Design and Analysis of DC Motor Speed Control by GA Based Tuning of Fuzzy Logic Controller

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***Abstract*:** **this paper describes the speed regulation of dc motor using Genetic algorithm (GA's) based tuning fuzzy logic controller (FLC). In this paper we used two approaches to tune fuzzy logic controller using genetic algorithm. First its developed stepwise method to tune a fuzzy logic controller with GA with reduced search space. And another approach we have been introduced so that a huge data base can be trained by lesser number of fuzzy logic controller design parameter. All the control strategies utilize the output speed error and its derivative as feedback damping signals.**

Index Terms: **DC motor, fuzzy controller, genetic algorithm, rule base (RB), Knowledge Base (KB), Membership Functions (MF's), Universe of Discourse (UPD), Scaling Factors, Speed Regulation.**

I. INTRODUCTION

The development of high performance motor drives is very important in industrial as well as other purpose applications such as steel rolling mills, electric trains and robotics. Generally, a better performance motor drive system have good dynamic response which perform task to speed command tracking and load regulating response [1,6]. DC drives consist of fewer complexes with a single power conversion from AC to DC. This is as a result of its simplicity, low cost design and robust performance in a wide range of operating conditions [1].The major problems in applying a conventional control algorithm (PI, PD, PID) in a speed controller are the effects of non-linearity in a DC motor Speed control of DC motor has attracted considerable research and several methods have created .proportional–integral control (PI) controller has been widely used for speed control of dc motor. kim et .al. [1,5]. we study the current state of the PD,PID and command matching controller for speed regulation of DC motor to reduce loading effect and minimize time delay and decrease rise time ,reduces peak time we have added a feed forward controller to the PID , fuzzy PD controller and optimized fuzzy PD controller using genetic algorithm and compare their performance on the basis of rise time , delay time and peak time [9].

These limitations of the conventional FLC motivated us to investigate methods of tuning based on expert's knowledge rather than the mathematical models. In the following, we propose a new and efficient two step approach for the tuning of FLC using Genetic algorithm. It was stated [10] that learning the two components of the KB (i.e., RB and DB) at the same time, have the possibility of generating better definitions but they deal with a larger search space that makes the learning process more difficult and slow. Taking care of this above problem, we are learning the data base (i.e., membership functions defining the premise and the consequent variables of a rule) after learning the scaling factors of premise and consequent variables. Much more emphasis has been given to reduce the number of variables to be learned by GA. The performance of the GA optimized Fuzzy Logic controller is compared with that of the conventional PID controller.

II. PHYSICAL SYSTEMS

Consider a Separately Excited DC motor whose electric circuit of the armature and the free body diagram of the rotor are shown in Figure 2.2

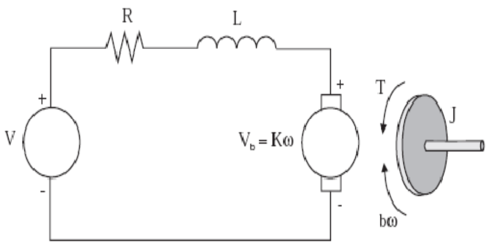

Fig. 1: Schematic representation of the considered DC motor

The rotor and the shaft of Separately Excited DC motor are assumed to be rigid. Consider the following values for the physical parameters [11]

Moment of inertia of the rotor

J =0.01 kg. m2

Damping of the mechanical system	b =0.1 $N.m.s$
Electromotive force constant	K =0.01 Nm/A
Electric resistance	R = 1 Ω
Electric inductance	L = 0.5 H
Rated speed	1200 r.p.m

The input is the armature voltage *V* in Volts (driven by a voltage source). Measured variables are the angular Velocity of the shaft in radians per second, and the shaft angle in radians.

