

SPEED CONTROL OF SEPARATELY EXCITED DC MOTOR USING NEURO FUZZY TECHNIQUE

A PROJECT THESIS SUBMITTED IN THE FULFILLMENT OF
THE

REQUIREMENTS FOR THE DEGREE OF
BACHELOR OF TECHNOLOGY

IN
ELECTRICAL ENGINEERING

BY

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National Institute of Technology Rourkela

Rourkela-769008, Orissa

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**UNDER THE GUIDANCE OF
PROF. J.K. SATAPATHY**



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NIT ROURKELA



NATIONAL INSTITUTE OF TECHNOLOGY ROURKELA CERTIFICATE

This is to certify that the progress report of the thesis entitled, "SPEED CONTROL OF SEPARATELY EXCITED DC MOTOR USING NEURO FUZZY TECHNIQUE" submitted by **Mr. Sanjeev Kumar and Mr. Vivek Baranwal** in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Electrical Engineering at the National Institute of Technology Rourkela (Deemed University), is an authentic work carried out by him under my supervision and guidance. To the best of my knowledge the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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ABSTRACT

This paper uses NEURO FUZZY TECHNIQUE in estimating speed and controlling it for a separately excited DC motor. The rotor speed of the dc motor can be made to follow an arbitrarily selected trajectory. The purpose is to achieve accurate trajectory control of the speed of saperately excited DC Motor, especially when the motor and load parameters are unknown.

Such a neuro fuzzy control scheme consists of two parts. One is the neural identifier which is used to estimate the motor speed error (state error or state error derivative). The second is the fuzzy logic controller which is used to generate a control signal for a chopper & speed control of separately excited DC Motor.

The purpose of this technique is to achieve accurate trajectory control of the speed.

Such a control scheme consists of two parts. One is the neural identifier which is used to estimate the motor speed. The other is the neural fuzzy logic controller which is used to generate the control signal (fuzzy output).

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Chapter 1

INTRODUCTION

The development of high performance motor drives is very important in industrial as well as other purpose applications. Generally, a high performance motor drive system must have good dynamic speed command tracking and load regulating response.

The dc motors are used in various applications such as defence, industries, Robotics etc. DC drives, because of their simplicity, ease of application, reliability and favourable cost have long been a backbone of industrial applications. DC drives are less complex with a single power conversion from AC to DC. DC drives are normally less expensive for most horsepower ratings. DC motors have a long tradition of use as adjustable speed machines and a wide range of options have evolved for this purpose. In these applications, the motor should be precisely controlled to give the desired performance. Many varieties of control schemes such as P, proportional integral (PI), proportional derivation integral (PID), adaptive, and fuzzy logic controller (FLCs), have been developed for speed control of dc motors. The proposed controller systems consist of multi-input fuzzy logic controller (FLC) and multi-input integrated fuzzy logic controller (IFLC) for the speed control.

Many practical control issues (motor control problems):

- Variable and unpredictable inputs
- Noise propagation along a series of unit processes
- Unknown parameters
- Changes in load dynamics

Major problems in applying a conventional control algorithm in a speed controller are the effects of non-linearity in a DC motor. The non-linear characteristics of a DC motor such as saturation and friction could degrade the performance of conventional controllers. Many advance model-based control methods such as variable-structure control and model reference adoptive control have been developed to reduce these effects. However, the performance of these methods depends on the accuracy of system models and parameters. Generally, an accurate non-linear model of an actual DC motor is difficult to find, and parameter values obtained from system identification may be only approximate values.

1.1 Advantages of using neuro fuzzy technique:-

- Fast adaptation
- High degree of tolerance
- Smoot operation
- Reduce the effect of Non-linearity
- Learning ability
- Inherent approximation capability

Emerging intelligent techniques have been developed and extensively used to improve or to replace conventional control technique because these techniques do not require a precise model. One of intelligent technique, fuzzy logic by Zadeh is applied for controller design in many applications. A fuzzy logic controller (FLC) was proved analytically to be equivalent to a non-linear PI controller when a non-linear defuzzification method is used. Also, the result

from the comparisons of conventional and fuzzy logic control techniques in the form of a FLC and fuzzy compensator showed fuzzy logic can reduce the effects of non-linearity in a DC motor and improve the performance of a controller.

1.2 Speed control techniques in separately excited dc motor:

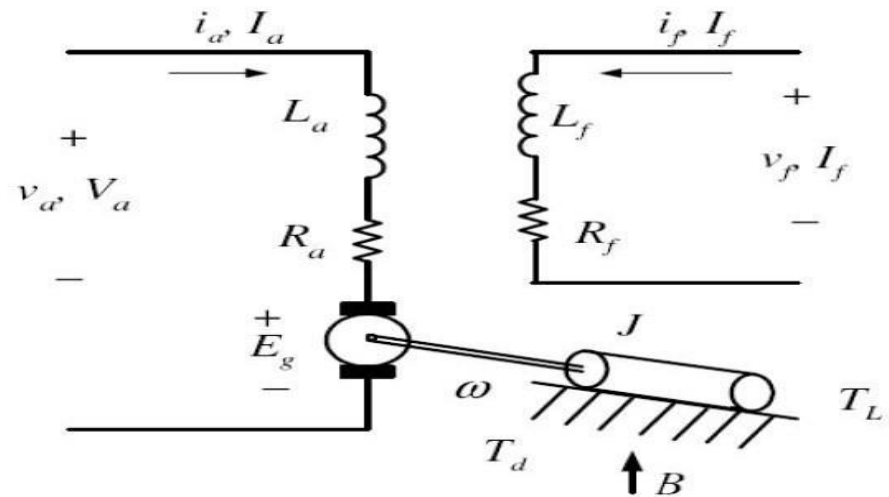
- Varying the armature voltage in the constant torque region.
- In the constant power region, field flux should be reduced to achieve speed above the rated speed.

1.3 Methods of speed control:

- Traditionally rheostat armature control method was used for low power dc motors.
- Use of conventional PID controllers.
- Neural network controllers (NNC).
- Constant power field weakening controller based on load-adaptive multi-input multioutput linearization technique (in high speed regimes).
- A single phase uniform PWM ac-dc buck-boost converter with only one switching device used for armature voltage control.
- Use of NARMA-L2 (Non-linear Auto-regressive Moving Average) controller in the constant torque region.
- Neuro fuzzy logic controller.

Chapter 2

SEPARATELY EXCITED DC MOTOR



Separately Excited DC Motor

- The field windings are used to excite the field flux.
- Armature current is supplied to the rotor via brush and commutator for the mechanical work.
- Interaction of field flux and armature current in the rotor produces torque.

2.1 OPERATION:

- When a separately excited motor is excited by a **field** current of i_f and an armature current of i_a flows in the circuit, the motor develops a back emf and a torque to balance the load torque at a particular speed.
- The i_f is independent of the i_a . Each windings are supplied separately. Any change in the armature current has no effect on the field current.
- The i_f is normally much less than the i_a .

2.2 FIELD AND ARMATURE EQUATIONS:

Instantaneous field current:

$$v_f = R_f i_f + L_f \frac{di_f}{dt}$$

Where R_f and L_f are the field resistance and inductor, respectively.

Instantaneous armature current :

$$V_a = R_a i_a + L_a \frac{di_a}{dt} + e_g$$

Where R_a and L_a are the armature resistance and inductor, respectively.

The motor back emf, which is also known as speed voltage, is expressed as:

$$e_b = K_v \omega$$

K_v is the motor voltage constant (in V/A-rad/s) and ω is the motor speed (in rad/sec)

2.3 BASIC TORQUE EQUATION:

For normal operation, the developed torque must be equal to the load torque plus the friction and inertia, i.e.:

$$T_d = J \frac{d\omega}{dt} + B\omega + T_L$$

The torque developed by the motor is:

$$T_d = K_t i_a$$

Where ($K_t = K_v$) is torque constant in V/A-rad/sec.

Sometimes it is written as:

$$T_d = K_t \phi i_a$$

For normal operation, the developed torque must be equal to the load torque plus the friction and inertia, i.e.:

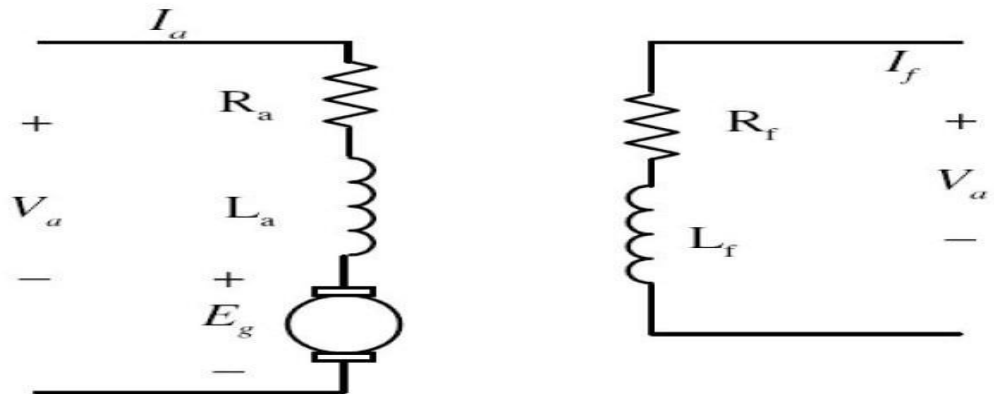
where

B : viscous friction constant, (N.m/rad/s)

T_L : load torque (N.m)

J : inertia of the motor (Kg.m^2)

2.4 STEADY STATE OPERATION:



Separately Excited DC Motor In Steady State

under study state operation, time derivatives is zero. Assuming the motor is not saturated.

For field circuit,

$$V_f = I_f R_f$$

The back emf is given by:

$$E_g = K_v \omega I_f$$

The armature circuit,

$$V_a = I_a R_a + E_g = I_a R_a + K_v \omega I_f$$

STEADY-STATE TORQUE AND SPEED:

the motor speed can be easily derived:

if R_a is a small value (which is usual), or when the motor is lightly loaded, i.e. I_a is small,

that is if the field current is kept constant, the motor speed depends only on the supply voltage.

