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Research Paper

Fuzzy Logic DC Motor Speed Controller Swarm Particle Modelling and Optimization

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Abstract
This research presents an application of particle swarm optimization- fuzzy logic control (PSO-FLC) for direct current motor speed.The mathematical model that describes the dynamic behaviour of the DC motor was developed by using Simulink, fuzzy set Guassian membership function, Mamdani fuzzy inference system(FIS) and centroid method of defuzification to optimize the fuzzy membership functions. The effectiveness of the control strategy was validated on Matlab/Simuink environment. For a normal load of 5000N, FLC attained a speed of 1432rpm with a percentage error of 0.49 while that of PSO-FLC 1434 had rpm with a percentage error of 0.14. As incremental load of 10%, 20% and 30% respectively was applied in succession, and the maximum speed attained by FLC kepton decreasing with a high percentage errorwhile thatof PSO was able to track the speed with minimal error.The results demonstrated that the designed PSO-FLC speed controller ismore effective for good dynamic behavior monitoring of the DC motor by providing better tracking and performance than fuzzy logic controller.

Keywords**: **Fuzzy logic, modeling, particle swarm, optimization, dc motor, speed controller

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I. Introduction

Electric motors play important roles in the operation ofmachines of various kinds in engineering applications. They come in different sizes and shapes. Electric motors can be classified as alternating current motors (AC) or direct current motors (DC).

DC motor falls into two classes namely: separately excited DC motor and self-excited DC motor[14]. Its operation is based on the principle of electromagnetic induction[15]. The various methods of controlling the speed of electric motors include: Field Resistance Control, Armature Voltage Control and Armature Resistance Control

Adirect current motor produces or uses direct current to drive in their energy transmission and conversion. Direct current motors find applications in steel rolling mills, electric screw drivers, sewing machines, hard disk drives, air compressors and reciprocating machine [1].

The speed controller of DC motors was first carried out bymeans of a voltage control in 1981 by Ward Leonard[2]. The regulated voltage sources used for DC motor speed control have gained more importance after the introduction of thyristors asswitching devices in power electronics[3].

Today most famous and most frequently used type of controller in industry is the proportional integral derivative (PID) controller[4], but PID controllers do not offer satisfactory results when adaptive algorithms are required [5],[6].

Proportional controller (P) causes oscillation if sufficiently aggressive in the presence of lags and/or dead time. The more lags (higher order), the more problem it causes. It also directly amplifies process noise[7].

In Proportional Integral controller (PI), the output of the controller is changed proportional to the integral of the error[8].

The aim of using proportional derivative (PD)controller is to increase the stability of the system by improving control since it has an ability to predict the future error of the systemresponse. In order to avoid effects of the sudden change in the value of the error signal, the derivative is taken from the output response of the system variable instead of the error signal[9].

Fuzzy logic controller (FLC) offers some solutions. A basic advantage of FLC is that it does not require knowing the complete mathematical model of the system[10],[11],[12],[13],[14].Popularity of FLC is explained with the fact that it puts clear and simple implementation of human thinking into controlling algorithms[15]. Fuzzy controllers are robust regarding dynamic changes and have a wide stability range[16]. FLC is only based on approximate and linguistic information[17].

The current concerns in the modern control industries is to develop methodologies, concepts, algorithms, technologies for the design of process control systems which must be able to evolve, self-develop, self-organize, and self-evaluate and to self-improve[18],[19]. Conventional control systems suffer from transient and steady state problems like overshoot, settling time and rise time. Automatic tuning procedures are required for satisfactory control of controller parameters[20].

Based on fuzzy logic, easily comprehensive rules can be used to implement control for complex systems [21]FLC system can be implemented in hardware in several ways such as microprocessors or microcontrollers, but there are digital signal processor based implementations as well[22].

Fuzzy logic can be described simply as "computing words rather than numbers" or "control with sentence rather than equations"[23].

Fuzzy theory was first proposed and investigated by[24]. The defuzzification is used to convert the fuzzy set produced by the inference mechanism into a crisp output to be used by the plant [25].

A rule base controller is easy to understand and easy to maintain for a non-specialist end user and an equivalent controller could be implemented using conventional techniques[26].

There are two famous type of system currently used in fuzzy logic which are:Mamdani fuzzy inference, and Sugeno fuzzy inference.

Fuzzy set is an extension of classical set. According to[24] fuzzy set is characterized by a membership (characteristic) function which assigns to each object a grade of membership ranging between zero and one.

A fuzzy set F in a universe of discourse U is characterized by membership function μFwhich takes values in the interval [0,1], that isμF: U [0 , 1] If U contains finite number of elements, fuzzy set F can bedenoted as shown in Equation 1:

$F = \{\mu F\,(u1)/u1, \mu F(u2)/u2, \ldots, \mu F(un)/un\}$ Equation 1

As in *Boolean* logic, we need to categorize it one of the two groups only, "tall" or "short". Even there is minor difference between two heights [29].Fuzzy set deal with different heights that can be "tall" to different degrees.
A membership function is curve that defines how each point in the input space is mapped to a membership value or degree of membership between 0 and 1.

