Simulation and Implementation of an Embedded Hybrid Fuzzy Trained Artificial Neural Network Controller for Different DC Motor

M.Muruganandam[#1] I.Thangaraju*[2] and M.Madheswaran[$3]

[#] Asst. Prof., Dept. of EEE, Muthayammal Engineering College, Rasipuram, Tamilnadu, India 637408.
[*] Asst. Prof., Dept. of EEE, Govt. College of Engineering, Bargur, Krishnagiri, Tamilnadu, India 635104.
[$] Professor, Dept. of ECE, Mahendra Engineering College, Mallasamudram, Tamilnadu, India 637503
[1] muruganm1@gmail.com,
[2] thangarajui@yahoo.co.in
[3] madheswaran.dr@gmail.com

***Abstract*— In this article, the speed of the DC motor is controlled by Hybrid Fuzzy-Neuro controller (FNC). The Hybrid Fuzzy-Neuro controller is designed and tested for different types of DC motors like DC separately excited motor and DC series motor. The motor is fed by DC-DC buck converter (DC chopper). The system has two loops of inner current controller loop and outer Fuzzy-Neuro based speed controller loop. The speed controller gives the duty cycle to generate the PWM signal for the control of chopper. There by the DC chopper controls the speed of the DC motor to the set value. The training data for training the FNC is acquired from Fuzzy Logic Controller (FLC). The performances of FNC are analyzed in respect of load variation and speed variation using MATLAB/Simulink. The FNC reduces the peak overshoot, settling time and steady state error of the DC motor. It is found that the FNC can have better control compared with FLC. This system is implemented in a NXP 80C51 family Microcontroller (P89V51RD2BN) based Embedded System.**

***Keyword*- DC Motor, Fuzzy Logic Controller, Fuzzy-Neuro Controller, DC Chopper, MATLAB/Simulink**

I. Introduction

This work encompasses the design, development, testing and analysis of an adjustable speed drive for DC motors. The proposed drive system consists of a power electronic circuit (DC Chopper) and its associated control circuits with intelligent controller [1]. Generally, the DC series motor and DC separately excited motors are utilized for high torque and low torque applications respectively. In such a way, that the DC series motor drives are engaged with many applications to handle heavy load, as they offer high starting torque. Most of their applications are of an industrial nature such as lifts, cranes, hoist and electric traction. DC series motors are an ideal choice for battery-operated equipment over AC motors, as they do not require the use of expensive inverter circuitry to convert the DC voltage to an AC voltage required by the motor. The separately excited motors are engaged with many applications to handle light load as they offer low starting torque. The applications of DC separately excited motors are machine tool movements, compressor, printing machine and blowers.

The applications like robotics and some other industries require both high torque and low torque motor drives. It is simple to implement if both DC series and DC separately excited motors are controlled by a generalized controller. Also in future the generated non-conventional power (Solar) will be stored in battery and it can be used for DC drive directly without the use of any power converter circuits [1].

Presently the Artificial Neural Network (ANN) has been widely used for various control applications including motor control. The ANN controller can give robust performance of a nonlinear parameter varying system with load disturbance. Earlier the conventional controllers like PI and PID controllers were widely used for motor control applications. But it failed to give satisfactory results when control parameters, loading conditions and the motor itself are changed. The main disadvantage with the conventional controller is the high computation time. It has been found that the computation burden of conventional controller can be reduced by Hybrid Fuzzy-Neuro controller [2-4]. The DC series motor drive fed by a single phase controlled rectifier (AC to DC converter) and controlled by fuzzy logic. It has been concluded that the fuzzy logic controller provides better control over the classical PI controller. [5].

The ANN controller for speed control of DC motor is designed, due to their high computation rate and ability to handle nonlinear functions. The training patterns for the neuron controller were obtained from the conventional PI controller and the effectiveness of the proposed neuron controller was studied using simulation studies [6, 7]. A low-cost fuzzy controller for closed loop control of DC drive fed by four-quadrant chopper was designed and the fuzzy controller was implemented in a low-cost 8051 micro-controller based embedded system [8].

A Fuzzy Controller for closed loop control of DC series motor drive fed by DC-DC converter was designed. The performance in respect of load variation and speed changes has been reported. The performance of the controller was compared with the reported results and found that the fuzzy based DC-DC drive can have better control [9, 10]. The Fuzzy Logic suffers from complex data processing; this problem is reduced by implementing a Fuzzy Logic Controller (FLC) on a neural network (NN). From the FLC design, a NN is trained by supervision to learn the input-output relationship of FLC [11, 12].