The developed torque is:

$$T_d = K_t I_f I_a = B\omega + T_L$$

The required power is:

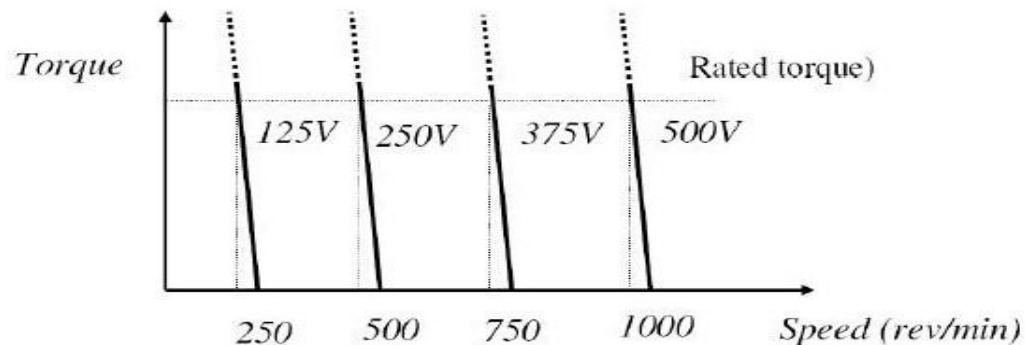
$$P_d = T_d \omega$$

TORQUE AND SPEED CONTROL:

From the derivation, several important facts can be deduced for steady-state operation of DC motor.

- For a fixed field current, or flux (I_f), the torque demand can be satisfied by varying the armature current (I_a).
- The motor speed can be varied by:
 - controlling V_a (voltage control)
 - controlling V_f (field control)
- These observations lead to the application of variable DC voltage for controlling the speed and torque of DC motor.

2.5 VARIABLE SPEED OPERATION:

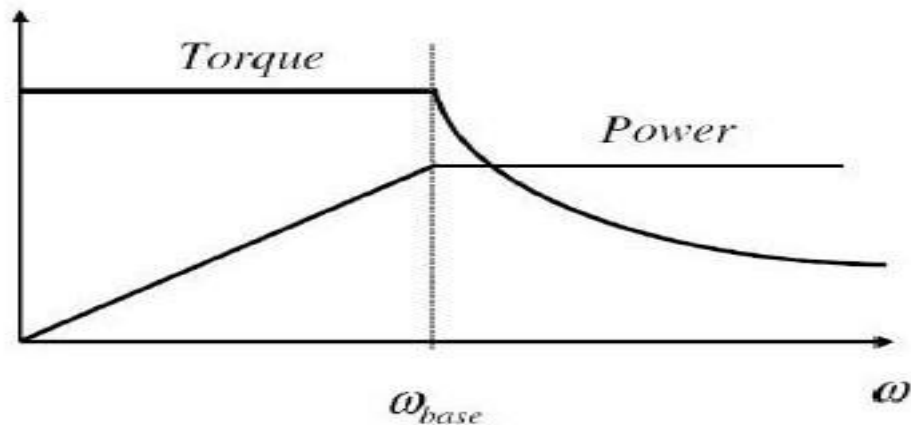


Torque Vs Speed Characteristic For Different Armature Voltages

Family of steady-state torque speed curves for a range of armature voltage can be drawn as above.

- The speed of DC motor can simply be set by applying the correct voltage.
- Note that speed variation from no-load to full load (rated) can be quite small. It depends on the armature resistance.

2.6 BASE SPEED AND FIELD-WEAKENING:



Torque Vs Speed And Power Vs Speed Characteristic Of Separately Excited DC Motor

Base speed: (ω_{base})

– the speed which correspond to the rated V_a , rated I_a and rated I_f .

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- **Constant Torque** region ($\omega < \omega_{base}$)

– I_a and I_f are maintained constant to met torque demand. V_a is varied to control the speed. Power increases with speed.

- **Constant Power** region ($\omega > \omega_{base}$)

– V_a is maintained at the rated value and I_f is reduced to increase speed. However, the power developed by the motor (= torque x speed) remains constant. This phenomenon is known as **field weakening**.

Chapter 3

FUZZY SETS

Fuzzy sets are sets whose elements have degrees of membership. Fuzzy sets were introduced by Lotfi A. Zadeh (1965) as an extension of the classical notion of set. In classical set theory, the membership of elements in a set is assessed in binary terms according to a bivalent condition — an element either belongs or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval $[0, 1]$. Fuzzy sets generalize classical sets, since the indicator functions of classical sets are special cases of the membership functions of fuzzy sets, if the latter only take values 0 or 1. A classical set is a set with a crisp boundary, a classical set “A” of real numbers greater than 6 can be expressed as

$$A = \{x \mid x > 6\}$$

Where there is a clear unambiguous boundary 6 such that if x is greater than this number, the x belongs to the set A, otherwise x does not belong to the set.

3.1 BASIC DEFINITIONS AND TERMINOLOGY:-

A fuzzy set is a pair (A, m) where A is a set and $m : A \rightarrow [0, 1]$.

For each $x \in A$, $m(x)$ is the **grade** of membership of x . If $A = \{x_1, \dots, x_n\}$ the fuzzy set (A, m) can be denoted $\{m(x_1) \mid x_1, \dots, m(x_n) \mid x_n\}$.

An element mapping to the value 0 means that the member is not included in the fuzzy set, 1 describes a fully included member. Values strictly between 0 and 1 characterize the fuzzy members. The set $\{x \in A \mid m(x) > 0\}$ is called the *support* of the fuzzy set (A, m) and the set $\{x \in A \mid m(x) = 1\}$ is called the *kernel* of the fuzzy set (A, m) .

Sometimes, a more general definition is used, where membership functions take values in an arbitrary fixed algebra or structure L ; usually it is required that L be at least a poset or lattice. The usual membership functions with values in $[0, 1]$ are then called $[0, 1]$ -valued membership functions. This generalization was first considered in 1967 by Joseph Goguen, who was a student of Zadeh.

If x is a collection of objects denoted generally by x then a fuzzy set A in x is defined as a set of ordered pairs.

$$A = \{x, \mu_A(x) \mid x \in x\}$$

Where, $\mu_A(x)$ = MF's for the fuzzy set A.

The MF's maps each elements of x to a membership grade (or membership value) between 0 and 1.

Usually x is refer to as the universe of discourse, or simply the universe and it may consist of discrete (ordered or unordered) objects or continuous space.

Fuzzy sets with a continuous universe-:

Let $x \in \mathbb{R}^+$ be the set of possible ages for human being. The fuzzy set B=" about 50 years old" may be expressed as

$$B = \{x, \mu_B(x) / x \in X\}$$

$$\text{Where, } \mu_B(x) = 1 / (1 + ((x-50)/100)^4)$$

So, the constructions of a fuzzy set depend on two things-:

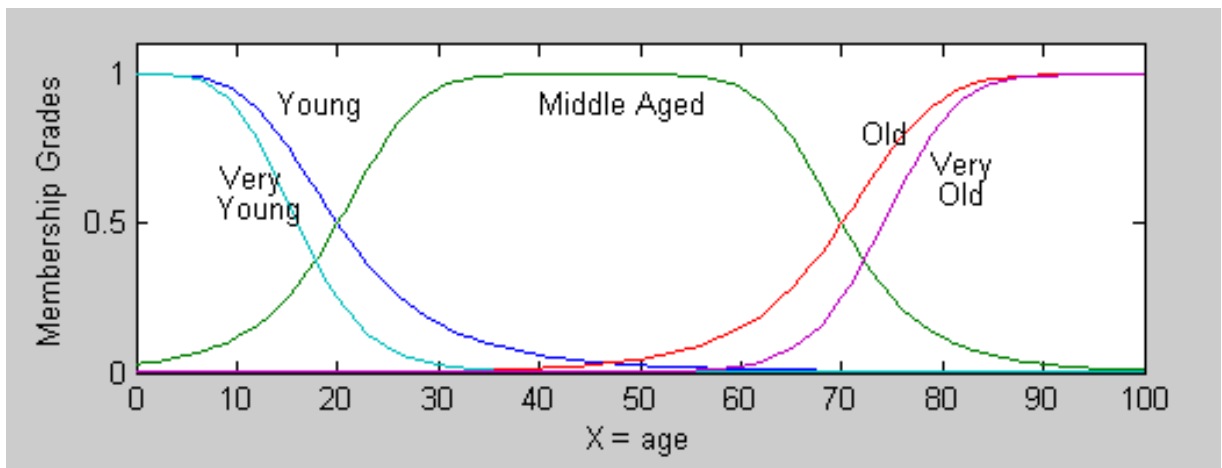
- (1) The identification of a suitable universe of discourse.
- (2) The specification of an approximate MF's. As MF's are subjective, which means MF's are specified for the some concept.

The subjectivity and no-randomness of fuzzy set is the primary difference between the study of fuzzy sets and probability theory.

LINGUISTIC VARIABLE AND LINGUISTIC VALUES-:

$X = \text{"AGE"}$ THEN WE CAN DEFINE FUZZY SETS "YOUNG", "MIDDLE AGE", AND "OLD" THAT ARE CHARACTERIZED BY MF'S $\mu_{\text{young}}(x)$, $\mu_{\text{middle age}}(x)$ and $\mu_{\text{old}}(x)$, respectively.

A linguistic variable "age" can assume different linguistic values such as young, middle age and old.