Particle swarm optimization is a technique used to explore the search space of a given problem to find the settings or parameters required to optimize a particular objective[30].

Particle Swarm Optimization (PSO) incorporates swarming behaviors observed in flocks of birds, schools of fish, or swarms of bees, and even human social behavior, from which the idea is emerged. PSO is a population-based optimization method first proposed by [31],[32].

In PSO, the potential solution called particles fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space whichare associated with the best solution (fitness) achieved so far. This value is referred to as pbest. Another best value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This value is called lbest. When a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest. The particle swarm optimization concept consists ofchangingthe velocity of (accelerating) each particle toward its pbest and lbest (for lbest version) at each time step. Acceleration is weighted by random term, with separate random numbers being generated for acceleration towards pbest and lbest locations. After finding the best values, the particle updates its velocity and positions with following Equations 2 and 3[33].

Vi(k+1) = Vi(k) + c1* rand( ) * (Pi(k) - Xi(k)) + c2* rand( ) * (g(k) - Xi(k)) Equation 2.

Xi(k+1) = Xi(k) + Vi(k+1) Equation 3

whereVi(k) is velocity of particle i at iteration k, Xi(k) is the position of particle i at iteration k, Vi(k+1) is velocity of particle i at iteration k+1, Xi(k+1) is the position of particle i at iteration k+1, rand( ) is random number between (0,1), c1 cognitive acceleration coefficient, c2 social acceleration coefficient.

The basic particle filter is suboptimal in the sampling step, by applying PSO to particle filter, particle impoverishment problem is avoided and estimation accuracy is improved. The PSO algorithms can also be applied in the job shop scheduling [34].

[35]proposed the controlling of a D.C. motor using fuzzy logic controller.The mathematical model of a D.C. motor was derived and a PID controller was used in conjunction with it.Four methods of tuning PID controller was involved, which includes the Ziegler Nichols (Z-N) tuning, hand tuning, MATLAB simulation tuning and FLC. Their responses were studied and results obtained were compared with respect to Maximum peak (%Mp), Rise time (Tr), Settling time (Ts) and conclusions drawn.

[36]investigated the control strategy of using Fuzzy-PID and PSO-PID technique for the control of a D.C. motor.The application of particle swarm for adjusting the gains of proportional-integral-derivative PID controller parameters of a DC motor is presented and alongside Fuzzy logic controller which involves the application of fuzzy set theory. Its major features are the use of linguistic variables; defined as variable whose values are sentences in natural language and maybe represented by fuzzy sets.

The PSO algorithm is mainly utilized to determine three optimal controller parameters Kp, Ki and Kd such that the controlled system could obtain a desired step response output.

While comparing the results from the PSO-PID and Fuzzy-PID, PSO-PID was seen to show better output.

The controller modelling process using particle swarm optimization algorithm is aimed at optimizing the fuzzy logic controller membership function that minimizes the considered objective function. The overall performance (speed of convergence, efficiency, and optimization accuracy) of PSO algorithm depends on objective function (OF), which monitors the optimization search. The OF is chosen to maximize the domain constrains or to minimize the preference constrains

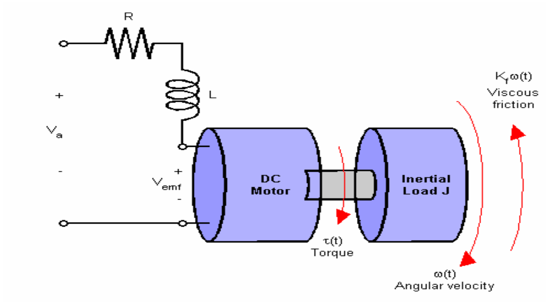
II. Methodology

An optimized membership function using particle swarm optimization was designed using feedback control mechanism.The torque generated in the armature is available to drive the inertial load connected to the motor shaft. In modelling the motor, the transfer function method was used to develop a linear approximation to theactual motor. Second-order effects such as hysteresis and voltage drop across the brushes were neglected. The motor system specifications and parameters are listed in Table 1.

Table 1: DC motor specifications and parameters

Motor parameters	Values
Moment of Inertia of the Rotor () [kgm^2]	0.001
Motor Viscous Friction Constant () [Nms]	0.001
Electromotive Force Constant ()[V/rad/s]	0.01
Motor Torque Constant () [Nm/A]	0.01
Electric Resistance () [Ω]	1
Electric Inductance () [H]	0.5
Force per Torque Constant ()	0.0155

In armature control of separately excited DC motors, the voltage applied to the armature of the motor is adjusted without changing the voltage applied to the field. In order to develop a model for the motor, the electrical and mechanical a parametres were considered. The input to the system is the voltage applied to the motors armature V_a, while the output is the angular velocity of the shaft (Ω). The effectiveness of any system depends on the perfection of the system modelling. The schematic diagram of a DC motor is shown in Figure 1; from the diagram the system differential Equation for the motor can be obtained.