An adaptive Neuro-Fuzzy controller for the control of DC motor speed was designed and simulated. The ANFIS has the combined advantage of expert knowledge of the Fuzzy inference system and the learning capability of neural networks [13-15]. The applicability of different types of artificial intelligence techniques were considered for the design of a speed controller to a speed sensorless electric drive [16]. The application of Neuro-Fuzzy hybrid system was exploited for Sumo Robots and several mobile robots navigation [17, 18].

Different approaches were made to develop the ANN controller and utilised for different special electric motors like PMDC motor, stepper motor, BLDC motor and switched reluctance motor. The performances of controller were evaluated by MATLAB simulation. Then the controllers were implemented in real time using microcontroller and DSP based embedded systems [19-24].

From the above literature, most of the work focused on separately excited DC motor, which limits the high torque application. Some paper demonstrated with DC series motor with fuzzy controller. In this proposed work two different DC motors were taken and which is controlled by hybrid Fuzzy-Neuro controller. The motor drive system mainly utilizes the FNC and DC chopper (DC-DC converter). Such a drive system has the characteristics of precise, fast, effective speed reference tracking with minimum overshoot/undershoot and minimal steady state error.

II. PROPOSED SYSTEM

Fig. 1 shows the block diagram of the system with hybrid Fuzzy-Neuro controller. The system consists of DC-DC buck converter to drive the DC motor. A Pulse type speed sensor is used to sense the actual speed (ω) and which is used for speed feedback. During the simulation the PWM signal is generated, by comparing the carrier signal (Repeating Sequence) and the duty cycle from the controller output. However in the implementation of the proposed system, a micro-controller is used to generate the PWM signal to switch the DC-DC buck converter. In this work a NXP 80C51 family microcontroller (P89V51RD2BN) based embedded system is utilised.

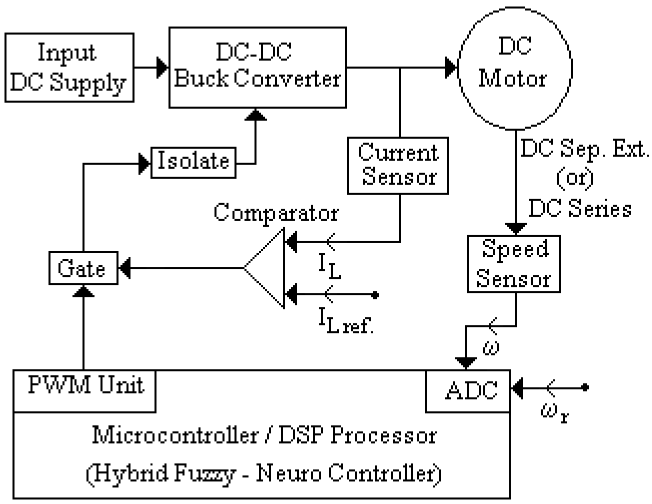

Fig 1. Block diagram of the proposed system

This system has two loops, namely an inner ON/OFF current control loop and an outer Fuzzy-Neuro speed control loop. The current control loop is used to block the PWM signal while the motor current exceeds the reference current (I_{Lref}). In outer speed control loop, the actual speed ω(k) is sensed by speed sensor. The error signal e(k) is obtained by comparing actual speed ω(k) with reference speed $\omega_r(k)$. The change in error Δe(k) can be calculated from the present error e(k) and pervious error $e_{previous}(k)$. The closed loop operation is simulated with the trained hybrid FNC to achieve the desired performance of both DC motors. The proposed work is implemented with a P89V51RD2BN Microcontroller and the experiment results are compared with the simulation results. The experimental results almost concur with the simulation results.

III. MATHEMATICAL MODELING OF DC MOTOR AND DC CHOPPER

A. DC Series Motor Model

Fig. 2 shows the equivalent circuit of DC series motor. From the equivalent circuit the voltage and torque equations are obtained, which is given in equation (1) and (2) respectively.