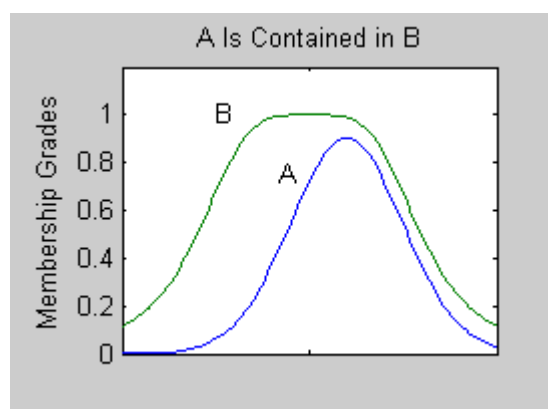
3.2 SET THEORETIC OPERATIONS-:

Union, intersection and compliment are the most basic operation on classical sets on the basic of these three operations, a number of identities can be established.

Corresponding to the ordinary set operations of union, intersection and compliment, fuzzy sets have similar operation.

CONTAINMENT OR SUBSET-:

Fuzzy set A is contained in fuzzy set B (or equivalently A is subset of B, or A is similar than or equal to B) if and only if $\mu_A(x) \leq \mu_B(x)$ for all x.



$$A \leq B \leftrightarrow \mu_A(x) \leq \mu_B(x).$$

UNION (DISJUNCTION)-:

The union of two fuzzy sets A and B is a fuzzy set C, written as $C=A \cup B$ or $C=A$ or B, where MF's is defined to those A and b by

$$\mu_C(x) = \text{Max} (\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x)$$

INTERSECTION (CONJUNCTION)-:

Then intersection of two fuzzy sets A and B are the fuzzy set C, written as $C=AB$ or $C=A$ AND B, where MF's related to those of A and B by

$$\mu_C(x) = \text{Min} (\mu_A(x), \mu_B(x)) = \mu_A(x) \wedge \mu_B(x)$$

COMPLIMENT (negation)-:

The compliment of fuzzy set a, denoted by \bar{A} (NOT A), is defined as

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x),$$

Standard fuzzy set operations

Standard complement

$$cA(x) = 1 - A(x)$$

Standard intersection

$$(A \cap B)(x) = \min [A(x), B(x)]$$

Standard union

$$(A \cup B)(x) = \max [A(x), B(x)]$$

Fuzzy complements

$A(x)$ is defined as the degree to which x belongs to A . Let cA denote a fuzzy complement of A of type c . Then $cA(x)$ is the degree to which x belongs to cA , and the degree to which x does not belong to A . ($A(x)$ is therefore the degree to which x does not belong to cA .)

Let a complement cA be defined by a function

$$c : [0,1] \rightarrow [0,1]$$

$$c(A(x)) = cA(x)$$

Fuzzy intersections

The intersection of two fuzzy sets A and B is specified in general by a binary operation on the unit interval, a function of the form

$$i:[0,1] \times [0,1] \rightarrow [0,1].$$

$$(A \cap B)(x) = i[A(x), B(x)] \text{ for all } x.$$

Fuzzy unions

The union of two fuzzy sets A and B is specified in general by a binary operation on the unit interval function of the form

$$u:[0,1] \times [0,1] \rightarrow [0,1].$$

$$(A \cup B)(x) = u[A(x), B(x)] \text{ for all } x$$

EXTENTION PRINCIPLE AND FUZZY RELATIONS-:

EXTENTION PRINCIPLE-:

The extension principle is a basic concept of fuzzy set theory that provides a general procedure for extending crisp domains of mathematical expression to fuzzy domains. This procedure generalize a common point to point mappings of a function $f(\cdot)$ to a mapping between fuzzy sets. More specifically suppose that f is a function from x to y and A is a fuzzy set on x defined as

$$A = \mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \dots + \mu_A(x_n)/x_n$$

Then the extension principle states that the image of fuzzy set A under the mapping $f(\cdot)$ can be expressed as fuzzy set B ,

$$B = \mu_A(x_1)/y_1 + \mu_A(x_2)/y_2 + \dots + \mu_A(x_n)/y_n$$

Where, $y_i = f(x_i)$, $i=1,2,3,\dots,n$

FUZZY RELATION-:

Binary fuzzy relation are fuzzy sets in $x*y$ which map each element in $x*y$ to a membership sets with two dimensional MF's .

BINARY FUZZY RELATION-:

Let x and y be two universe of discourse, then

$$R = \{(x,y), \mu_R(x,y) / (x,y) \in x*y\} \mu_A(x),$$

Is a binary fuzzy relation in $x*y$

FUZZY IF-THEN RULES

A fuzzy if-then rule (also known as fuzzy rule, fuzzy implication or fuzzy conditional statements) assume the form.

If x is A then y is B.

Where, A and B are linguistic values defined by fuzzy sets on universe of discourse X and y, respectively after “x is A” is called the antecedent or premise will “y is B” is called the consequence or conclusion.

- If pressure is high, then volume is small
- If the road is slippery, then driving is dangerous
- If tomato is red, then it is ripe.
- If the speed is high, then apply the brake a little.

A relation between two variables x & y; this suggest that a fuzzy if then rule be defined as a binary fuzzy relation R on the product space X*Y.

Generally speaking, there are two ways to interpret the fuzzy

$$A \rightarrow B = A * B = \int_{x*y} \mu_A(x) * \mu_B(y) / (x, y).$$

Chapter 4

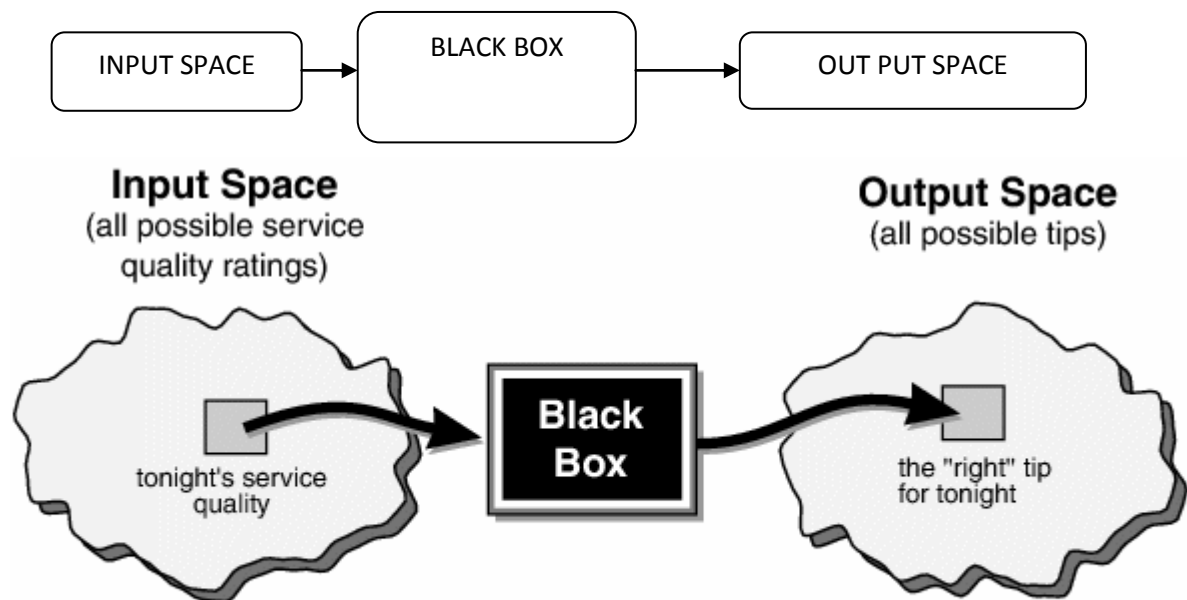
FUZZY LOGIC

Fuzzy logic has two different meanings, in a narrow sense, fuzzy logic is a logical system, which is an extension of multivolume’s logic, and however, in a wider sense fuzzy logic is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with un-sharp boundaries in which membership is a matter of degree. In this perspective fuzzy logic in its more narrow definition, fuzzy logic differs both in concept and substance from traditional multi-valued logical system.

Fuzzy logic is a convenient way to map input space to an output space. Mapping input to output is the starting point for everything.

The main objectives of this study are:-

- To understand the fuzzy logic and how fuzzy rule base system can be applied in derivation of rules for power system planning, operation and control.
- To study the MATLAB fuzzy toolbox and understand the concept of member function & rule base.
- To derive optimal power system operation rules at the macro level for better performance and control of the power system.
- To develop a fuzzy logic tool for deriving optimal operational rules at the macro level for better performance and control of power system.



An input-output map for the tipping problem:
 “Given the quality of service, how much should I tip?”

4.1 WHY USE FUZZY LOGIC?

Fuzzy logic offers several unique features that make it a particularly good choice for many control problems.

- Fuzzy logic is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple. Fuzzy logic is a more intuitive approach without the for-reach complexity. Fuzzy logic is flexible. Fuzzy logic is tolerant of imprecise data. Fuzzy logic can model non-linear function of arbitrary complexity. Fuzzy logic is based on natural language.
- It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth control function despite a wide range of input variations.
- Since the Fuzzy logic controller processes user-defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules.
- Fuzzy logic is 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.
- Because of the rule-based operation, any reasonable number of inputs can be processed (1-8 or more) and numerous outputs (1-4 or more) generated, although defining the rule base quickly becomes complex if too many inputs and outputs are chosen for a single implementation since rules defining their interrelations must also be defined.
- It would be better to break the control system into smaller chunks and use several smaller Fuzzy logic controllers distributed on the system, each with more limited responsibilities.
- Fuzzy logic can control nonlinear systems that would be difficult or impossible to model mathematically. This opens doors for control systems that would normally be deemed unfeasible for automation.