The torque T generated on the motor shaft is linearly proportional to armature current as shown in Equation 4.
$T=K_Ti_a$ Equation 4
where is the current an K the viscous friction.
The back emf is proportional to the angular velocity)of the shaft by a constant factor Equation 5
The motor torque) and back electromotive force constants are equal, that is therefore, is used to represent both the motor torque constant and the back electromotive force constant.
From the Figure 1 the following differential Equations based on Newton's second law and Kirchhoff's voltage law are derived;
Equation 6
Equation 7
The transfer function by eliminating between Equations 6 and 7 results in Equation 8:
Equation 8
Equation 8 can also be represented in state-space model by choosing themotor rotational speed and armature current as the state variables. The state of the system is described by a set of differential equations in terms of state variables (i) and the output (u_1, u_2.....u_n). The state-space model of the DC motor speed controlsystem is given in Equation 9.
Equation 9
The DC motor has three main components input, plant and output. Theuncompensated motor can only rotate at 500 rad/sec with an input voltage of 12 volts.Figure 2 shows a model of a DC without a controller

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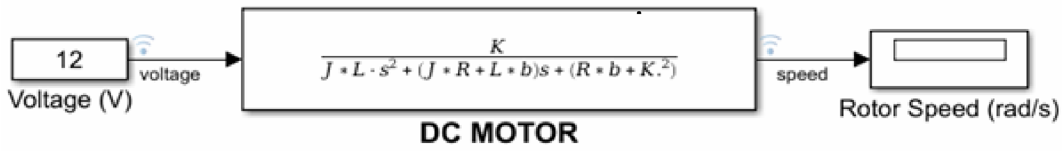

Figure 2: Simulink model of a DC motor without a controller.

The transfer function model in Equation 8 and the is expressed in Equation 9.
P(s) = Equation 9

A 12 voltage source was used to energize the DC motor while the output is the angular speed which was fed into any drive system to vary its speed. Many researches on control, data transmission have been published by [40],[41],[42].

3.1Modelling of DC Motor speed Control with a FLC Controller

Fuzzy logic systems(FLS) use ‘if then’ conditions to characterize the behavior of a system. These rules are usually based on expert practical knowledge about any system. FLS is an analytical way used to represent the human way of thought process, imprecise and inexact phenomena. The membership function is a relation that provides for every element of the set a particular membership value. The fuzzy set is a set where every element associates itself with the set with a membership value; its range is between 0 and 1.
The specific dynamic model utilizes a set of fuzzy rules in order to describe global nonlinear systems in terms of sets of local models which smoothly connect the membership functions. This controller has two input (speed error and change in speed error), one output (speed) fuzzy controller with the first input denoted as error = x.

The second input is the error_dot = y (time derivative of the error). The fuzzy membership functions for the first and second inputs are Gaussian memberships (seven membership functions for each input).
Membership function was used to map the inputs of the controller to their corresponding fuzzy sets and subsequent crisp output values determined. Table 2 defines the linguistic variables for input and output variables (membership function) used in designing the fuzzy logic motor control system for this research.

Table 2: Membership function terms

Membership Terms	Description
NL	Negative Large
NM	Negative Medium
NS	Negative Small
Z	Zero
PS	Positive small
PM	Positive Medium
PL	Positive Large

The fuzzification module of the fuzzy logic controller involves converting or mapping the crisp values (input values) into a fuzzy set using membership functions. Knowledge base module stores the rules for the fuzzy controller. The fuzzy controller has forty nine rules; these set of rules were built into the knowledge base in the form of 'if then else' structures. The rules are computed using R_{ij} for i=1:7 and j = 1:7 as given below:
R_{11}: (if x is NL) and (y is NL) then (z is NL)
R_{21}: (if x is NM) and (y is NL) then (z is NL)
R_{31}: (if x is NS) and (y is NL) then (z is NL)
R_{41}: (if x is Z) and (y is NL) then (z is NL)
R_{51}: (if x is PS) and (y is NL) then (z is NM)
R_{61}: (if x is PM) and (y is NL) then (z is NS)
R_{71}: (if x is PL) and (y is NL) then (z is Z)
The rule base evaluations were done inside the Simulink subsystem. Table 3 summarizes the set of rules and was also used to create the relationship between the two inputs and the output.