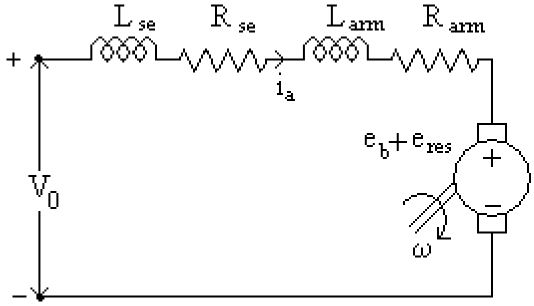

Fig 2. Equivalent Circuit of DC Series Motor

Consider, $R_a = R_{arm} + R_{se}$; $L_a = L_{arm} + L_{se} + 2M$

$$V_o = i_a R_a + L_a \frac{di_a}{dt} + e_b + e_{res} \tag{1}$$

$$T = J \frac{d\omega}{dt} + B\omega + T_L \tag{2}$$

where,

$i_a = i_{se}$ - Motor current
V_0 - Motor terminal voltage
R_{arm} - Armature resistance
R_{se} – Series field resistance
R_a – Total resistance
L_{arm} - Armature inductance
L_{se} – Series field inductance
L_a - Total inductance
M- Mutual inductance
e_b- Back emf
e_{res}- emf due to residual magnetic flex
T - Deflecting torque
J - Moment of inertia
B - Friction coefficient
ω - $\frac{d\theta}{dt}$ - Angular speed
θ-Angular displacement
φ-Series field flux
T_L - Load torque
K_{af} - Armature voltage constant and
K_{res} - Residual magnetism voltage constant

$$e_b \ \alpha \ \varphi\omega \ \ and \ \varphi \alpha \, i_a \ \ (i.e \, BeforeSaturaion)$$

$$\therefore e_b \ \alpha \ i_a \, \omega$$

$$e_b = K_{af} \ i_a \, \omega$$

$$\omega = \frac{d\theta}{dt} = Angular \ Speed$$

Similarly,

$$e_{res} \ \alpha \ \omega$$

$$e_{res} = K_{res} \ \omega$$

$$\therefore e_{res} = K_{res} \ \frac{d\theta}{dt}$$

By rearranging the equation (1) by replacing e_b and e_{res}

$$V_o = R_a i_a + L_a \frac{di_a}{dt} + K_{af} i_a \frac{d\theta}{dt} + K_{res} \frac{d\theta}{dt} \tag{3}$$

$$\frac{di_a}{dt} = \frac{1}{L_a}\left[V_o - R_a i_a - K_{af} i_a \frac{d\theta}{dt} - K_{res} \frac{d\theta}{dt} \right] \tag{4}$$

Similarly the torque equation also derived as follows,

$$T \ \alpha \ \varphi \, i_a \ and \ \varphi \ \alpha \ i_a \ (Before \, Saturation)$$

$$\therefore T \alpha \, i_a^2$$

$$T = K_{af} \ i_a^2$$

$$\omega = \frac{d\theta}{dt} = AngularSpeed$$

By rearranging the equation (2) by replacing T

$$K_{af} i_a^2 = J \frac{d^2\theta}{dt^2} + B \frac{d\theta}{dt} + T_L \quad (5)$$

$$\frac{d^2\theta}{dt^2} = \frac{1}{J}\left[K_{af} i_a^2 - B\frac{d\theta}{dt} - T_L\right]$$

(or)

$$\frac{d\omega}{dt} = \frac{1}{J}\left[K_{af} i_a^2 - B\omega - T_L\right] \quad (6)$$

B. DC Separately Excited Motor Model

The voltage and torque equations for DC Separately Excited motor are given in equation (7) and (8) respectively.

$$V_o = i_a R_a + L_a \frac{di_a}{dt} + e \quad (7)$$

$$T = J\frac{d\omega}{dt} + B\omega + T_L \quad (8)$$

By rearranging the equation (7) & (8), the following equations were obtained,

$$\frac{di_a}{dt} = \frac{1}{L_a}\left[V_o - R_a i_a - K_{af}\omega\right] \qquad \because e = K_{af}\omega \quad (9)$$

$$\frac{d\omega}{dt} = \frac{1}{J}\left[K_{af} i_a - B\omega - T_L\right] \qquad \because T = K_{af} i_a \quad (10)$$

The DC separately excited motor has been modeled with the equations (9) and (10).

Such an equation modeling is more effective than the transfer function model. In transfer function model, it is mandatory to develop different model for every input and output parameter changes. In this modeled equation modeling the voltage and load torque are the input parameters, the output parameters are speed, current and deflecting torque etc.