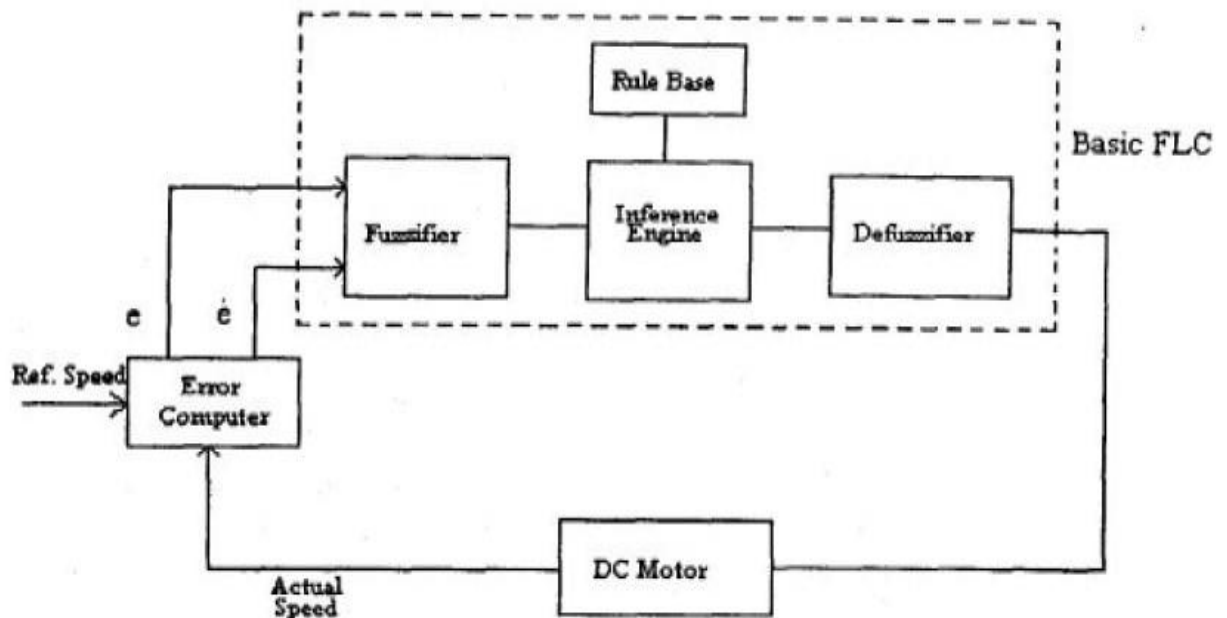
4.2 HOW FUZZY LOGIC IS USED?

- 1) Define the control objectives and criteria: What am I trying to control? What do I have to do to control the system? What kind of response do I need? What are the possible (probable) system failure modes?
- 2) Determine the input and output relationships and choose a minimum number of variables for input to the Fuzzy logic engine (typically error and rate-of-change-of-error).
- 3) Using the rule-based structure of Fuzzy logic, break the control problem down into a series of IF X AND Y THEN Z rules that define the desired system output response for given system input conditions.
- 4) Create Fuzzy logic membership functions that define the meaning (values) of Input /Output terms used in the rules.
- 5) Create the necessary pre- and post-processing Fuzzy logic routines if implementing in software, otherwise program the rules into the Fuzzy logic hardware engine.
- 6) Test the system, evaluate the results, tune the rules and membership functions, and retest until satisfactory results are obtained.

Chapter 5

FUZZY CONTROLLER

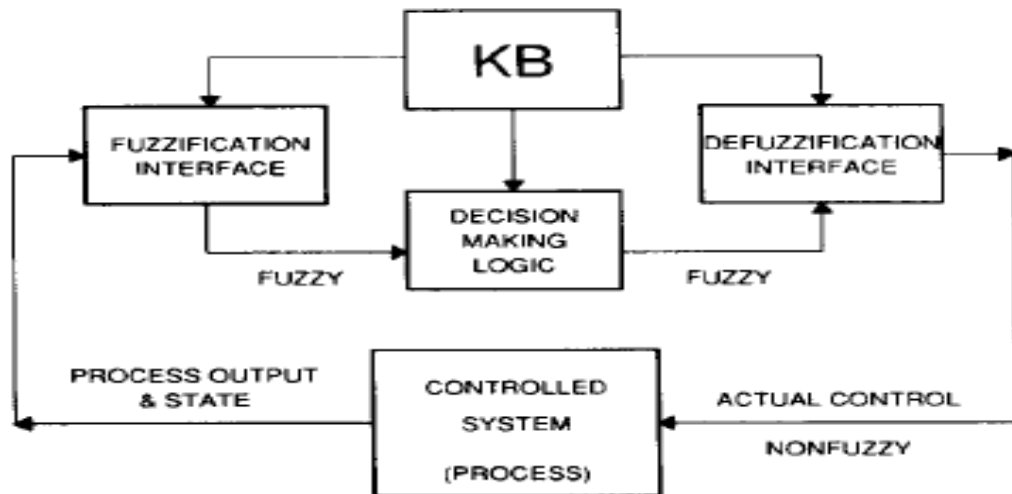
Fuzzy logic control is a control algorithm based on a linguistic control strategy, which is derived from expert knowledge into an automatic control strategy. Fuzzy logic control doesn't need any difficult mathematical calculation like the others control system. While the others control system use difficult mathematical calculation to provide a model of the controlled plant, it only uses simple mathematical calculation to simulate the expert knowledge. Although it doesn't need any difficult mathematical calculation, but it can give good performance in a control system. Thus, it can be one of the best available answers today for a broad class of challenging controls problems.



Block diagram of Fuzzy Logic Controller

5.1 BASIC CONFIGURATION OF FUZZY LOGIC CONTROLLER (FLC):-

BLOCK DIAGRAM:-



Basic configuration of fuzzy logic controller (FLC).

Fuzzy logic control is derived from fuzzy set theory. In fuzzy set theory, the transition between membership and non-membership can be graded. Therefore, boundaries of fuzzy sets can be vague and ambiguous, making it useful for approximate systems. Fuzzy Logic Controller (FLC) is an attractive choice when precise mathematical formulations are not possible. Other advantages are

- It can work with less precise inputs.
- It doesn't need fast processors.
- It needs less data storage in the form of membership functions and rules than conventional look up table for nonlinear controllers.
- It is more robust than other non-linear controllers.

There are three principal elements to a fuzzy logic controller.

- a. Fuzzification module (Fuzzifier)
- b. Rule base and Inference engine
- c. Defuzzification module (Defuzzifier)

5.2a Fuzzification: -

The first step in designing a fuzzy controller is to decide which state variables represent the system dynamic performance must be taken as the input signal to the controller. Fuzzy logic uses linguistic variables instead of numerical variables. The process of converting a numerical variable (real number or crisp variables) into a linguistic variable (fuzzy number) is called Fuzzification. System variables, which are usually used as the fuzzy controller inputs includes states error, state error derivative, state error integral or etc. In power system, based on previous experience, Area Control Error and its derivative ($d(ACE)/dt$) are chosen to be the input signals of fuzzy AGC.

The membership function is a graphical representation of the magnitude of participation of each input. There are different memberships functions associated with each input and output response. In this study, we use the trapezoidal membership function for input and output variables. The number of membership function determines the quality of control which can be achieved using fuzzy controller. As the number of membership function increases, the quality of control improves. As the number of linguistic variables increases, the computational time and required memory increases. Therefore, a compromise between the quality of control and computational time is needed to choose the number of linguistic variables.

For the speed control of DC motor study, five linguistic variables for each of the input and output variables are used to describe them, as in the following Table.

5.2b DEFUZZIFICATION:-

The reverse of Fuzzification is called Defuzzification. The use of Fuzzy Logic Controller (FLC) produces required output in a linguistic variable (fuzzy number). According to real world requirements, the linguistic variables have to be transformed to crisp output. Centre of gravity method is the best well-known defuzzification method and used in this research work. Sugeno type of defuzzification method is adopted in this work. It obtains the center of area occupied by the fuzzy set. It is given by the expression.

$$X = \frac{\int \mu(x) \cdot x \, dx}{\int \mu(x) \, dx}$$

Defuzzification is the process of producing a quantifiable result in fuzzy logic. Typically, a fuzzy system will have a number of rules that transform a number of variables into a "fuzzy" result, that is, the result is described in terms of membership in fuzzy sets. For example, rules

designed to decide how much pressure to apply might result in "Decrease Pressure (15%), Maintain Pressure (34%), Increase Pressure (72%)". Defuzzification would transform this result into a single number indicating the change in pressure. The simplest but least useful defuzzification method is to choose the set with the highest membership, in this case, "Increase Pressure" since it has a 72% membership, and ignore the others, and convert this 72% to some number. The problem with this approach is that it loses information. The rules that called for decreasing or maintaining pressure might as well have not been there in this case.

A useful defuzzification technique must first add the results of the rules together in some way. The most typical fuzzy set membership function has the graph of triangle. Now, if this triangle were to be cut in a straight horizontal line somewhere between the top and the bottom, and the top portion were to be removed, the remaining portion forms a trapezoidal. The first step of defuzzification typically "chops off" parts of the graphs to form trapezoids (or other shapes if the initial shapes were not triangles). For example, if the output has "Decrease Pressure (15%)", then this triangle will be cut 15% the way up from the bottom. In the most common technique, all of these trapezoids are then superimposed one upon another, forming a single geometric. Then, the centroid of this shape, called the *fuzzy centroid*, is calculated. The x coordinate of the centroid is the defuzzified value.

5.3 Fuzzy control in detail:-

Fuzzy controllers are very simple conceptually. They consist of an input stage, a processing stage, and an output stage. The input stage maps sensor or other inputs, such as switches, thumbwheels, and so on, to the appropriate membership functions and truth values. The processing stage invokes each appropriate rule and generates a result for each, then combines the results of the rules. Finally, the output stage converts the combined result back into a specific control output value.

The most common shape of membership functions is triangular, although trapezoidal and bell curves are also used, but the shape is generally less important than the number of curves and their placement. From three to seven curves are generally appropriate to cover the required range of an input value, or the "universe of discourse" in fuzzy jargon.

As discussed earlier, the processing stage is based on a collection of logic rules in the form of IF-THEN statements, where the IF part is called the "antecedent" and the THEN part is called the "consequent". Typical fuzzy control systems have dozens of rules.

Consider a rule for a thermostat:

"IF temperature is COLD then heater is HIGH"

This rule uses the truth value of the "temperature" input, which is some truth value of "cold", to generate a result in the fuzzy set for the "heater" output, which is some value of "high".