Table 3: Fuzzy based initial rules for the FLC

CE/E	**NL**	**NM**	**NS**	**Z**	**PS**	**PM**	**PL**
NL	NL	NL	NL	NL	NM	NS	Z
NM	NL	NL	NL	NM	NS	Z	PS
NS	NL	NL	NM	NS	Z	PS	PM
Z	NL	NM	NS	Z	PS	PM	PL
PS	NM	NS	Z	PS	PM	PL	PL
PM	NS	Z	PS	PM	PL	PL	PL
PL	Z	PS	PM	PL	PL	PL	PL

The FLC is a two input and one output fuzzy inference system (FIS) with the first input being the speed error, the second input is change in speed error, and the output is the speed. Inputs universe of discourse or speed error range was taken between -80 to 80 rpm while the output was fixed at 0 to 80 rpm respectively. Each input and output had seven membership functions of the Gaussian type whose linguistic variables are specified as NL (Negative Large), NM (Negative Medium), NS (Negative Small), Z (Zero), PS (Positive Small), PM (Positive Medium), PL (Positive Large). The membership functions were used to form 49 rules based as shown in Table 6, while the MF shapes is shown in Figure 3.

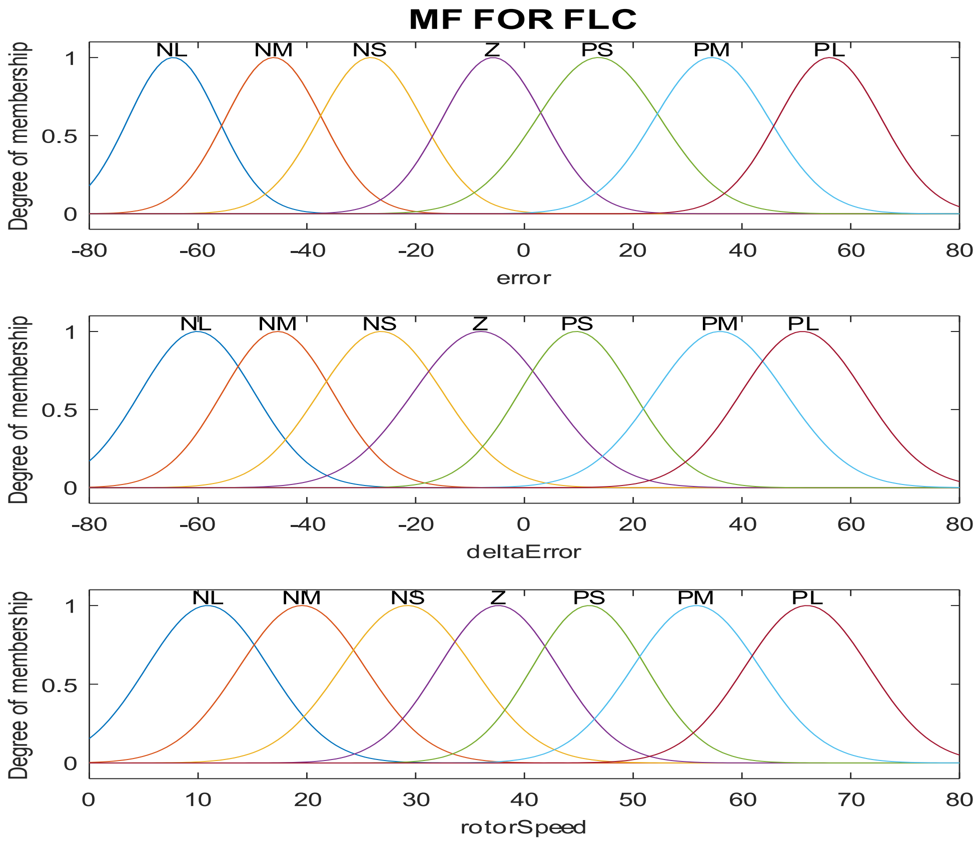

Figure 3: Membership functions of the FLC

3.2 Mathematical Modellingof PSO

PSO utilizes a very simplified model of social behavior to solve the optimization problems in a cooperative and intelligent framework.

Evaluating the ranges of membership function within the fuzzy logic controller was done. After getting the optimal parameter the full model was implemented in MatlabwithSimulink where the PSO created optimal topologies to achieve a possible solution to this problem allowing each particle vector containing the potential range of optimal membership for the fuzzy system and to obtain a better result in the simulation. As the error achieved by the plant is covered, the cost of the particle was saved as the minimum cost of such a particle to subsequently save the best overall result from all over the swarm. The velocity is changed iteratively for each particle by its personal best position, which is found by the particle, and also the best position found by the particles in its neighborhood.

At each step a new velocity and position is updated for each particle as given in Equations 10 and 11.

$V_{i(t+1)} = wV_{i(t)} + C_1(P_{i(t)} - X_{i(t)}) + C_2(g_{(t)} - X_{i(t)})$ Equation 10

$X_{i(t+1)} = X_{i(t)} + V_{i(t+1)}$ Equation 11

whereXi is the position of the ith position, C_1 and C_2 are positive constants, w is the inertia weight

$P_{i(t)}$ is the local best for previous position; (position of the best fitness value) of the ith particle, $g_{(t)}$ is the position of the best particle among particles in the population, $V_{i(t)}$ is the Change of velocity for particle ith.