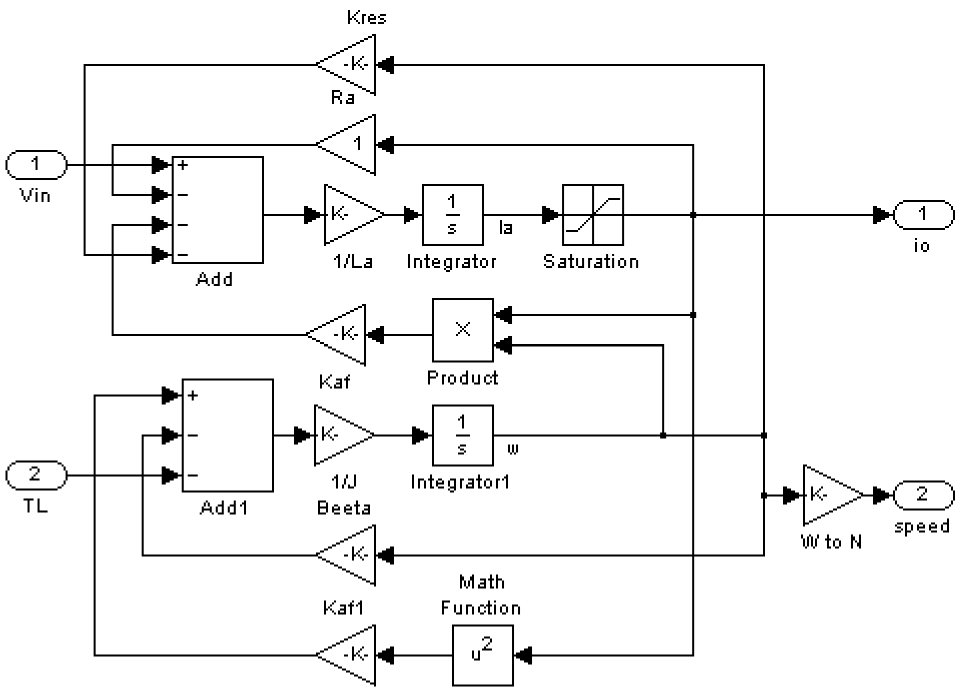

Fig 3. Simulink model of DC series motor

From the equations (4) and (6) the simulink model of DC series motor was obtained also from equation (9) and (10) the simulink model of DC separately excited motor was obtained and given in Fig. 3 & 4 respectively.

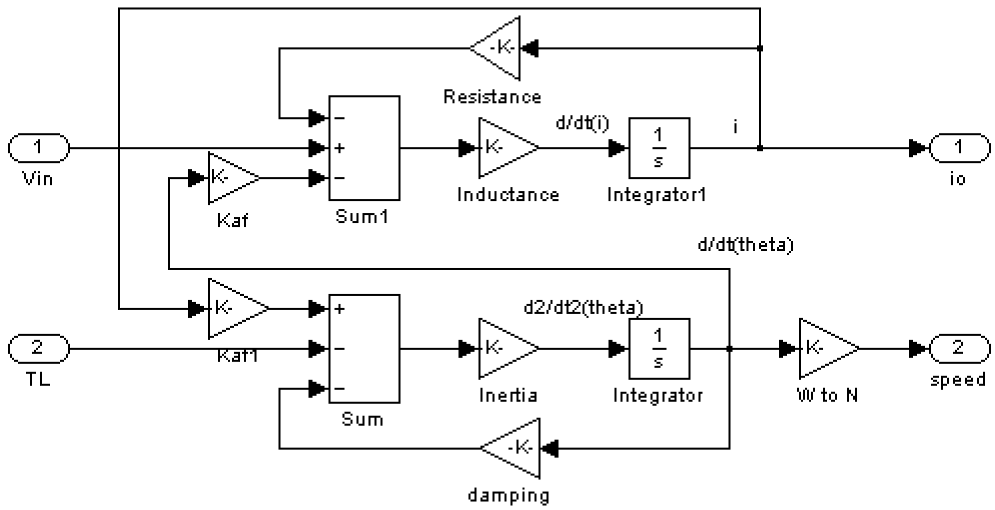

Fig 4. Simulink model of DC separately excited motor

C. DC Chopper

The DC chopper switch can be a Power Transistor, SCR, GTO, IGBT, Power MOSFET or similar switching device. In order to get high switching frequency (upto 100 KHz) the Power MOSFET may be taken as a switching device also the on state voltage drop in the switch is small and it is neglected. Hence the power MOSFET is designated as a switching device for the DC chopper. When the gate pulse is applied the device is turned on, during the period the input supply connects with the load. When the gate pulse is removed the device is turned off and the load is disconnected from the input supply. The circuit and waveform of DC chopper is shown in Fig. 5.

