion has been established, controller tuning can be undertaken. Approach taken for controller parameter adjustments depends on the availability of a suitable plant mathematical model which is rarely available (Case-2&3). Experimental determination of controller setting can yield satisfactory results, even if there is no information about the plant transfer function. This approach is generally utilized to verify results, even if the plant model is known. These procedures aim to find the optimum tuning coefficients for the three term PID controller. These approaches are based upon experience gathered by control engineers in operations and control of various plants over the years. There are two main approaches for determining coefficients, and both are based upon the pioneering work of two control practitioners, J.G.Ziegler and N.B.Nichols. Both methods strive to provide a slightly undamped response with a decay ratio of 1:4. These settings tend to provide a reasonably fast response with small settling time. A PID controller has three tuning parameters. If these are adjusted in an ad hoc fashion, it may take a while for satisfactory performance to be obtained. Also, each tuning technician will end up with different set of tuning parameters. There is a plenty of motivation, then, to develop an algorithmic approach to controller tuning. The first widely used method for PID tuning was published by Zeigler and Nichols.

5.3 TUNING METHODS

5.3.1 CONVENTIONAL

5.3.1.1 CONTINUOUS CYCLING METHOD

It is also called closed loop method using stability limit. The Zeigler and Nichols closed loop tuning technique was perhaps the first rigorous method to tune PID Controllers. The technique is not widely used today because the closed-loop behaviour tends to be oscillatory and sensitive to uncertainty. As a start-up to tuning field we study these methods now a day. The Zeigler and Nichols method consists of the following steps.

- With P-only closed-loop control, increase the magnitude of proportional gain until the closed-loop is in continuous oscillation. For slightly larger value of controller gain, the closed-loop system is unstable, while for slightly lower values the system is stable.

- The value of controller propotional gain that causes the continuous oscillation is called the critical(or ultimate) gain, K_u. The peak to peak period (time between successive peaks in the continuously oscillating process output) is called the critical(or ultimate) period, T_u .
- Depending upon the controller chosen, P, PI,or PID, use the values in Table-5.1 for the tuning parameters, based on the critical gain and period.

Table-5.1 Control Parameters suggested by Zeigler and Nichols

	K_p	T_i	T_d
P	$0.5K_u$	-	-
PI	$0.45K_u$	$T_u/1.2$	-
PID	$0.6K_u$	$T_u/2$	$T_u/8$

Tyreus and Luben have suggested tuning parameter rules that results in less oscillatory response and are less sensitive to changes in parameter. Their rules are shown in Table-5.2.

Table-5.2 Control Parameters suggested by Tyreus and Luben

	K_p	T_i	T_d
P	$0.5K_u$	-	-
PI	$K_u/3.2$	$2.2T_u$	-
PID	$K_u/2.2$	$2.2T_u$	$T_u/6.3$

5.3.1.2 REACTION CURVE METHOD

The previous tuning rules were based on tests that forced a process into continuous oscillation. Obvious disadvantage to the technique are that the system is forced to edge of instability, and it may take a while to iteratively adjust the controller to obtain a continuous oscillation. The method using Process reaction curve method is a open loop method. Zeigler and Nichols also proposed tuning parameters for a process that has been identified as integrator + time-delay based on an open loop process step response,

$$g_p(S) = k\frac{e^{-\theta S}}{S}$$

Since the first order + time delay process have maxim slope of K=K_p/T_p at t=θ For a unit step input change, these same rules can be used for first order + time delay process,

$$g_p(S) = \frac{K_p e^{-\theta S}}{T_p S + 1}$$

Their recommended tuning parameters, which should give roughly ¼ decay ratio are listed in Table-5.3

Table-5.3 Control Parameters suggested by Zeigler and Nichols

	K_p	T_i	T_d
P	$\frac{1}{k\theta}$ or $\frac{T_p}{K_p\theta}$	-	-
PI	$\frac{0.9}{k\theta}$ or $\frac{0.9T_p}{K_p\theta}$	3.3 θ	-
PID	$\frac{1.2}{k\theta}$ or $\frac{1.2T_p}{K_p\theta}$	2 θ	0.5 θ

The method was developed by Cohen and Coon in1953. A set of tuning parameters was empirically developed to yield a closed loop response with a decay ratio of ¼ (similar to Zeigler and Nichols method). The tuning parameters as a function of model parameters are listed in Table-5.4.

The major problem with Cohen and Coon parameters is that they tend not to be very robust; that is, a small change in the process parameters can cause the closed-loop system unstable.

Table-5.4 Control Parameters suggested by Cohen and Coon

	K_p	T_i	T_d
P	$\frac{T_p}{K_p\theta}\left[1+\frac{\theta}{3T_p}\right]$	-	-
PI	$\frac{T_p}{K_p\theta}\left[0.9+\frac{\theta}{12T_p}\right]$	$\frac{\theta[30+3\theta/T_p]}{9+20\theta/T_p}$	-
PID	$\frac{T_p}{K_p\theta}\left[\frac{4}{3}+\frac{\theta}{4T_p}\right]$	$\frac{\theta[32+6\theta/T_p]}{13+8\theta/T_p}$	$\frac{4\theta}{11+2\theta/T_p}$

5.3.2 NON- CONVENTIONAL

Fuzzy logic provides an inference morphology that enables approximate human reasoning capabilities to be applied to knowledge-based systems. The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning. The conventional approaches to knowledge representation lack the means for representating the meaning of fuzzy concepts. As a consequence, the approaches based on first order logic and classical probability theory do not provide an appropriate conceptual framework for dealing with the representation of common sense knowledge, since such knowledge is by its nature both lexically imprecise and non-categorical. The development of fuzzy logic was motivated in large measure by the need for a conceptual frame work which can address the issue of uncertainty and lexical imprecision.