II. A. System Equations

The motor torque, *T*, is related to the armature current, *i*, by a constant factor *K*

$$T = Ki$$

The back electromotive force (emf), *Vb*, is related to the angular velocity by

$$J\frac{d^2\theta}{dt^2} + b\frac{d\theta}{dt} = K$$

II.B.Transfer Function

Using the Laplace transform, equations (3) and (4) can be written as:

$$Js^2\theta(s) + bs\theta(s) = KI(s).......(5)$$

$$LsI(s) + RI(s) = V(s) - Ks\theta(s)$$

Where s denotes the Laplace operator. From (6) we can express $I(s)$:

$$I(s) = \frac{V(s) - Ks\theta(s)}{R + Ls}$$

And substitute it in (5) to obtain:

$$Js^2\theta(s) + bs\theta(s) = K\frac{Vs - Ks\theta(s)}{R + Ls}..........(8)$$

This equation for the DC motor is shown in the block diagram in Figure 2.

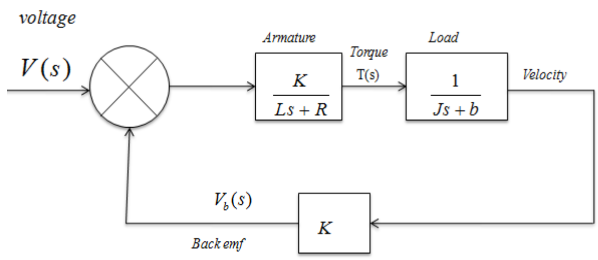

Fig. 2: A block diagram of the DC motor

From the block diagram in Fig. 2.3, it is easy to see that the transfer function from the input voltage, *V (s),* to the angular velocity *w* is.

III. FUZZY LOGIC CONTROLLERS

A FLC has a fixed set of control rules, usually derived from expert's knowledge. The membership functions (MF's) of the associated input and output linguistic variables are generally predefined on a common universe of discourse. For successful design of FLC's proper selection of input and output scaling factors (SF's) and/ or tuning of the other controller parameters are crucial jobs, which in many cases are done through trial and error or based on some training data.

The design parameters include scaling factors, fuzzification methods, rule base and data base. The design parameters of the rule base include the choice of process state and control output variables, choice of content of rule-antecedent and the rule consequent, choice of term sets for the process state and control output variables, derivation of the set of rules. While the design parameters of the data base include the choice of Membership functions and the choice of scaling factors. There is a need for the tuning of fuzzy logic controller (FLC) so as to obtain the better performance.

III.A.TUNING OF FUZZY LOGIC CONTROLLER (FLC)

In this section, we propose a two step approach to automatically generate the knowledge base (KB) of a fuzzy rule based system (FRBS) based on a new learning approach composed of two different goals.

- A genetic learning process for the scaling factors that allow us to define the scaling factor for the input and the output variables. First, the GA is applied for the tuning of the scaling factors of the premise and consequent variables of a fuzzy rule set of a fuzzy logic controller with a predefined knowledge base.

- The genetic learning process derives the DB of a fuzzy logic controller (FLC). In our approach the learning is for adjusting the membership function parameters, keeping the number of rules and number of premise and consequent parameters in each rule fixed.

IV. EVOLUTIONARY OF GENETIC ALGORITHM

Basically, GA consists of three main stages: Selection, Crossover and Mutation. This algorithm is repeated for many generations and finally stops when Reaches that the optimum solution problem. Main feature of Genetic Algorithms are search and optimization which inspired by two biological principles namely the process of .natural selection. In this way, a Genetic algorithm can, in effect, often seek many local minima and increase the likelihood of finding the global minima representing the problem goals.