This result is used with the results of other rules to finally generate the crisp composite output. Obviously, the greater the truth value of "cold", the higher the truth value of "high", though this does not necessarily mean that the output itself will be set to "high", since this is only one rule among many. In some cases, the membership functions can be modified by "hedges" that are equivalent to adjectives. Common hedges include "about", "near", "close to", "approximately", "very", "slightly", "too", "extremely", and "somewhat". These operations may have precise definitions, though the definitions can vary considerably between different implementations.

In practice, the fuzzy rule sets usually have several antecedents that are combined using fuzzy operators, such as AND, OR, and NOT, though again the definitions tend to vary: AND, in one popular definition, simply uses the minimum weight of all the antecedents, while OR uses the maximum value. There is also a NOT operator that subtracts a membership function from 1 to give the "complementary" function.

There are several different ways to define the result of a rule, but one of the most common and simplest is the "max-min" inference method, in which the output membership function is given the truth value generated by the premise.

Rules can be solved in parallel in hardware, or sequentially in software. The results of all the rules that have fired are "defuzzified" to a crisp value by one of several methods. There are dozens in theory, each with various advantages and drawbacks.

The "centroid" method is very popular, in which the "centre of mass" of the result provides the crisp value. Another approach is the "height" method, which takes the value of the biggest contributor. The centroid method favors the rule with the output of greatest area, while the height method obviously favors the rule with the greatest output value.

The diagram below demonstrates max-min inferencing and centroid defuzzification for a system with input variables "x", "y", and "z" and an output variable "n". Note that "mu" is standard fuzzy-logic nomenclature for "truth value":

5.4 Principles of neuro-fuzzy modeling:

The general algorithm for a fuzzy system designer can be synthesized as follows.

FUZZIFICATION

- 1) Normalize of the universes of discourses for the fuzzy input and output vectors.
- 2) Choose heuristically the number and shape of the membership functions for the fuzzy input and output vectors.
- 3) Calculate of the membership grades for every crisp value of the fuzzy inputs.

FUZZY INFERENCE

- 4) Complete the rule base by heuristics from the view point of practical system operation.
- 5) Identify the valid (active) rules stored in the rule base.
- 6) Calculate the membership grades contributed by each rule and the final membership grade of the inference, according to the chosen fuzzification method.

DEFUZZIFICATION

- 7) Calculate the fuzzy output vector, using an adequate defuzzification method.
- 8) Simulation tests until desired parameters are obtained.
- 9) Hardware implementation.

From the beginning, a fuzzy-style inference must be accepted and the most popular are:

MAMDANI-style inference, based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes that expects all output membership functions to be fuzzy sets. It is intuitive, has widespread acceptance, is better suited to human input, but its main limitation is that the computation for the defuzzification process lasts longer.

SUGENO-style inference, based on Takagi-Sugeno-Kang method of fuzzy inference, in their common effort to formalize a systematic approach in generating fuzzy rules from an input-output data set, that expects all membership functions to be a singleton. It has computational efficiency, works well with linear techniques (e.g. PID control, etc.) works well with optimization and an adaptive techniques guarantees continuity of the output surface, is better

suitable to mathematical analysis. The results are very much similar to Mamdani-style inference.

5.5 MAIN IDEAS OF FUZZY LOGIC CONTROLLER:-

FLC comprises four principle components:-

A fuzzification interface

A knowledge base

Decision making logic

A defuzzification interface

(1)The fuzzification interface involve the following function:-

- (a) Measure the value of input variables.
- (b) Performs a scale mapping that transfers the range of value of input variables in to corresponding universe of discourse.
- (c) Performs the function of fuzzification that converts input data in to suitable linguistic values which may be viewed as labels of fuzzy sets.

(2)The knowledge base comprises knowledge of the application domain and the attendant control goals. It consists of a data “base” and a linguistic (fuzzy) control rule base.

- (a)The data base provides necessary definitions, which are used to define linguistic control rules and fuzzy data manipulation in an FLC.
- (b)The rule base characteristics the control goals and control policy of the domains experts by means of a set of linguistic control rules.

(3)Decision making logic is the kernel of an FLC. It has the capability of simulating human decision making based on fuzzy concepts and of interring fuzzy control actions employing fuzzy implication and the rules of inference in fuzzy logic.

(4)The defuzzification interface performs the following functions.

- (a)A scale mapping, this converts the range of values of output variables in to corresponding universe of discourse.
- (b) Defuzzification , which yields a non fuzzy control action from an inferred fuzzy control action.

5.6 Fuzzy Logic Based Controller:

There is a currently a significant and growing interest in the application of artificial intelligence (AI) type models to the problem of modelling the dynamics of complex, nonlinear processes. By far the most popular type of AI model for these purposes has been the neural network, which attempts to produce 'intelligent' behaviour by recreating the hardware involved in the thinking process. Another type of AI model is the fuzzy model, which defines its inputs and outputs as qualitative values (actually fuzzy reference sets) and then defines the strength of the relationships between these input and output reference sets. First of all mathematical model is necessary while making experimentation for control systems but it may not be always possible in practice. Sometimes in spite of creating true model, using of this model makes some complicated problems at the implementation. When confronted with like these problems, knowledge and experience of expert people is utilized. These people develop flexible control mechanism by using the words frequently in our life ,like "suitable", "not very suitable", "high", "a little high", "more", "very more" which are defined special variable. Fuzz logic control which has experimentation of fuzzy cluster theories and fuzzy logic, has been set up like logical relatives. A fuzzy logic system is based on 4 main parts which are illustrated in figure.

- 1-) Input units which has been known fuzzifier
- 2-) Rule base
- 3-) Inference mechanism
- 4-) Output units which has been known Defuzzifier

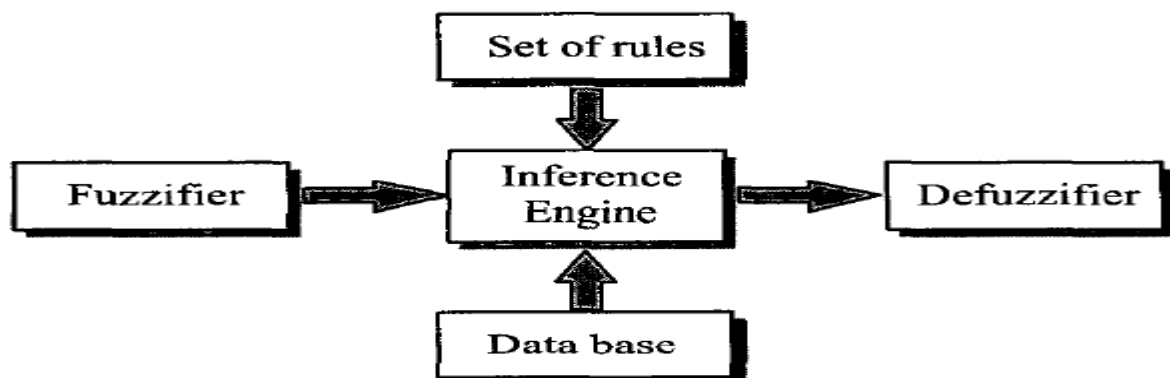


Figure 2: Block diagram of the fuzzy logic controller

5.7 SUGENO:

What is Sugeno-Type Fuzzy Inference?

The fuzzy inference process discussed so far is Mamdani's fuzzy inference method, the most common methodology. This section discusses the so-called Sugeno, or Takagi-Sugeno-Kang, method of fuzzy inference. Introduced in 1985, it is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

A typical rule in a Sugeno fuzzy model has the form

If Input 1 = x and Input 2 = y , then Output is $z = ax + by + c$

For a zero-order Sugeno model, the output level z is a constant ($a=b=0$).

The output level z_i of each rule is weighted by the firing strength w_i of the rule. For example, for an AND rule with Input 1 = x and Input 2 = y , the firing strength is

$$w_i = \text{AndMethod}(F_1(x), F_2(y))$$

where $F_{1,2}(\cdot)$ are the membership functions for Inputs 1 and 2.

The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final Output} = \frac{\sum_{i=1}^N w_i z_i}{\sum_{i=1}^N w_i}$$

where N is the number of rules.

Comparison of Sugeno and Mamdani Methods:

Because it is a more compact and computationally efficient representation than a Mamdani system, the Sugeno system lends itself to the use of adaptive techniques for constructing fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system best models the data.

The following are some final considerations about the two different methods.

Advantages of the Sugeno Method

- It is computationally efficient.
- It works well with linear techniques (e.g., PID control).
- It works well with optimization and adaptive techniques.
- It has guaranteed continuity of the output surface.
- It is well suited to mathematical analysis.

Advantages of the Mamdani Method

- It is intuitive.
- It has widespread acceptance.
- It is well suited to human input.

Chapter 6

Introduction to neural networks

6.1 NEURAL NETWORK:

Neural networks are wonderful tools, which permit the development of quantitative expressions without compromising the known complexity of the problem. This makes them ideal in circumstances where simplification of the problem, in order to make it mathematically tractable, would lead to an unacceptable loss of information. As pointed out by Ziman, there is a fine balance between over-idealizing the initial hypothesis in order to make it amenable to mathematical analysis, and abandoning reality.

6.2 What is a Neural Network?

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following two ways:

1. A neural network acquires knowledge through learning.
2. A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is true of ANNs as well.

The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics.

6.3 Historical background:

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras.

Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding.