These illustrate how the velocity components contribute to move the particles towards the global best position at time steps t and t + 1 respectively.

Equation of updating velocity and position of particle i; are presented in Equations 12 and 13.

$V_{ij(t+1)} = wV_{ij(t)} + [r_1C_1(P_{ij(t)} - X_{ij(t)})] + [r_2C_2(g_{j(t)} - X_{ij(t)})$ Equation 12 $X_{ij(t+1)} = X_{ij(t)} + V_{ij(t+1)}$ Equation 13

where r_1 and r_2 are random numbers between 0 and 1, w is the inertia weight.

In order to achieve the said goals of using PSO to optimize the fuzzy logic membership functions such that the steady state error of the system response is zero the following evolution procedure of PSO were taken into consideration:

i. Initialize a group of particles including the random positions, velocities and accelerations of particles.
ii. Evaluate the fitness of each particle.
iii. Compare the individual fitness of each particle to its previous pbest. If the fitness is better, update the fitness as pbest.
iv. Compare the individual fitness of each particle to its previous gbest. If the fitness is better, update the fitness as gbest.
v. Update velocity and position of each particle according to 6.
vi. Go back to step 2 of the process and keep repeating until some stopping condition is met.

The fuzzy controller was applied to the speed control of DC motor. The PSO code was used to achieve this research with a maximum number of iteration of 250 and time steps of 50. To design the optimal fuzzy controller, the PSO algorithms are applied to search the globally optimal parameters of the fuzzy logic. The birds of the PSO algorithms include the range of the membership functions (error and change in error) and the shape of the membership functions (NL, NM, NS, Z, PS, PM, PL) that makes the output voltage to be optimal such that the steady state error of the response is effectively minimized.

The optimized membership function structure is shown in Figure 4which is quite different from the results obtained from the manually designed FLC in Figure 3.