Artificial neural systems can be considered as simplified mathematical models of brain-like systems and they function as parallel distributed computing networks. However, in contrast to conventional computers, which are programmed to perform specific task, most neural networks must be taught, or trained. They can learn new associations, new functional dependencies and new patterns. Perhaps the most important advantage of neural networks is their adaptivity. Neural networks can automatically adjust their weights to optimize their behavior as pattern recognizers, decision makers, system controllers, predictors, etc. Adaptivity allows the neural network to perform well even when the environment or the system being controlled varies over time. There are many control problems that can benefit from continual nonlinear modeling and adaptation.

Hybrid systems combining fuzzy logic, neural networks, genetic algorithms, and expert systems are proving their effectiveness in a wide variety of real world problems.

5.3.2.1 LEARNING METHODS

Learning in a neural network can be equated to data (or pattern) storage. It is the capacity of a system to absorb information from its environment without requiring some external intelligence to 'program' it. Learning is defined as any change in the weights the network. Learning can be supervised (a process that incorporates an external teacher and/or global information) or unsupervised. (The network is self-organizing; collective properties emerge as it is presented data). In supervised learning, the external teacher tells the network how to change, i.e., adjusts the weights based on the results of a learning pass. One category of supervised learning is reinforcement learning, in which the network is told simply if the output of the network is good or bad A parallel to human learning is apparent. The rate at which a neural network learns can be governed by learning rates. These learning rates are parameters which accelerate or retard the learning process.

Artificial neural networks operate in two modes, learning and operation. Compared to conventional computing, the learning mode, or training mode, is the process of loading data into memory. In neural network terns, it is the process of assigning an appropriate function to every neuron by changing the weights on its input connections. The operational mode is equivalent to data retrieval.

Artificial neural network technology offers a number of benefits to users:

Generalization: Neural networks have the ability to deduce the structure of underlying data Noise Immunity. Such systems are tolerant of noise.

Graceful degradation : The failure of one neuron or one connection does not cause a neural network system to crash.

Adaptability : Neural network systems can adapt to varied situations, and in some architectures, can adapt on their own.

Nonlinearity : Neural networks promise to be able to solve many problems which require complex messing. For example, many control problems are nonlinear.

Parallelism : Artificial neural Networks are very fast.