6.4 Why use neural networks?

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

Other advantages include:

1. **Adaptive learning:** An ability to learn how to do tasks based on the data given for training or initial experience.
2. **Self-Organisation:** An ANN can create its own organisation or representation of the information it receives during learning time.
3. **Real Time Operation:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. **Fault Tolerance via Redundant Information Coding:** Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

6.5 Neural networks versus conventional computers:

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to be solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

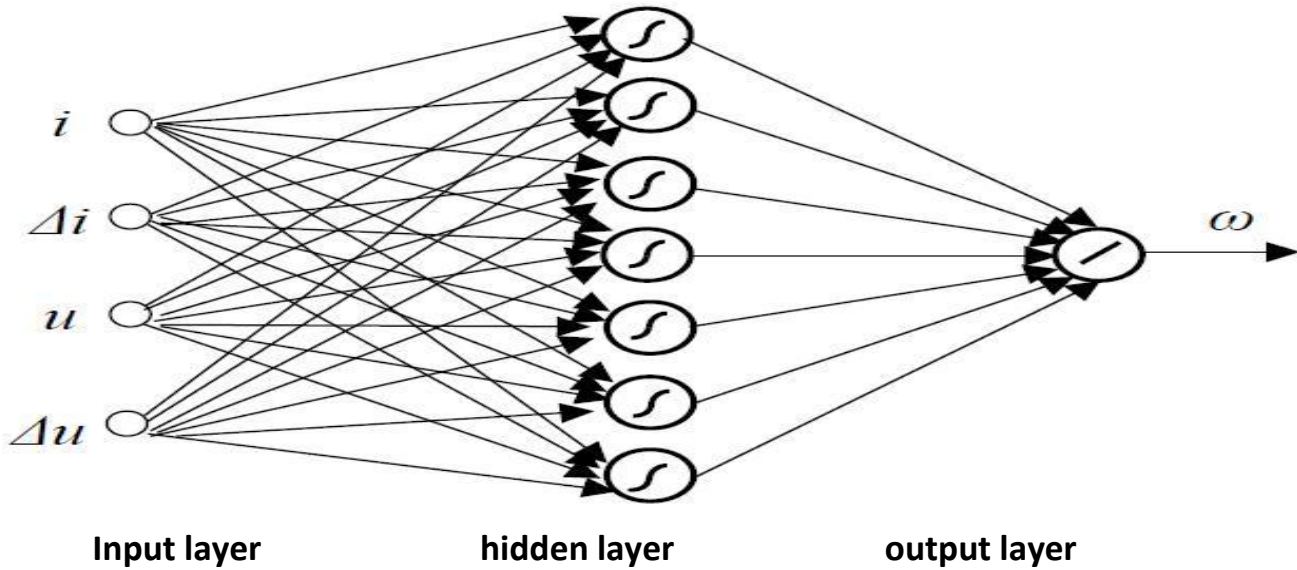
Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency.

6.6 Estimating the speed using neural network:

The rotor speed can be obtained by measuring the armature voltage, armature current and the derivative of the armature current. Because the armature voltage is varying between $\{ d d \} -U , +U$, the armature current also has fluctuation. Thus, before calculating the change of armature current it should be filtered (we are not interested in the derivative of the fluctuation, only in the trend of the change of the armature current). Experience shows that much better results can be achieved if the derivative of the armature voltage is also supplied to the neural network (in the same way as the armature current). The time-constant of the RiCi circuit for the derivative of armature voltage and current is calculated on the basis of equation. Thus, the neural network has four inputs:

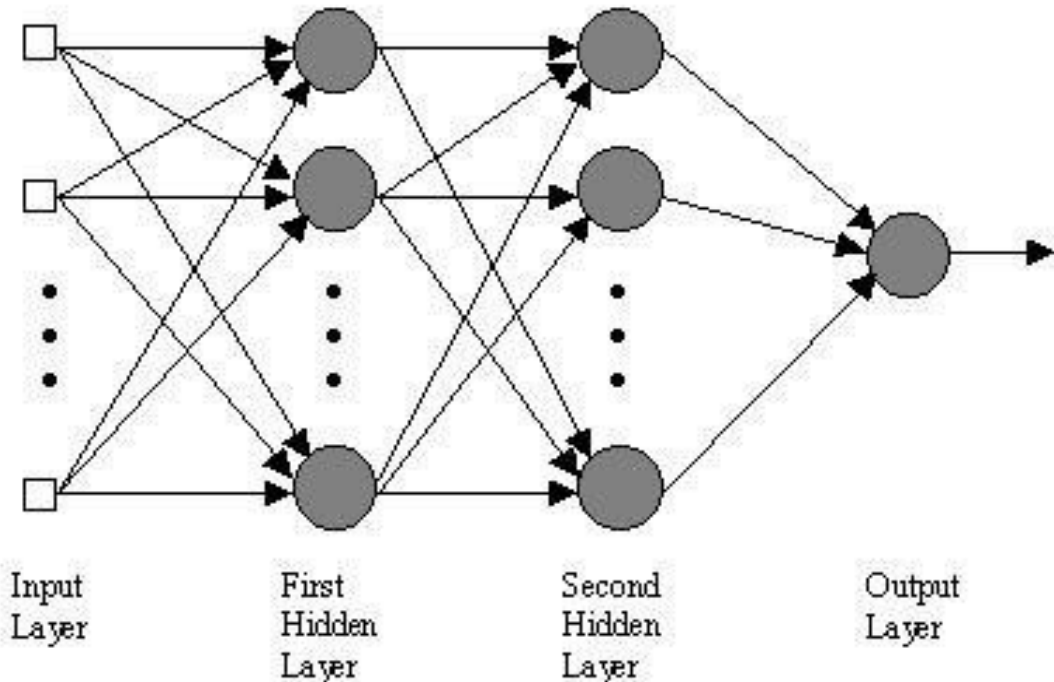
$U, du/dt, i, di/dt$ while the output is the estimated rotor speed ω .

SIMPLE NEURAL NETWORK:



The structure of the neural network

The most common neural network model is the multilayer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A graphical representation of an MLP is shown below.



Block diagram of a two hidden layer multi-layer perceptron (MLP).

Chapter 7

MAIN OBJECTIVE

The neuro fuzzy is a combination between neural network and fuzzy logic,

7.1 FUZZY RULE BASE FOR SPEED CONTROL OF DC MOTOR:

- The algorithm for fuzzy speed control in details can be summarized as follows. A numerical example is included in each step for clarity of understanding the principle.
- The triangular membership functions for input variable speed error (**e**), change in speed error (**ce**) and control output (**du**) i.e. change in firing angle are shown in normalized units.

The general considerations in the design of the controller are:

- If both **e** and **ce** are zero, then maintain the present control setting i.e. $du=0$
- If **e** is not zero but is approaching this value at a satisfactory rate, then maintain the present control setting.
- If **e** is growing then change the control signal **du** depending on the magnitude and sign of **e** and **ce** to force **e** towards zero.
- **e** and **ce** are speed error and change of speed error respectively (normalized).
- **du** is the change in firing angle (normalized).
- Linguistic fuzzy sets are defined as below.
 - ❖ Z = zero
 - ❖ PS = Positive medium
 - ❖ PM = Positive Big
 - ❖ NS = Negative small
 - ❖ NM = Negative medium
 - ❖ NB = Negative Big

The table below shows the corresponding rule table for the speed controller.

The top row and left column of the matrix indicate the fuzzy sets of the variable **e** and **ce** respectively and the membership function of the body of the matrix.

There may be $7 \times 7 = 49$ possible rules in the matrix, where a typical rule reads as

IF **e** = PS and **ce** = NM then **du** = NS

$\begin{matrix} du \nearrow \\ \swarrow \\ ce \end{matrix}$		e	NB	NM	NS	Z	PS	PM	PB
		NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NB	NM	NS	Z	PS		
NS	NB	NB	NM	NS	Z	PS	PM		
Z	NB	NM	NS	Z	PS	PM	PB		
PS	NM	NS	Z	PS	PM	PB	PB		
PM	NS	Z	PS	PM	PB	PB	PB		
PB	Z	PS	PM	PB	PB	PB	PB		

7.2 Rule Matrix for Fuzzy Speed Control

Identify the four valid rules from the rule matrix table for Z and PS values of e and ce.

These are:

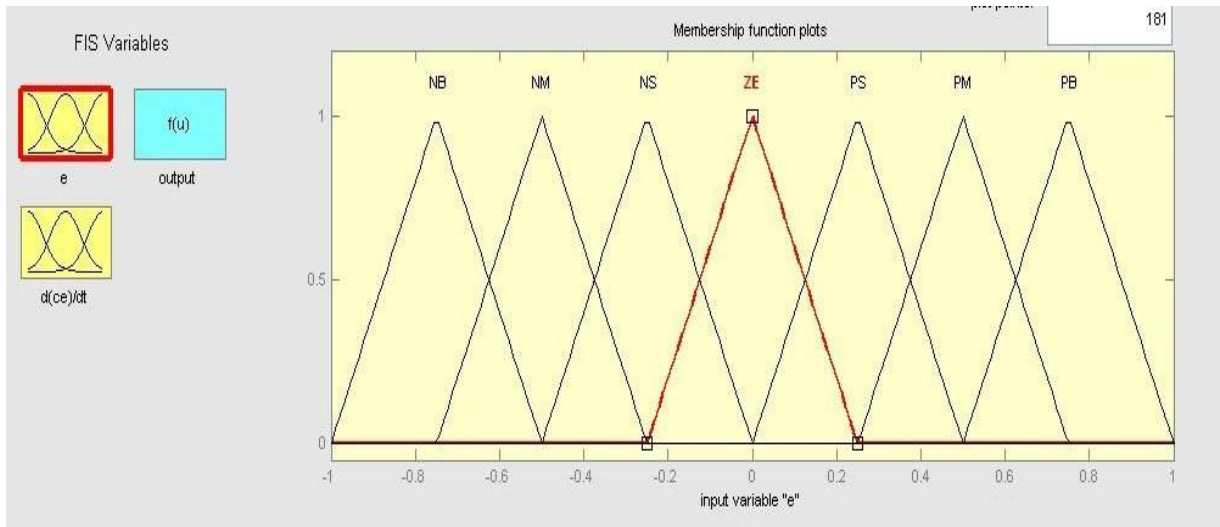
R1: IF **e=Z** AND **ce= Z** THEN **du = Z**