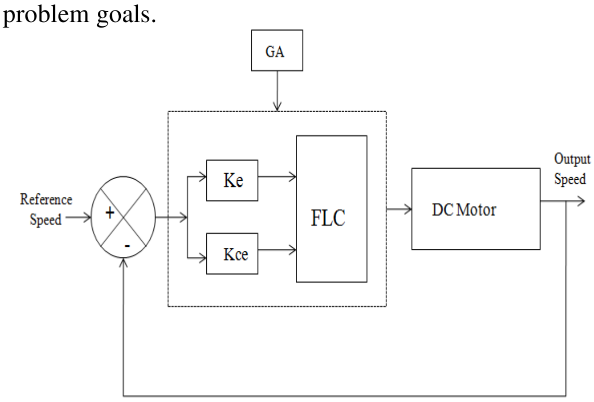

Fig. 3. FLC with GAs structure

Population Size

Determining the number of population is the one of the important step in GA. There are many research papers that dwell in the subject.

Reproduction

During the reproduction phase the fitness value of each chromosome I assessed. This value is used in the selection process to provide bias towards fitter individuals.

Crossover

Crossover occurs when two parents exchanged parts of their corresponding chromosomes once the selection process is completed, the crossover algorithm is initiated.

V. SIMULATION RESULTS

Conventional PID controller: The transfer function of the DC motor is used in the modeling of the PID controller. The overall system model is represented form of a block diagram in Fig. 4.

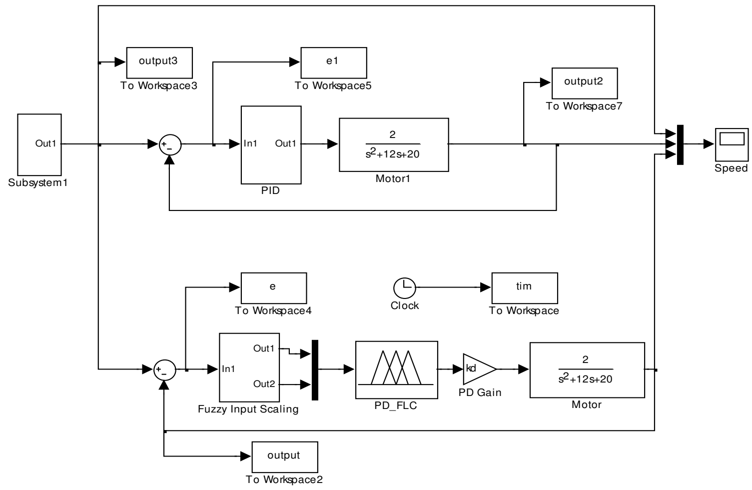

Fig. 4.System Model of Fuzzy Scaling Factor

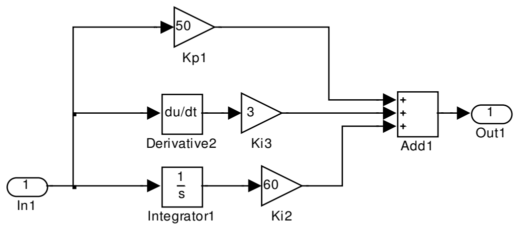

Fig. 5 PID Controller subsystem

The PID Controller subsystem (Fig. 5) contains the proportional gain scaling factor (*Kp*), the derivative gain scaling factor (*Kd*) and the integral gain scaling factor (*Ki*).The PID controller model is hand-tuned by first increasing the value of the proportional gain, *Kp*, until the a desirable response is obtained. The derivative gain *Kd* and the integral gain *Ki*, are then adjusted to improve and optimize the response of the system. A fairly optimal response is achieved for a proportional gain value of 50, a derivative gain value of 60 and an integral gain of 4. The output response of DC motor compared with each output of the desired speed (reference) of DC motor.

Scaling Factors Learning

In the learning of scaling factors i.e., *K1* and *K2*, we have selected two premise variables i.e., error (e) and change of error (Δe) and one output variable (u). Thus, there are only three parameters which we are learning i.e..., *Ke* , *Kce*, *Ku* A common term set have been used for the premise and consequent variables. The linguistic variables of each premise/consequent variable can be represented by a set of six Parameters [a1 a2 a3 a4 a5 a6] = [-3/3,-2/3,-1/3, 1/3, 2/3, 3/3]

Where, {NB, NM, NS, Z, PS, PM, PB} over the universe of discourse (UOD) [-1, 1].