CHAPTER VI

RESULTS AND DISCUSSION

6.1 DC MOTOR

6.1.1 DC MOTOR PARAMETERS

Rating	:	2 h.p.
Voltage	:	230V DC
Current	:	8.5A
Rated Speed	:	1500 rpm

6.1.2 CONTROLLER PARAMETERS

K_p	:	49.41
K_i	:	0.075
K_d	:	0.01875

6.1.3 DC MOTOR WITH PID CONTROLLER

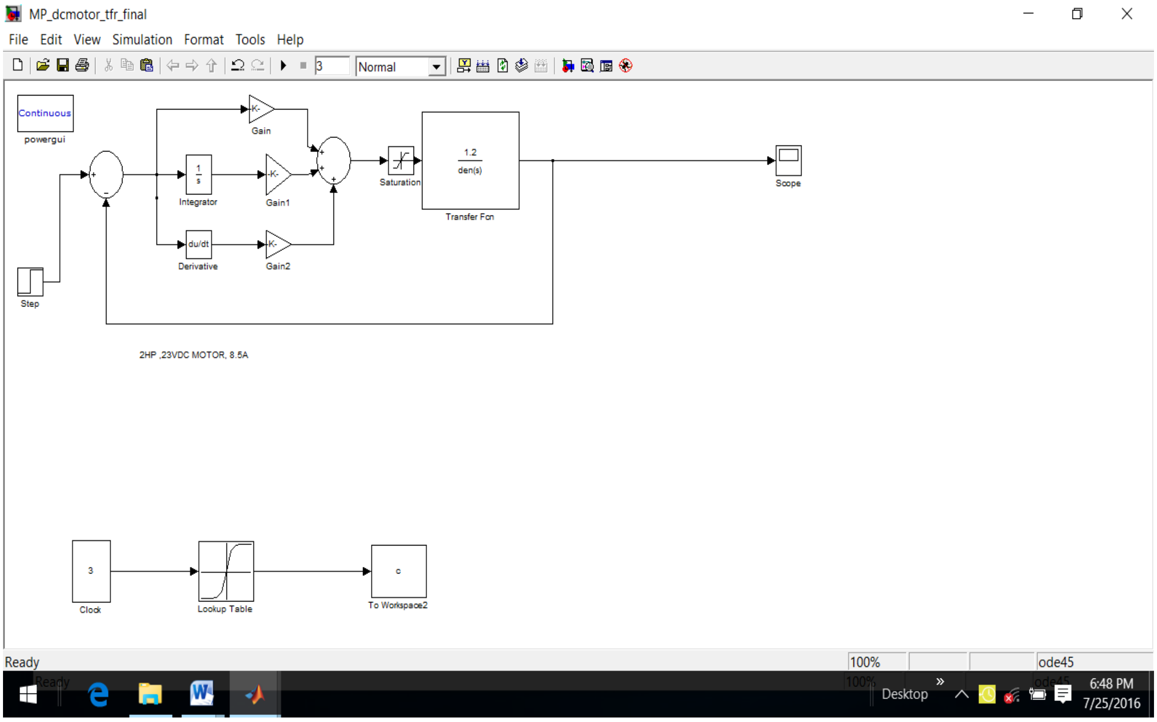

Fig 6.1 Simulink model of DC motor with PID controller

6.1.4 DC MOTOR WITH ANFIS CONTROLLER

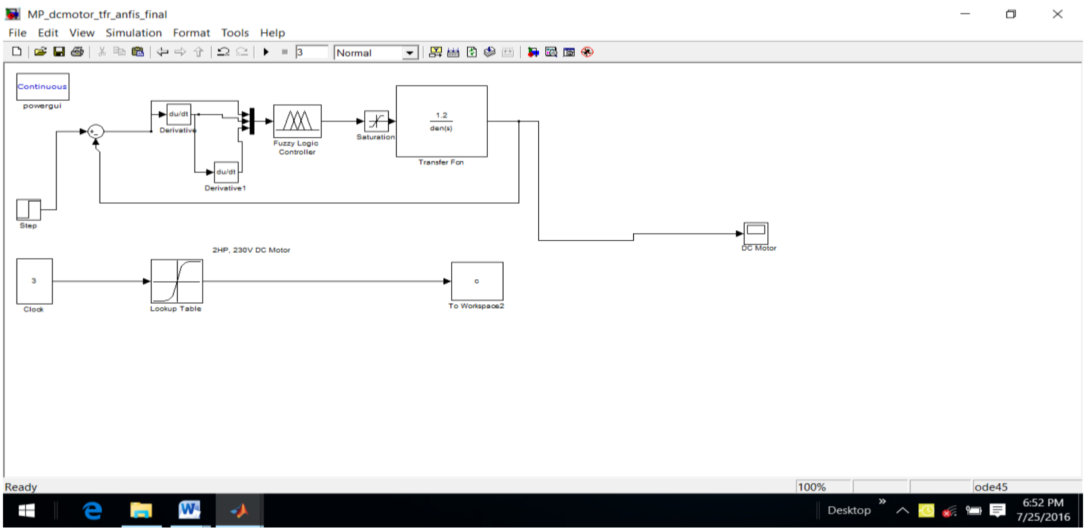

Fig 6.2 Simulink model of DC motor using Adaptive Neuro-Fuzzy controller

6.1.5 RESULT OF DC MOTOR AT FIXED LOAD

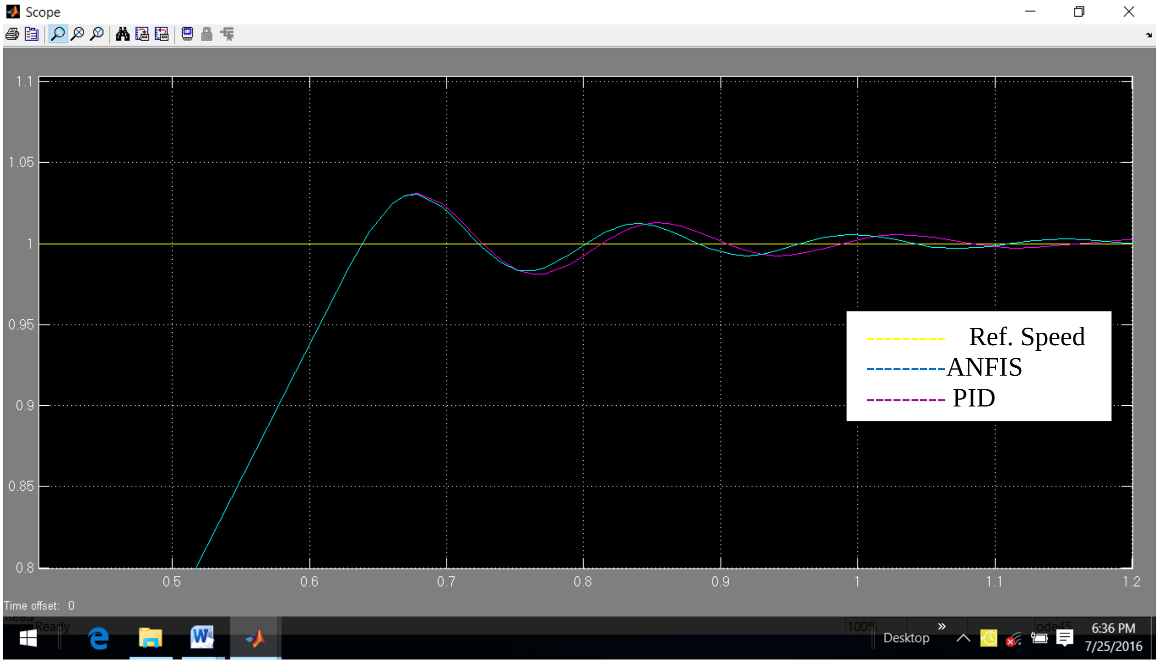

Fig. 6.3 DC Motor at fixed load with PID & ANFIS Controller

6.1.6 RESULT OF DC MOTOR WITH PARAMETER VARIATION

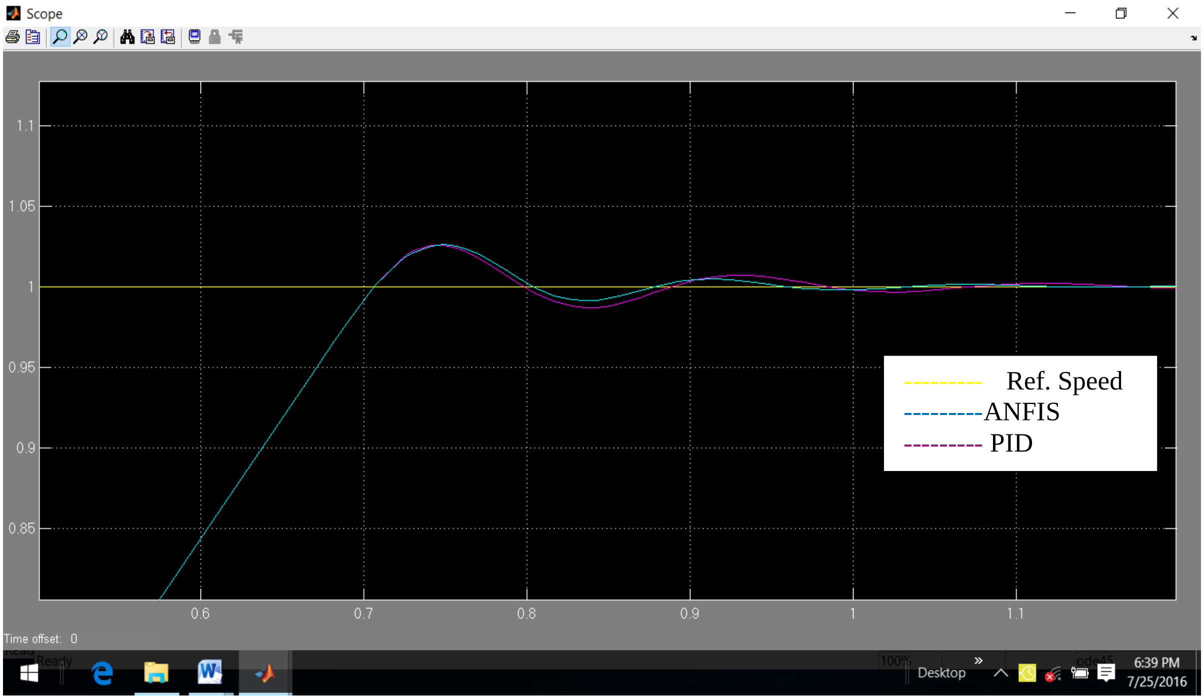

Fig 6.6 DC motor Parameter Variation with PID & ANFIS Controller

6.1.7 DISCUSSION

The results in terms of performance indices Peak Overshoot (M_p) and Settling Time (T_{ss}) are tabulated below as

Table 6.1 Transient response sheet of DC motor

	M_p		T_{ss}	
	PID	ANFIS	PID	ANFIS
No Load	2.8	3	0.76	0.76
Parameter Change	2.65	2.6	0.81	0.8

Thus from the above results we see the ANFIS gives comparable result in terms of above parameters but from the graph we see faster speed of response for ANFIS controller. When transfer function models were taken, many environmental non-linearity were unaccounted for. So, we can say that this controller works at par with PID in ideal situations as well.

6.2 BRUSHLESS DC MOTOR

6.2.1 BLDC MOTOR PARAMETERS

Stator Phase Resistance	:	2.875 Ohm
Inductance	:	8.5 mH
Flux Linkage	:	0.175 V/sec
Moment of Inertia	:	0.8*10^-3
No. of Poles	:	4