R2: IF **e=Z** AND **ce= PS** THEN **du = PS**

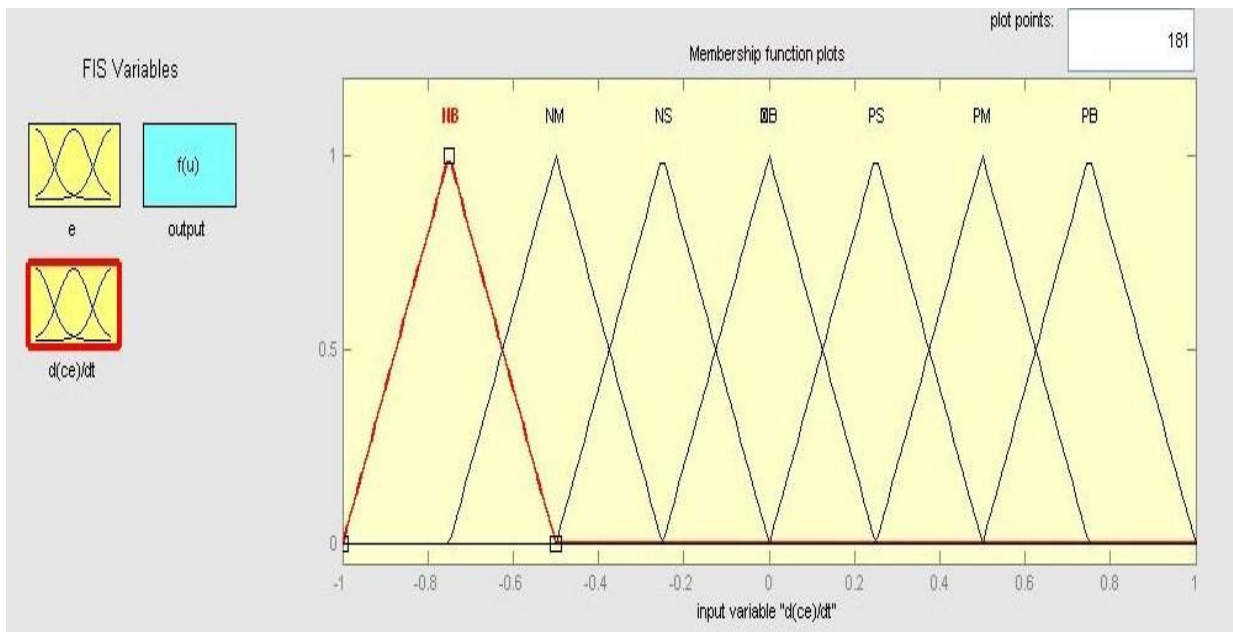
R3: IF **e=PS** AND **ce= Z** THEN **du= PS**

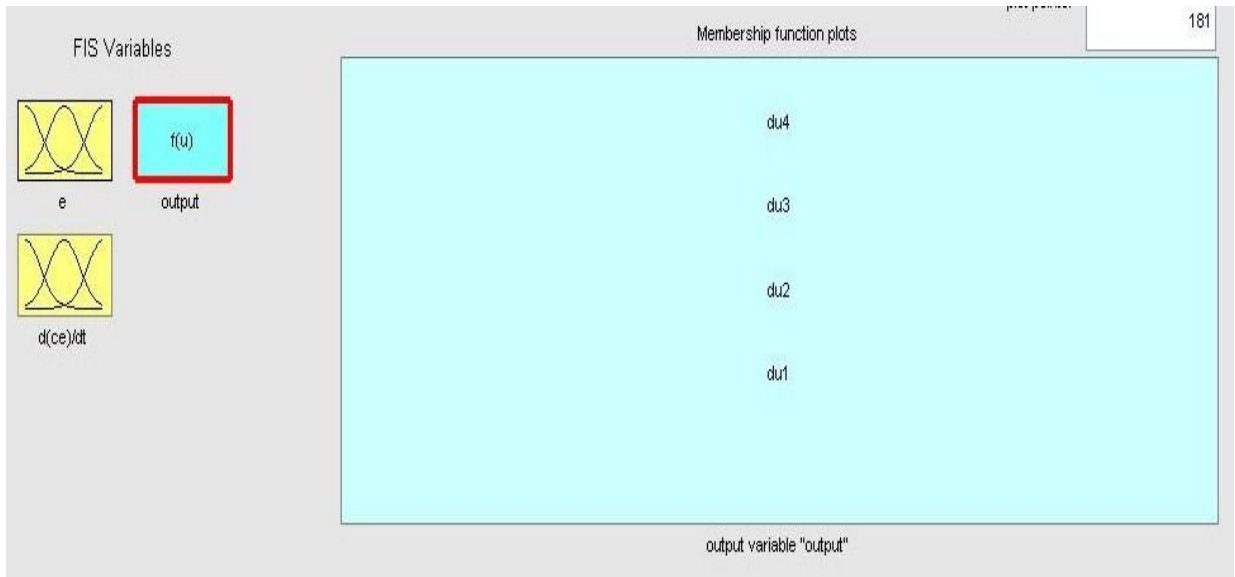
R4: IF **e=PS** AND **ce= PS** THEN **du= PM**

7.3 Membership functions: Membership function for e :



Membership function for ce:





Calculate the DOB (degree of belongingness) of each rule using the AND or min operator

$$DOB_1 = \min \{ \mu_z(e), \mu_z(ce) \} = \min \{ 0.6, 0.3 \} = 0.3$$

$$DOB_2 = \min \{ \mu_z(e), \mu_{PS}(ce) \} = \min \{ 0.6, 0.7 \} = 0.6$$

$$DOB_3 = \min \{ \mu_{PS}(e), \mu_z(ce) \} = \min \{ 0.4, 0.3 \} = 0.3$$

$$DOB_4 = \min \{ \mu_{PS}(e), \mu_{PS}(ce) \} = \min \{ 0.4, 0.7 \} = 0.4$$

Sample speed ω_r^* and ω_r

Compute error e and change in error ce

$$\mathbf{e(k) = \omega_r^* - \omega_r}$$

$$\mathbf{ce(k) = e(k) - e(k-1)}$$

From the figure $e=0.008$ and $ce=0.13$

Calculate the degree of membership of e and ce for the relevant fuzzy sets

$$\mu_z(e)=0.6 \text{ and } \mu_{ps}(e) =0.4$$

$$\mu_z(ce)=0.3 \text{ and } \mu_{ps}(ce) =0.7$$

Retrieve the amount of correction d_{ui} ($i=1,2,3,4$) corresponding to each rule in the table

$$D_{u_1}=0 \text{ for Z corresponding to } DOB_1=0.3$$

$$D_{u_2}=0.25 \text{ for PS corresponding to } DOB_2=0.6$$

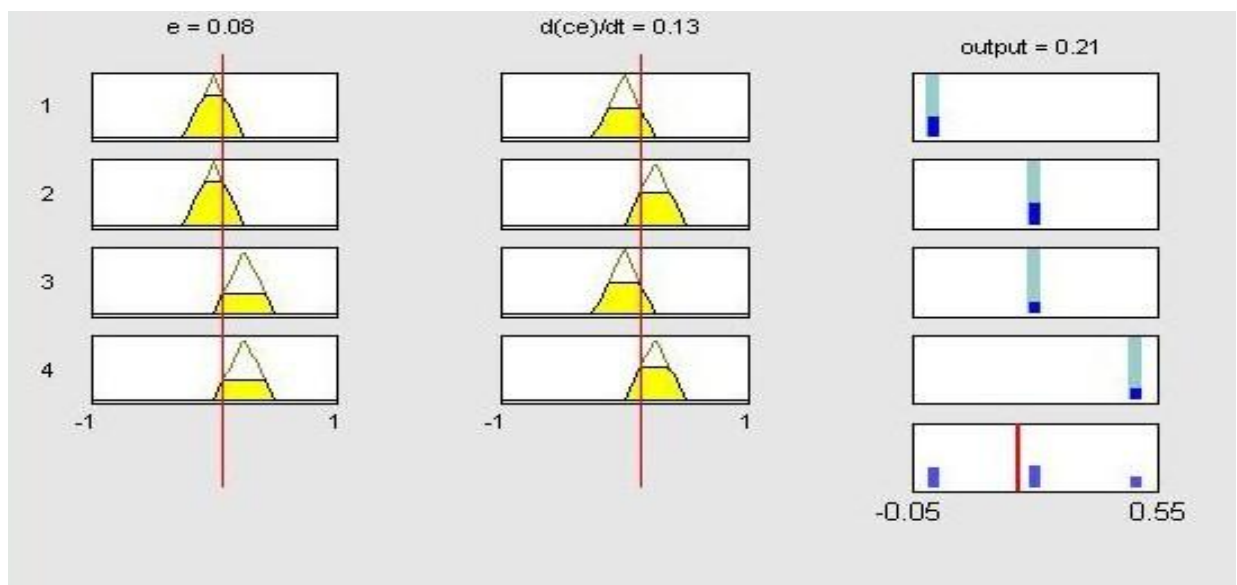
$$D_{u_3}=0.3 \text{ for PS corresponding to } DOB_3=0.3$$

$$D_{u_4}=0.4 \text{ for PM corresponding to } DOB_4=0.4$$

Calculate the crisp du by weighted average defuzzification method

$$du = \frac{0.3 \times 0.6 + 0.6 \times 0.25 + 0.3 \times 0.25 + 0.4 \times 0.5}{0.21}$$

$$du = 0.21$$



7.4 Specification of the separately excited DC Motor:

Armature resistance(R_a) = 0.6Ω

Armature inductance (L_a)= 0.012 H

Armature voltage (V_a)= 400 V

Mechanical inertia(J_m) = 0.15 Kg.m²

Friction coefficient (b_f) = 0.008 N.m/rad/sec

Back emf constant (k) = 1.8 V/rad/sec

Rated speed = 2100 r.p.m

7.5 Calculation:

Speed at full load when " $\omega=222$ rad/sec"