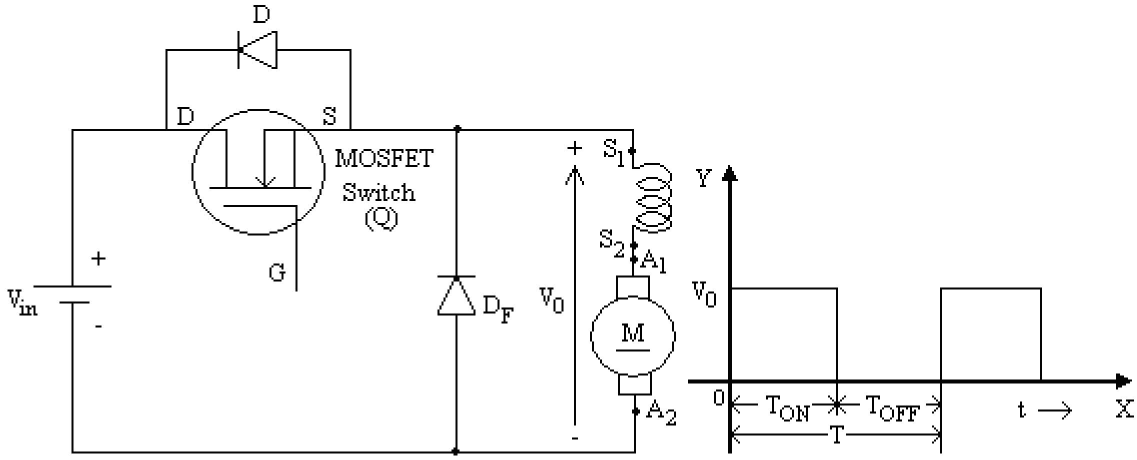

Fig 5. DC chopper circuit and waveform

The modeling for DC chopper is given in equation 11.

$$V_o = \delta V_s \tag{11}$$

$$\delta = \frac{T_{ON}}{T} \tag{12}$$

$$T = T_{ON} + T_{OFF} \tag{13}$$

where V_0 – Output Voltage
V_S – Input Voltage
T_{ON} – ON Time
T_{OFF} – OFF Time
T – Total Time
δ - Duty Cycle

IV. Simulation of The System Using MATLAB / Simulink

A. Simulation of Fuzzy Logic Controller

The Fuzzy Logic Controller is designed and simulated with DC series motor and DC separately excited motor models. The performance of the fuzzy logic controller is examined with MATLAB/Simulink in terms of speed variation and load variation. Then the designed FLS is implemented for both the motors. The designed FLC is explained in this section.

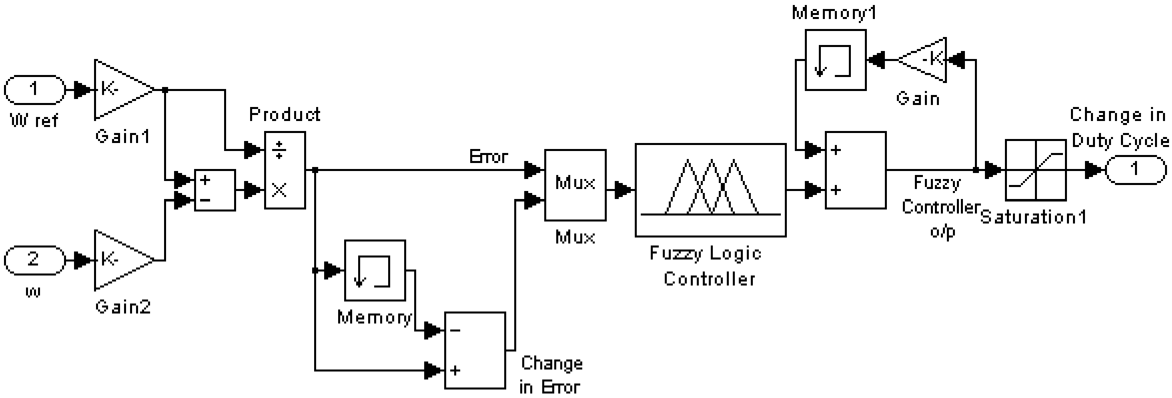

Fig 6. Structure of the fuzzy controller

The fuzzy logic has emerged as a tool to deal with uncertainty, imprecise or qualitative decision making problems [5-6]. The FLC involves three stages namely Fuzzification, Rule-Base and Defuzzification. There are two types of FLC named Mamdani type and Sugeno type. In this work the Sugeno type controller is utilized because it has a singleton membership function in the output variable. Moreover it can be easily implemented and also the number of calculations can be reduced [6]. The Structure of the fuzzy controller used in the proposed system is shown in Fig. 6.

1) Fuzzification:

In Fuzzy logic system the linguistic variables are used instead of numerical variables. The process of converting a numerical variable (real number or crisp variables) in to a linguistic variable (fuzzy number or fuzzy variable) is called fuzzification.