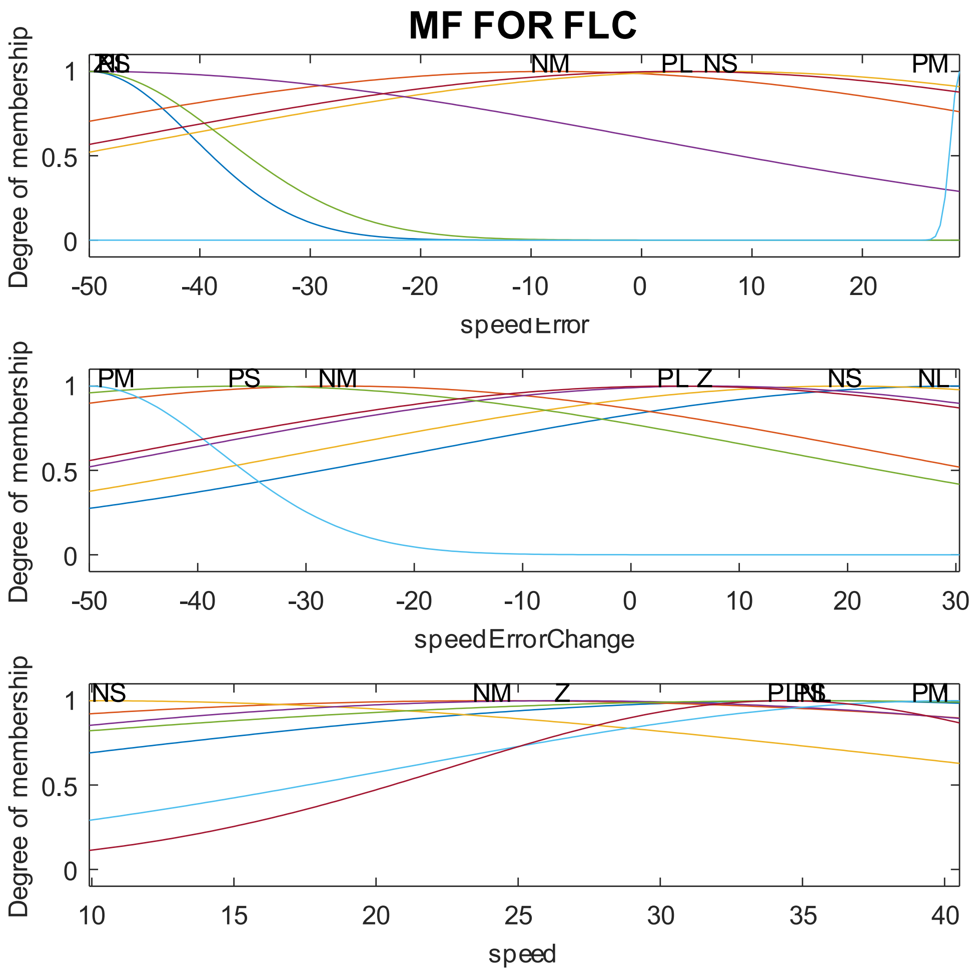

Figure 4:Membership functions of the FLC optimized with PSO

From the graph, the PSO was initialized at lower and upper bounds for speed error as -50 to 50 rad/sec, and -50 to 50 rad/sec for change in speed error, and 0 to 50 rad/sec for the output speed, which later yielded optimized final lower and upper bounds of -50 to 28.8 rad/sec for input one, -50 to 30.3 rad/sec for input two, and 9.9 to 40.5 rad/sec for the FLC output. All the membership function parameters were PSO optimized to fall within the range of -50 to 40.5 rad/s in order to obtain FLC which was able to track the reference speed signal to 1432 rpm.

For FLC to be efficient, the controller must be able to track the reference speed of the system with little or no steady state error. A reference speed ofref_{speed}, 150 rad/s (1432 rpm) was considered and the system output denoted bysys_{speed}, yielded the equation for the objective function (f), as shown I Equation 14.

Equation 14

Gaussian MF is given by Equation 15.

Equation 15

where c and are the centre and the width of the ith fuzzy set.

In Table 3, there are 7 membership function for each input and output, constituting 14 decision variables for input one (speed error), 14 for input two (change in speed error), and 14 for output one (speed). A total of 42 MF decisions variables are to be optimized by the PSO algorithm. Each of these has input and output associated with two parameters which gives a total of 6 variables. In all, a total of 48 variables would be optimized or tuned to yield or minimize the system steady state error.

The PSO was initialized with lower and upper bound of -50 to 50 rad/s for input one, -50 to 50 rad/s for input two, and 0 to 50 rad/s for output.From given range, the initial values are obtained for the 42 MF decision variables. A PSO algorithm was developed in MATLAB with a swarm population size of 10 members. The PSO wasiterated for about 250 times and the Simulink DC motor model in Figure 3 simulated online for about 2500 times before the FLC structure was fully optimized.

The objective function minimized or maximized is the steady state error of the Simulink model shown in Figure 5 and given in Equation 14. The steady state error is the difference between the DC motor rotor speed and the reference speed fed to the fuzzy logic controller.

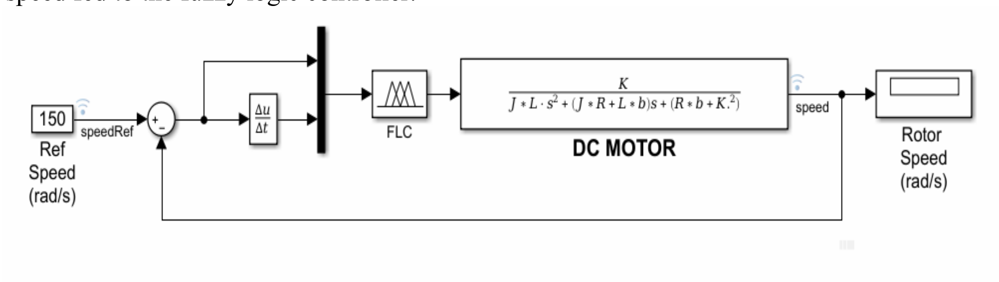

Figure 5: Simulink model with FLC for particle swarm optimization

During the initialization process of the PSO, the particles positions and velocity are updated and the best position within the swarm is used to evaluate the objective function. The particle position that gives the lowest values of the objective function is stored as the best global positions or FLC membership function parameters. This process is repeated at every iteration until the steady state error of the DC motor model falls within the stipulated tolerance of less than or equal to 0.2 rpm.

III. Results and Discussion

3.1 Results

Simulations were carried out with DC Motor at 12V without controller, DC Motor with FLC and DC Motor with PSO-FLC at a normal load of 5000 N which gives a speed of 1432 rpm. The load was then varied and simulation was carried out on the DC Motor with the different loads.

3.1.1 Simulation Results at Normal Load (5000N)

The speed response of the different controllers at normal load of 5000 N is presented in Figure 6. The differential percentage errors is as presented in Table 7.