'NB' defined by a triangular membership function as [-4/3 a1 a2]

'NM' defined by a triangular membership function as [a1 a2 a3]

'NS' defined by a triangular membership function as [a2 a3 0]

'Z' defined by a triangular membership function as [a3 0 a4]

PS' defined by a triangular membership function as [0 a4 a5]

'PM' defined by a triangular membership function as [a4 a5 a6]

'PB' defined by a triangular membership function as [a5 a6 4/3].

ce → 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

Fig 6: Rule Matrix used for learning of scaling factors

When the Genetic algorithm is applied for 100 generations, the result obtained as:

$Ke = 0.7506 \quad Kce = 19.4921 \quad Kdu = 355.5359$

The plot of the max fitness of every generation is shown in fig (7). The final best response obtained at the above obtained values of scaling factors is shown in fig (9), with better performance as compared to PID controller performance. But still the steady state error is not equal to zero, so finer tuning is required by updating the data base.

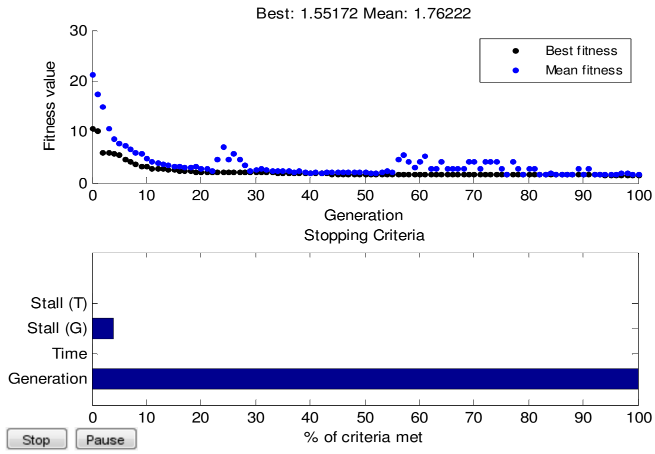

Fig. 7. Best fitness obtained after each generation in the learning of Data Base

DB Learning

In the learning of DB, the scaling factors are kept fixed (at the values obtained in the scaling factors learning) and the number of rules 'r' is taken as 49 (fig 6). The chromosome in this learning consist of $X = [\, X_1 \; X_2 \; X_3 \,]$, X_i describing the data set of each premise or consequent variable, given

$$X_i = [\, a_{i_1} \; a_{i_2} \; a_{i_3} \; a_{i_4} \; a_{i_5} \; a_{i_6} \,]$$

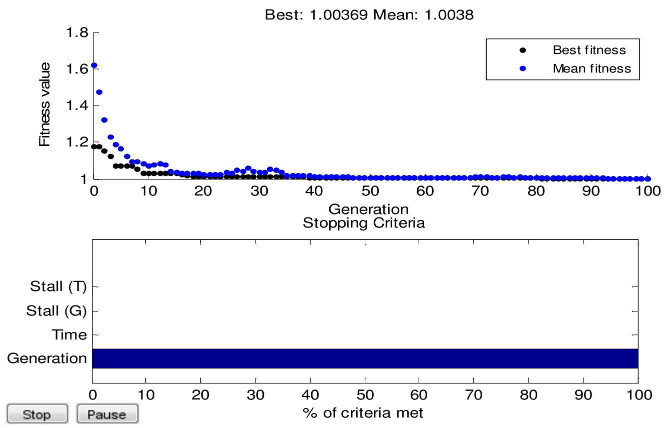

Fig.8. Best fitness function obtained after each generation in the learning of KB

The Genetic algorithm is applied for 100 generations the plot of fitness value and the best output response of DC motor obtained is shown in figure (9) and (10).