6.2.2 CONTROLLER PARAMETERS

K_p	:	50
K_i	:	2.5

6.2.3 BLDC MOTOR WITH PID CONTROLLER

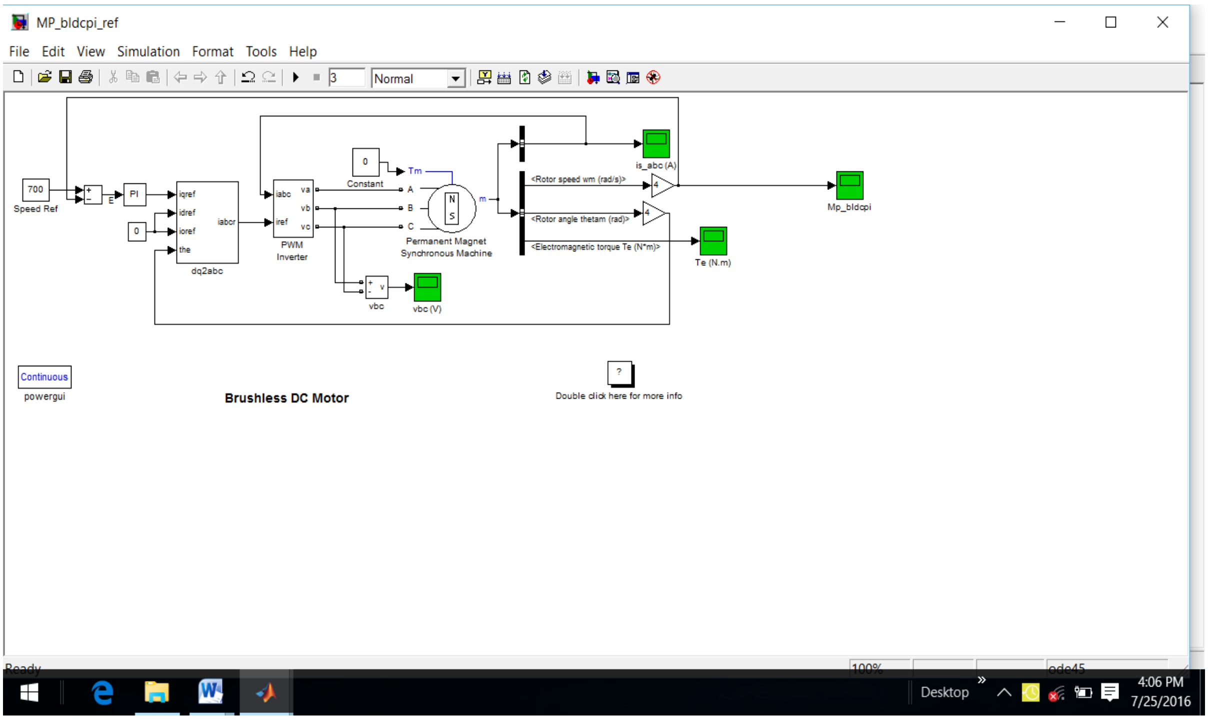

Fig 6.7 BLDC motor using PID controller

6.2.4 NEURO-FUZZY CONTROLLER

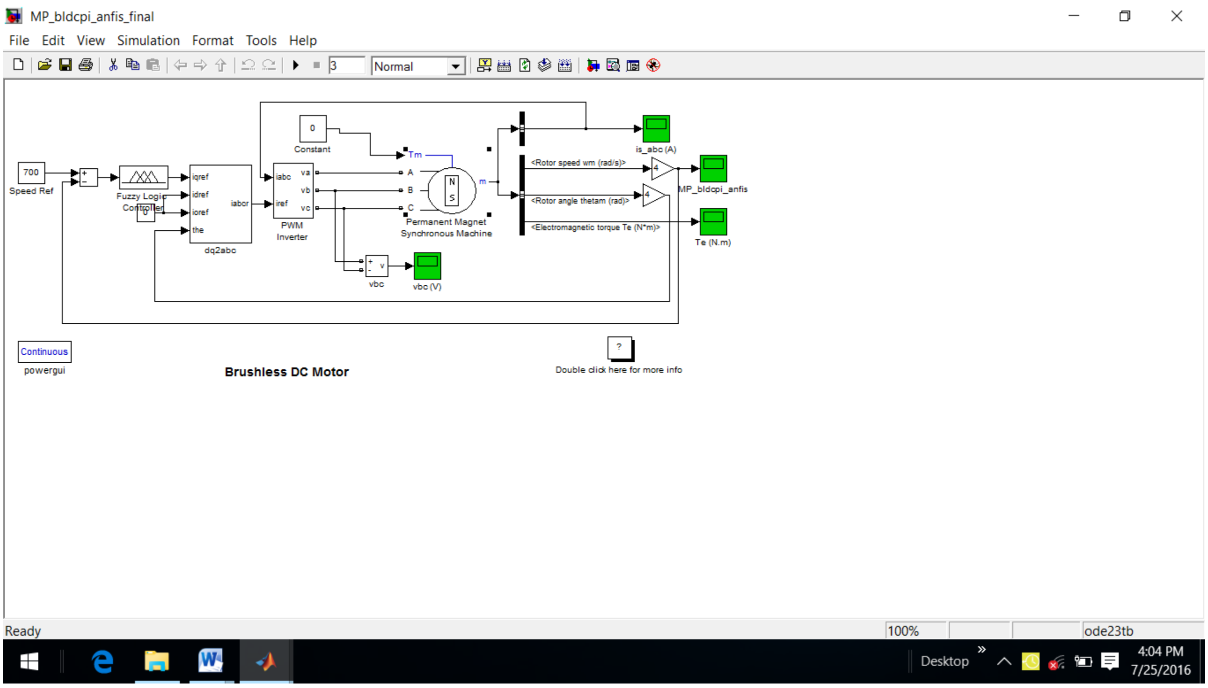

Fig 6.8 BLDC motor using Adaptive Neuro-Fuzzy controller

6.2.5 RESULT OF BLDC MOTOR AT NO LOAD

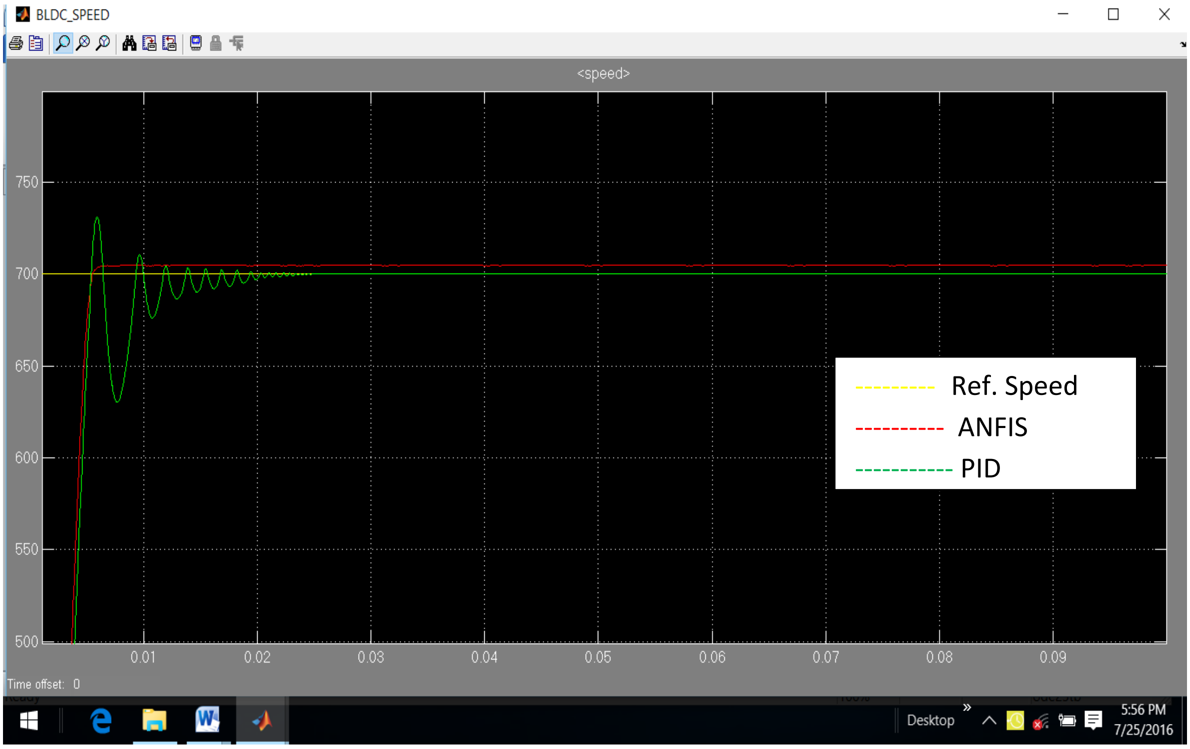

Fig 6.9 BLDC motor at no load with PI AND ANFIS Controller

6.2.6 RESULT OF BLDC MOTOR AT STEP LOAD

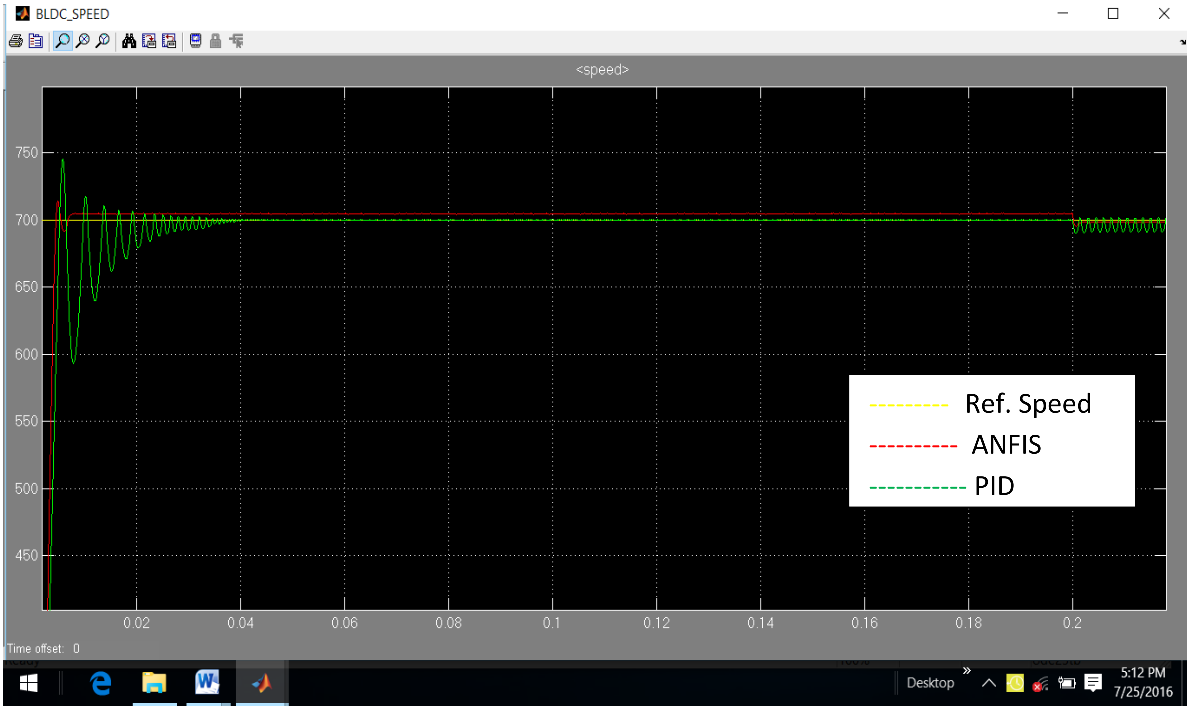

Fig 6.9 BLDC motor at Step load with PI AND ANFIS Controller

6.2.7 RESULT OF BLDC MOTOR AT NOISY LOAD

Fig 6.10 BLDC motor at Noisy Load with PI & ANFIS Controller

6.2.8 RESULT OF BLDC MOTOR AT SINOSOIDAL LOAD

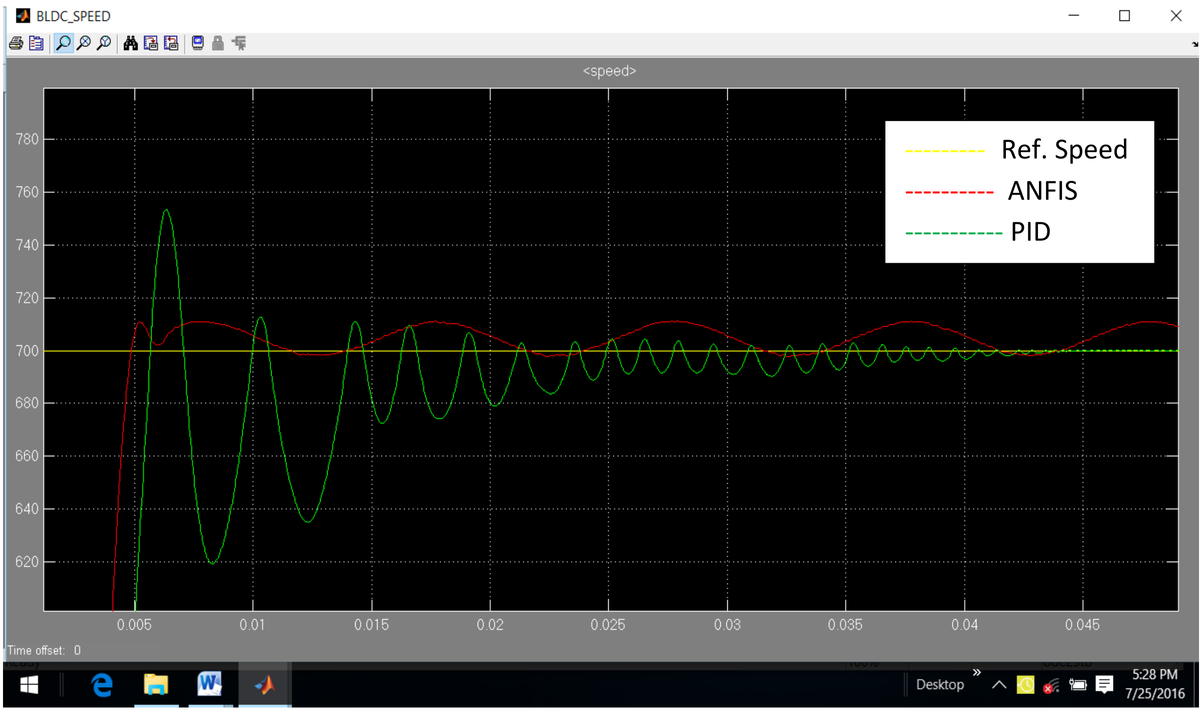

Fig 11BLDC motor at sinusoidal load with PI & ANFIS Controller

6.2.9 RESULT OF BLDC MOTOR WITH PARAMETER VARIATION

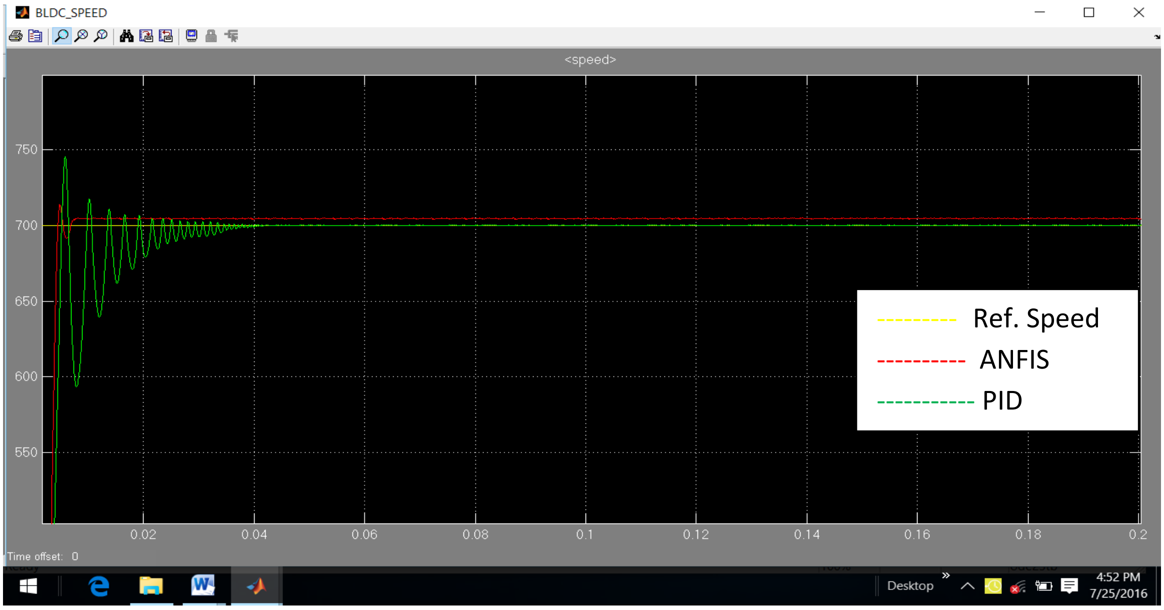

Fig 6.12 BLDC motor parameter variation with PI & ANFIS Controller

6.2.10 DISCUSSION

The results in terms of performance indices Peak Overshoot (M_p) and Settling Time (T_{ss}) are tabulated below as

Table 6.2 Transient response sheet of DC motor

	M_p		T_{ss}	
	PI	ANFIS	PI	ANFIS
No Load	5	0.7	0.013	0.006
Step Load	1.1	0.6	-	-
Noisy Load	3	1.5	-	-