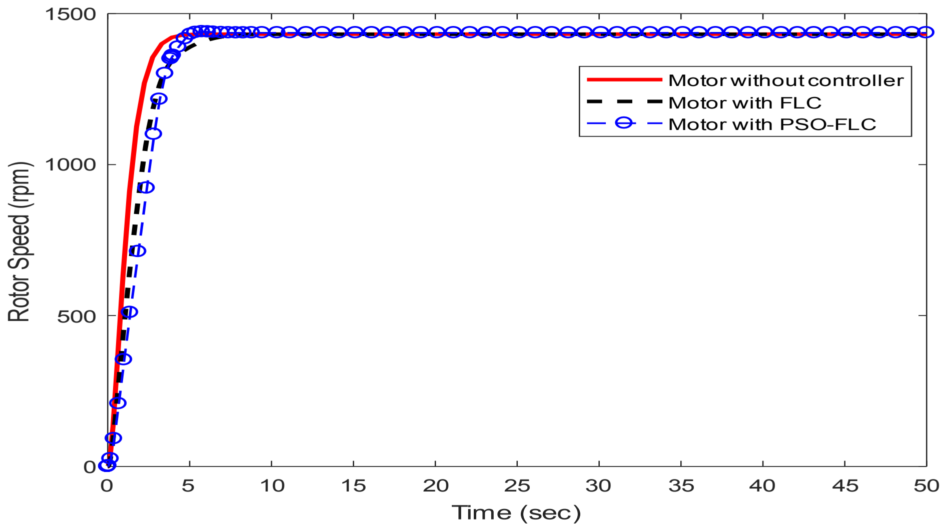

Figure 6: DC motor speed response without controller, with FLC and PSO optimized FLC at normal load (5000N).

Table 7: Summary of speed response of DC motor at normal load (5000N), 10%,20% and 30%

Model	Speed (rpm)	Percentage Error (%)
No Controller(500N)	1432	0
FLC(500N)	1425	0.49
No Controller (10%)	1267	11.52
FLC(10%)	1342	6.28
PSO Optimized FLC(10%)	1454	1.54
No Controller(20%)	1132	20.95
FLC(20%)	1279	10.68
PSO Optimized FLC(20%)	1455	1.61
No Controller(30%)	1016	29.05
FLC(30%)	1225	14.4
PSO Optimized FLC310%)	1337	6.63

3.1.2 Simulation Results at 10% Load Increase

The speed response of the different controllers at 10% load increase is presented in Figure 7.

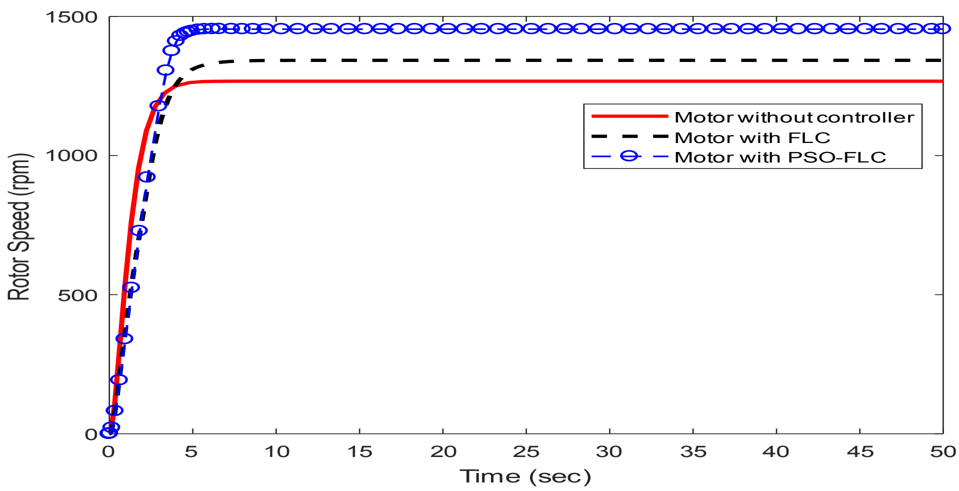

Figure 7: DC motor speed response without controller, with FLC and PSO optimized FLC at 10% load Increase

The speed response of the different controllers at 20% load increase is presented in Figure 8.

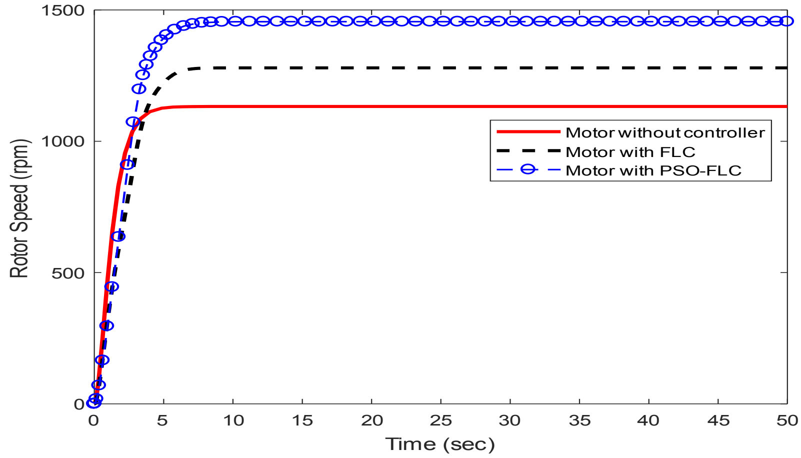

Figure 8: DC Motor Speed response without Controller, with Fuzzy Logic Controller and PSO optimized FLC at 20% load Increase.

The speed response of the different controllers at normal load of 5000N is presented in Figure 9.