In this work, the motor speed is controlled by FLC. The error e(k) and change in error $\Delta e(k)$ is given to the FLC as input variable. As explained in section 2 the error is calculated by comparing the actual speed $\omega(k)$ with reference speed $\omega_r(k)$. From the error e(k) and pervious error $e_{pervious}(k)$ the change in error $\Delta e(k)$ is calculated. Then the error and change in error are fuzzified [7]. The equation for error and change in error are specified in equation (14) and (15).

$$e(k) = \varpi_r(k) - \varpi(k) \tag{14}$$

$$\Delta e(k) = e(k) - e_{Pervious}(k) \tag{15}$$

Five linguistic variables are used for the each input variable error e(k) and change in error $\Delta e(k)$. Those are Negative Big (NB), Negative Small (NS), Zero (Z), Positive Small (PS) and Positive Big (PB). In FLC there are many types of membership functions available, those are triangular-shaped, Gaussian, sigmoidal, pi-shaped, trapezoidal-shaped, bell-shaped etc. In this work the triangular membership function is used for simplicity and also to reduce the calculations [6, 7 & 8]. Normally seven membership functions are preferred for accurate result [5]. In this present work only five membership functions are used for the input variables error and change in error. In order to reduce the number of membership function and maintain the same performance characteristics the width of the membership functions are kept different [7]. Here the width of center membership function is considered narrow and it is wide towards outer. The input and output fuzzy membership functions are shown in Fig. 7.

2) Rule Table and Inference Engine

According to general knowledge of the system behaviour, the perception and experience, the control rules are derived between the fuzzy outputs to the fuzzy inputs. However, some of the control rules are developed using “trial and error” method. In general the rules can be written as “**if e(k) is X and Δe (k) is Y, then Δdc(k) is Z”,** where X, Y and Z are the fuzzy variable for e(k), Δe(k) and Δdc(k) respectively. The rule table for the designed fuzzy controller is specified in the Table I [8]. The element in the first row and first column means that **if error is NB, and change in error is NB then output is NB.**