Sinusoidal Load	6	1.6	0.0135	-
Parameter Change	6.2	2	0.0225	0.006

Thus from the above results we see the ANFIS gives better result when actual models were taken . Peak overshoot is reduced and speed of response is faster but it had some bad features like speed above trained ref. speed cannot be taken and it possess small percentage of error in steady state though very less.

CHAPTER VII

CONCLUSION AND FUTURE SCOPE

8.1 CONCLUSION

We see from the above response that the response by Non- Conventional Controller (ANFIS) are better than the Conventional controller (PID). Results given by Non- Conventional Controller (ANFIS) were comparable in case of transfer function model of 2 h.p. DC motor. Results given by Non- Conventional Controller (ANFIS) were better in case of Brush-less DC motor. Speed of response is faster than their PID counterpart also reducing the Percentage Peak Overshoot(M_P), Settling time(T_{SS}) also less but, steady state error(Ess) is slightly more than PID though within limit. Thus from above results we see that Non-Conventional Controller (ANFIS) gives better results at high speed application. In case of Conventional controller (PID) control parameter change is required a complex task but, not required in case of Non-Conventional controller (ANFIS) controller. In case of Non-Conventional controller (ANFIS) controller training requires time only one time and can be updated often just by updating the linking file. This feature makes this controller especially useful to be remotely operated and controlled over networking lines. If you are using current network the on line training and prediction task can also be performed.

8.2 FUTURE SCOPE

The first applications of fuzzy neural networks to consumer products appeared on the (Japanese and Korean) market in 1991. Some examples include air conditioners, electric carpets, electric fans, electric thermo-pots, desk-type electric heaters, forced flue kerosene fan heaters, kerosene fan heaters, microwave ovens, refrigerators, rice cookers, vacuum cleaner, washing machines, clothes driers, photocopying machines, and word processors.

- Ricoh Co. has applied two neural networks to control electrostatic latent image conditions at necessary potential, as well as a neural network to figure optimum developing bias voltage from image density, temperature, humidity, and copy volume.
- Sanyo uses neural networks for adjusting auto-exposure in their photocopying machine.

In non- engineering fields also there is vide scope of Adaptive neural network based systems some of them are currently in use:

- Nikko Securities uses a neural network to improve the rating of convertible bonds. The system learns from the reactions of an expert rating instruction, which can change according to the actual economic situation. It analyzes the results, and then uses them to give advice[22].
- Further this can be used to predict stock market shares.
- Further this can be used to predict short term load forecasting at distribution Sub-Station to cater for early arrangement and better management of power hence quality to consumers.

It can be used to make a system sensor less with the help of prediction capability and ease of adaptability to new control parameter setting it can be used in the following fields:

- Sensor Less speed control of Motors.
- SCADA Systems
- Robotics
- Cancer detection in tissues (Bio- Medical).
- Identification Type of Defects in the Material.
- Remote Sensing and Telemetry
- Short term load forecasting and automatic implementation at Sub-Station
- SCADA Systems

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[1] Ujjwal Kumar, Narendra Kumar, "Simulation Of PID-ANN Controller For PMDC Motor" ICATET 2015 BKIT, Kota.

[2] Ujjwal Kumar, Narendra Kumar, "Comparative Analysis of Speed Control of BLDC Motor Using PI and Neuro-Fuzzy Controller" 7^{th} IICPE 2016, Thapar University, Patiala.