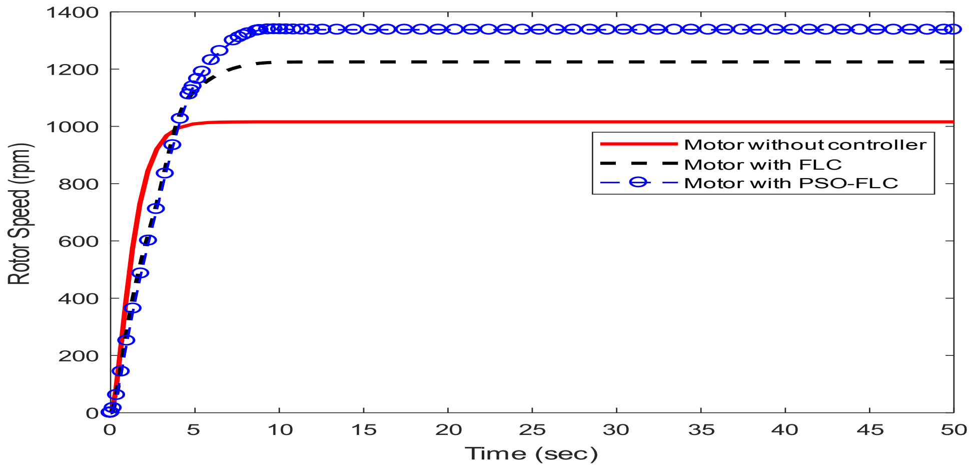

Figure 9: DC motor speed response without controller, with FLC and PSO optimized FLC at 30% load Increase.
Source: Developed by the researcher (2019).

3.2 Discussion

From Figure 6and Table7**,** at normal load, DC Motor without controller attained a maximum speed of 1432rpm. FLC was able to track the speed to 1425 rpm registering a percentage error of 0.49%. PSO-FLC attained a speed of 1434 rpm and a percentage error of 0.14 was recorded.

As the Load was increased by 10% as seen in Figure 7, DC Motor without controller reached a maximum speed of 1267 rpm, recording a large error percentage 11.52%. FLC gained a maximum speed of 1342 rpm and a percentage error of 6.28%. PSO-FLC was able to attain a speed of 145 rpm, recording a percentage error of 1.54%.

As can be seen in Figure 8**,** at 20% load increase, DC Motor without controller attained a maximum speed of 1132 rpm and recorded a high percentage error of 20.94%. FLC attained a speed of 1279 rpm and registered a percentage error of 10.68%. PSO-FLC reached a speed of 1455 rpm and a percentage error of 1.61% was recorded.

As the load increased by 30% as can be seen in Figure 9, DC Motor without controller recorded a maximum speed of 1016 rpm while FLC attained a speed of 1225 rpm with a percentage error of 29.05% and 14.46% respectively. PSO-FLC was able to attain a maximum speed of 1337 rpm and a percentage error of 6.63%.

With the results of the discussion presented, it can be seen that the maximum speed attained by DC Motor without controller and with FLC kept decreasing and with a high percentage error recorded as the loads were varied while the PSO-FLC was able to track the speed of 1432 rpm at normal load (5000N) with minimal percentage error recorded. With these results, PSO-FLC efficiently is better than the traditional FLC in tracking the speed of the DC Motor. The PSO-FLC is the best controller which presented satisfactory performance.

By comparing the results obtained in this study to those obtained in [38]shows that a better result is achievable with PSO-Fuzzy. [38]investigated the design of a PID controller using PSO algorithm for speed control of a DC motor. Table 3 which is the step response performance for PID controllers gives the comparative results of the PID controllers. It can be seen that the least steady state error obtained is 48.0% compared to 0.14% attained in this research work.

IV. Conclusion

The presented simulation results demonstrate that the proposed speed control system is feasible and has certain advantage. Simulations were carried out with DC Motor at 12V without controller, DC Motor with FLC and DC Motor with PSO-FLC at a normal load of 5000N which gives a speed of 1432 rpm. The load was then varied and simulation was carried out on the DC Motor with the different loads. With the results achieved, it is seen that the maximum speed attained by DC Motor without controller and with FLC keeps decreasing and with a high percentage error recorded as the loads were varied while the PSO-FLC was able to track the speed of 1432 rpm at normal load (5000N) with minimal percentage error recorded. With these results, PSO-FLC efficiently is better than the traditional FLC in tracking the speed of the DC Motor. The PSO-FLC is the best controller which presented satisfactory performance.

The PSO based fuzzy controller modelled using block was able to optimize the fuzzy membership function parameters resulting in zero steady state error after little iteration. Further studies such as utilization of other intelligent controllers such as neural network control (data driven modelling), Bayesian control, neuro-fuzzy, expert system, sliding mode control and genetic control should be investigated in speed control systems.Other optimizers such as differential optimization should also be used.

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