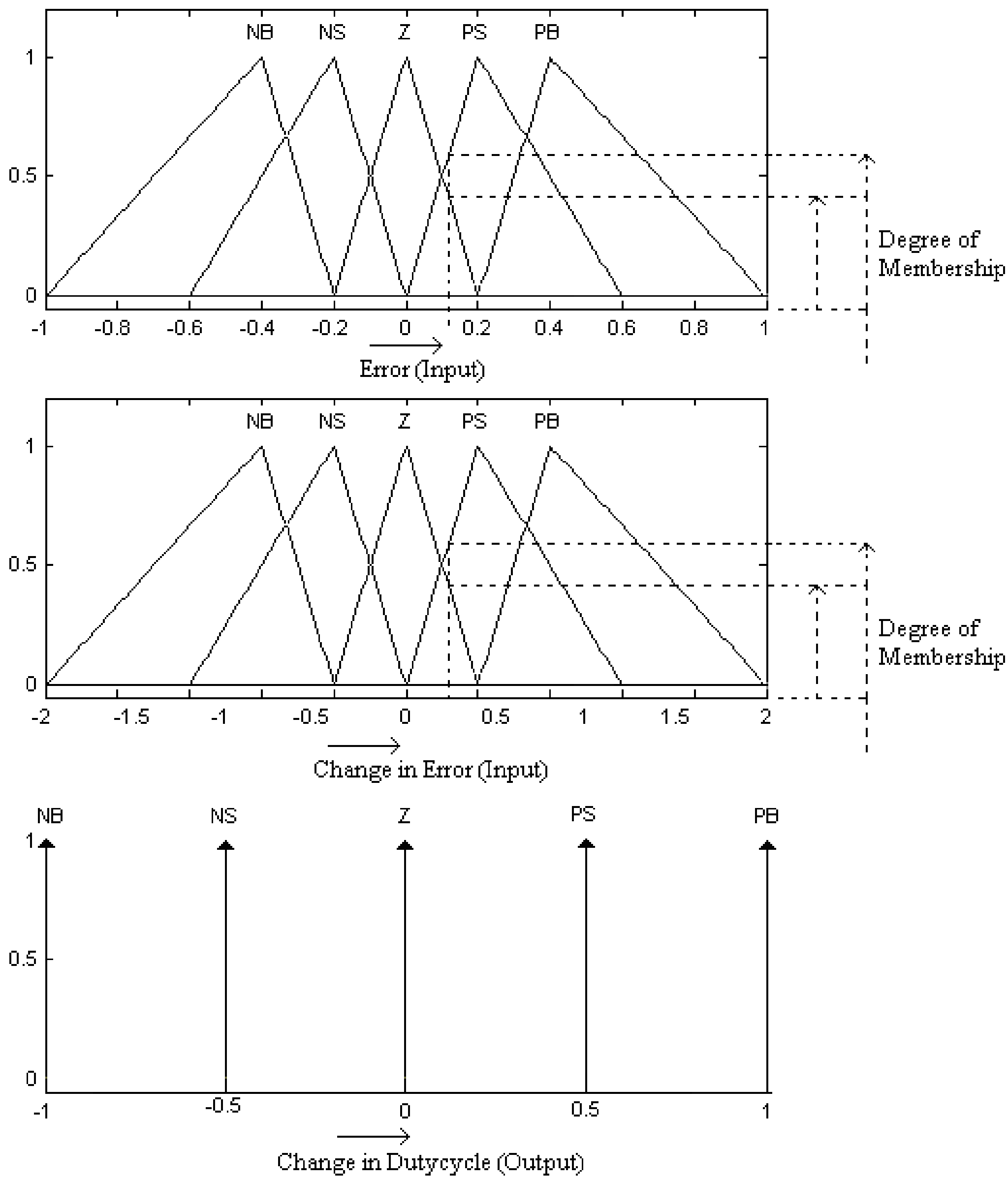

Fig 7. Fuzzy memberships used for simulation

TABLE I
Fuzzy Rules

	NB	**NS**	**Z**	**PS**	**PB**
NB	NB	NB	NB	NS	Z
NS	NB	NB	NS	Z	PS
Z	NB	NS	Z	PS	PB
PS	NS	Z	PS	PB	PB
PB	Z	PS	PB	PB	PB

3) Defuzzification

The inverse process of fuzzification is called defuzzification. In this process the linguistic or fuzzy variables are converted in to numerical or crisp variable [6]. Here the best well-known weighted sum method is considered for defuzzification method. The defuzzified output is the duty cycle dc(k). The change in duty cycle Δdc (k) can be obtained by adding the pervious duty cycle $dc_{previous}$ (k) with the duty cycle dc(k) which is specified in equation (16).

$$\Delta dc(k) = dc(k) + pdc(k) \qquad (16)$$

This type of controllers can be easily implemented in any embedded system. The Sugeno type of controller is selected mainly for implementation in real-time embedded based processors [6].The designed FLS is simulated with DC series motor through DC chopper. The Simulink Model of the system with Fuzzy Logic Controller is shown in Fig. 8.

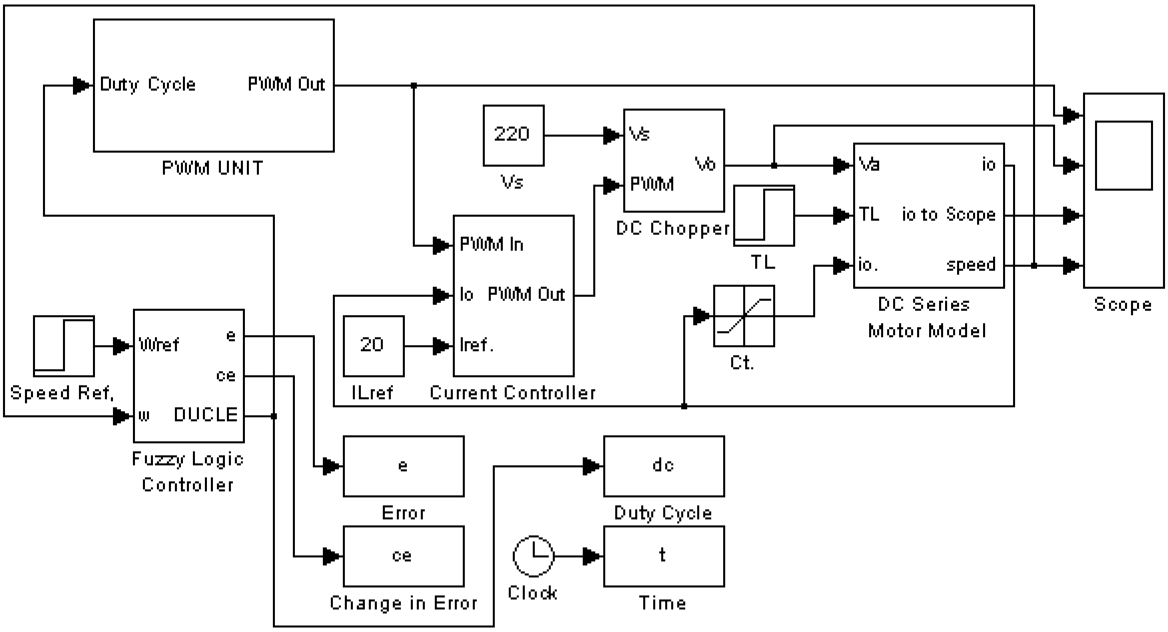

Fig 8. Simulink Model of the system with Fuzzy Logic Controller

The performance characteristics of speed variation and load changes with FLC fed DC series motor is given in section 5 as result and discussion. But the performance of FLC fed DC series motor is not satisfactory. The main disadvantage with the FLC is the high computation time. It is found that the computation burden of FLC can be reduced by hybrid Fuzzy-Neuro Controller. The ANN required training data to train the neurons in the ANN controller. The designed FLC is simulated with the drive system for extracting the training data.