$$E_b = 1.8 \times 222 = 399.6 \text{ V}$$

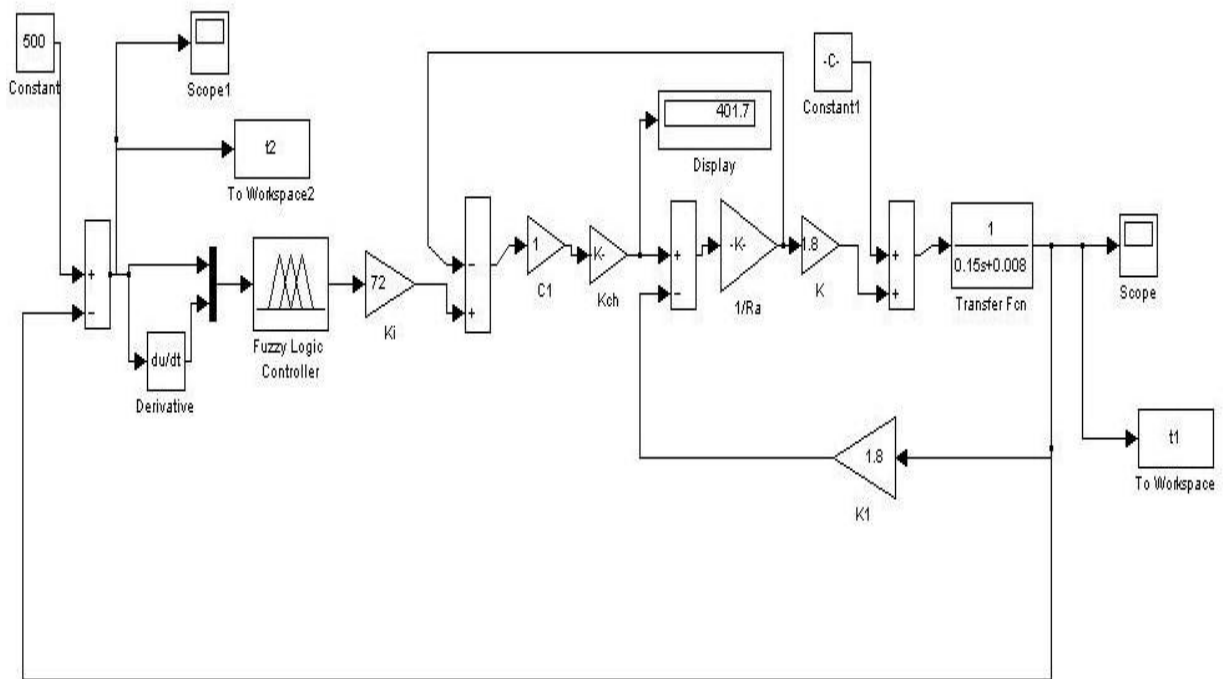
$$V_a = E_b + I_a R_a$$

$$400 = 399.6 + I_a R_a$$

$$I_a = 0.667 \text{ Amps}$$

At time $t=10$ sec we have taken a external load torque 3Nm

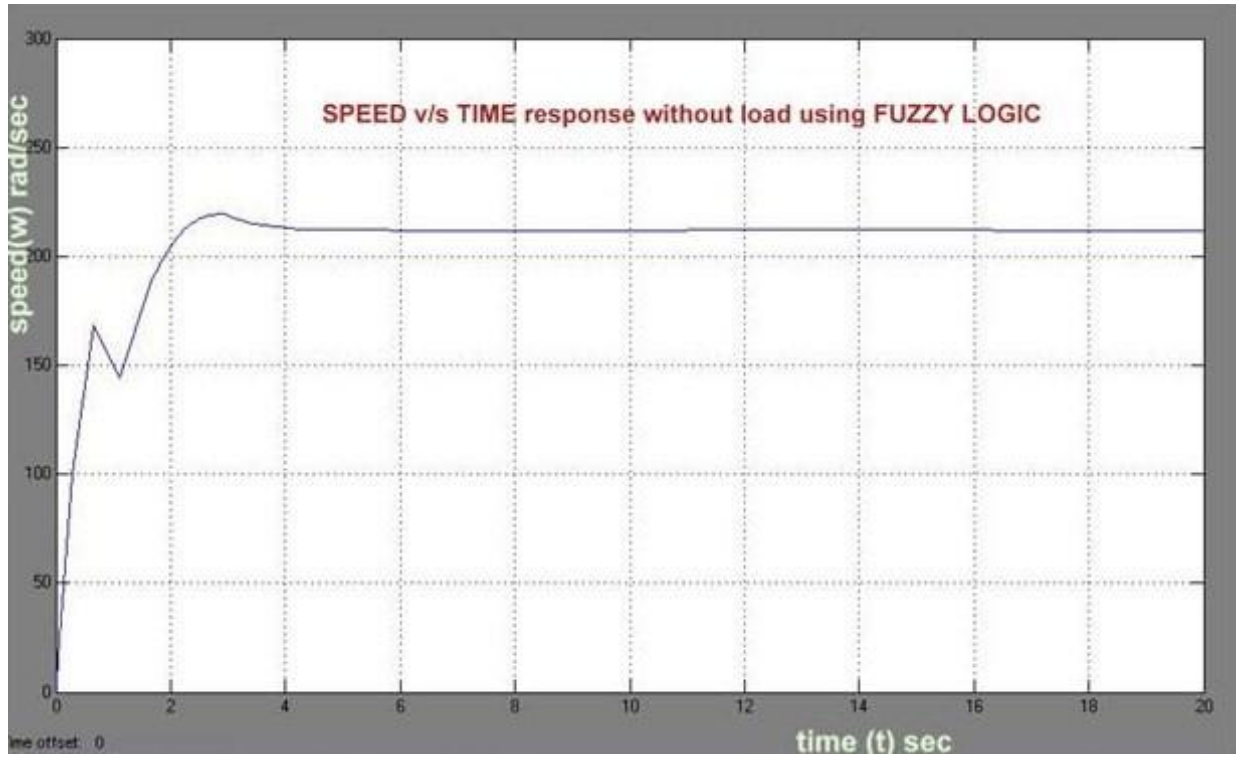
7.6 SIMULINK MODEL



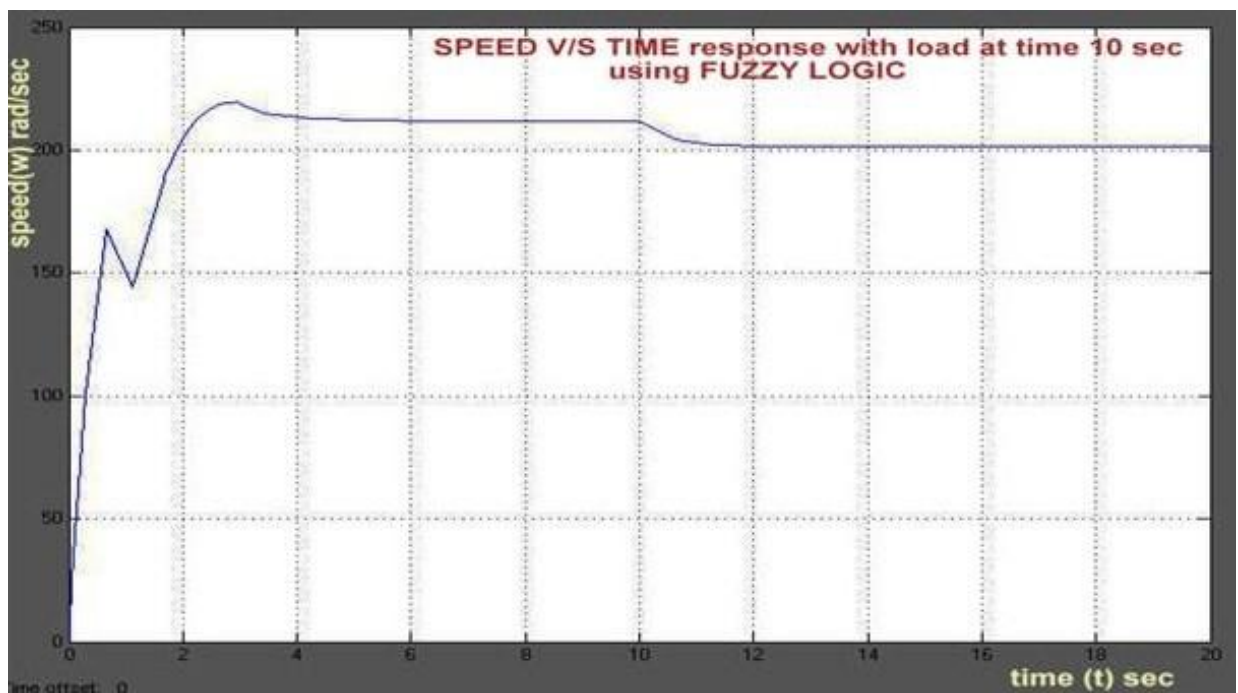
We are using the fuzzy logic controller for both the speed.

7.7 SIMULATION RESULT:

SPEED V/S TIME RESPONSE WITHOUT LOAD USING FUZZY LOGIC



SPEED V/S TIME RESPONSE WITH LOAD AT TIME 10 SEC USING FUZZY LOGIC



DISCUSSION:-

The background of DC Motors is studied. The study of Characteristics of separately excited DC motor is done. The steady state operation and its various torque-speeds, torque-current characteristics of DC motor are studied.

We have studied basic definition and terminology of fuzzy logic and neural network with the help of matlab and Wikipedia and some other websites.

Due to simple formulas and computational efficiency, both triangular MFs has been used to design fuzzy industrial controllers especially in real-time implementation.

The speed of a separately excited DC Motor has been successfully controlled by using fuzzy logic controller technique. A multilayer perceptron is used to identify the motor dynamics.

Graph for the speed response of separately excited DC Motor using fuzzy logic controller is compare with graph for the speed response of separately excited DC Motor without fuzzy logic controller.

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