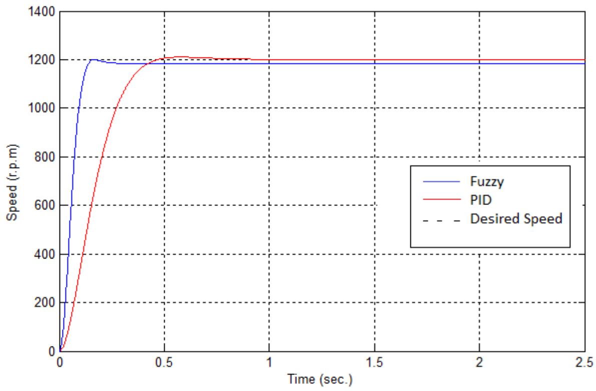

Fig.9 Output response of DC motor obtained after learning of scaling factors

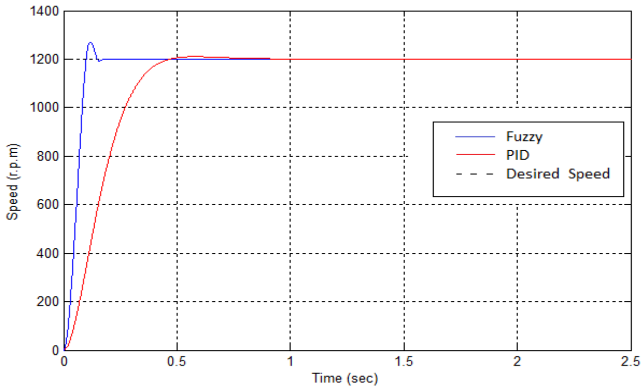

Fig. 10 Output response of DC motor obtained after learning KB

The comparative output response of DC Motor analysis with respect auto delay time (td), rise time (tr) and peak time (tp) can be tabulated as:

Table 1: Comparison Table of Controllers

Parameter / Controllers	Delay time(td) in sec.	Rise time(tr) in sec.	Peak time(tp) in sec.	Settling time(ts) in sec.	Maximum overshoot %(Mp)	IAE
Conventional PID controller	0.1540	0.4700	0.5800	0.4090	86.97	2.2291
Fuzzy scaling factors	0.0570	---	0.1670	0.1350	-------	1.4782
Fuzzy data base (DB)	0.0560	0.1000	0.1190	0.1210	5.8466	1.0040

.

It can be noted that the FIS is tuned much better when fine tuning is done by training the data base after the learning of scaling factors Also the results are much better in comparison to the work done by Sheroz *et al* [1]. For variable reference level the optimal fuzzy controller also has a better performance as seen from fig .

7 CONCLUSIONS

In this paper we have discussed the speed control of DC motor Drive by different approach of fuzzy controller .the optimal fuzzy logic is designed using genetic algorithm. The generation of the knowledge base (KB) of a fuzzy rule-based system (FRBS) presents several difficulties because the DB depends on the concrete applications, and this makes the accuracy of the FRBS directly dependent on its composition.

In our approach we have selected GA's as the learning algorithm as GA's consider many points in the search space and therefore have a reduced chance of converging to local optima. It is to be noted that learning the DB with large number of variables have the possibility of generating better definitions but they deal with a larger search space that makes the learning process more difficult and slow.

Taking care of this above problem, we have learned the data base (i.e., membership functions defining the premise and the consequent variables of a rule) after tuning the scaling factors of premise and consequent variables. Special attention has also been given to reduce the number of parameters required to tune the membership functions.

In context to the previous work [1] for the same problem, we have come out with better results by splitting the search variables in two parts (i.e., scaling factors and data base). Also we have introduced with the use of the genetic algorithm for the optimization of fuzzy controller on data base to reduced the 49 rule merely 21 parameter to give better response of speed control of DC motor in term of rise time peak time ,delay time and IAE and finally the proposed controller provide drive robustness improvement.

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