The above model shown in Fig. 8 is simulated for 5 seconds with the sampling time of 0.0001seconds. Totally 50000 data is obtained from the system with FLC. Out of 50000 only 6000 data are taken for training the ANN controller by removing the repeated data. Some of the sample data are given in Table II.

TABLE III
Sample Data from Fuzzy Logic Controller

Input Data	**Error**	0.751943	0.643007	0.549257	0.468761	0.399851	0.340646	0.288901
	Change in Error	-0.00038	-0.00034	-0.00026	-0.00025	-0.00022	-0.00017	-0.00016
Target Data	**Corresponds to δ**	-1391.85	-13094	-12201.8	-5248.34	-1667.23	-5399.63	-4781.01

B. Simulation of Fuzzy-Neuro Controller

The performance of FLC based control of DC series motor is depicted in reference [7]. But the results are needed to be improved further. In order to improve the performance of DC series motor, the Fuzzy-Neuro based controller (FNC) is designed. The Artificial Neural Network control algorithm is designed with the outcome of Fuzzy Logic controller data. The Hybrid Fuzzy-Neuro controller is working properly because of its trained network and also it reduces the computational time. In this section, the implementation of FLC in ANN is presented.

The ANN controller uses a complex network structure in many works. In this work a simple ANN controller is designed with few neurons and one hidden layer. The feed forward neural network is formed with two neurons in the input layer, three in the hidden layer and one neuron in the output layer.

The error e(k) and change in error Δe(k) are the two inputs of the designed network and the neurons are biased properly. The pure linear activation function is used for input and hidden neurons, the tangent sigmoidal activation function for output neuron. The designed network is then trained with the set of inputs and desired outputs from the FLC [6]. A supervised feed forward back propagation neural network-training algorithm is used and it is trained with minimum error goal. The output of the network is change in the duty cycle Δdc(k).

The designed FNC is trained with the error goal of 0.0067113 at 11 epochs. The performance plot of ANN during supervised back propagation training is graphically shown in Fig. 9. The complete configuration of the trained network with the weights and bias is shown in Fig. 10. [6, 21-25].

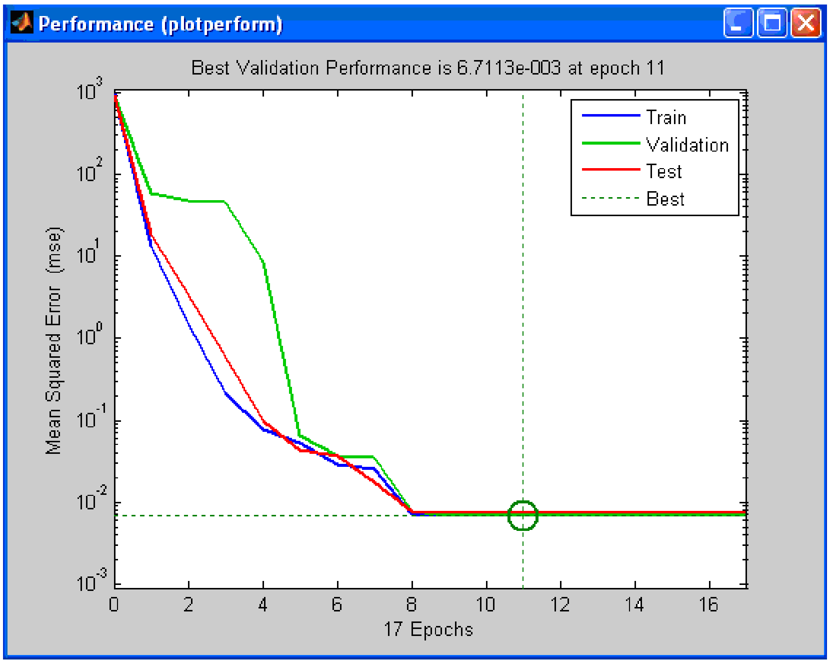

Fig. 9. Performance plot of ANN during training

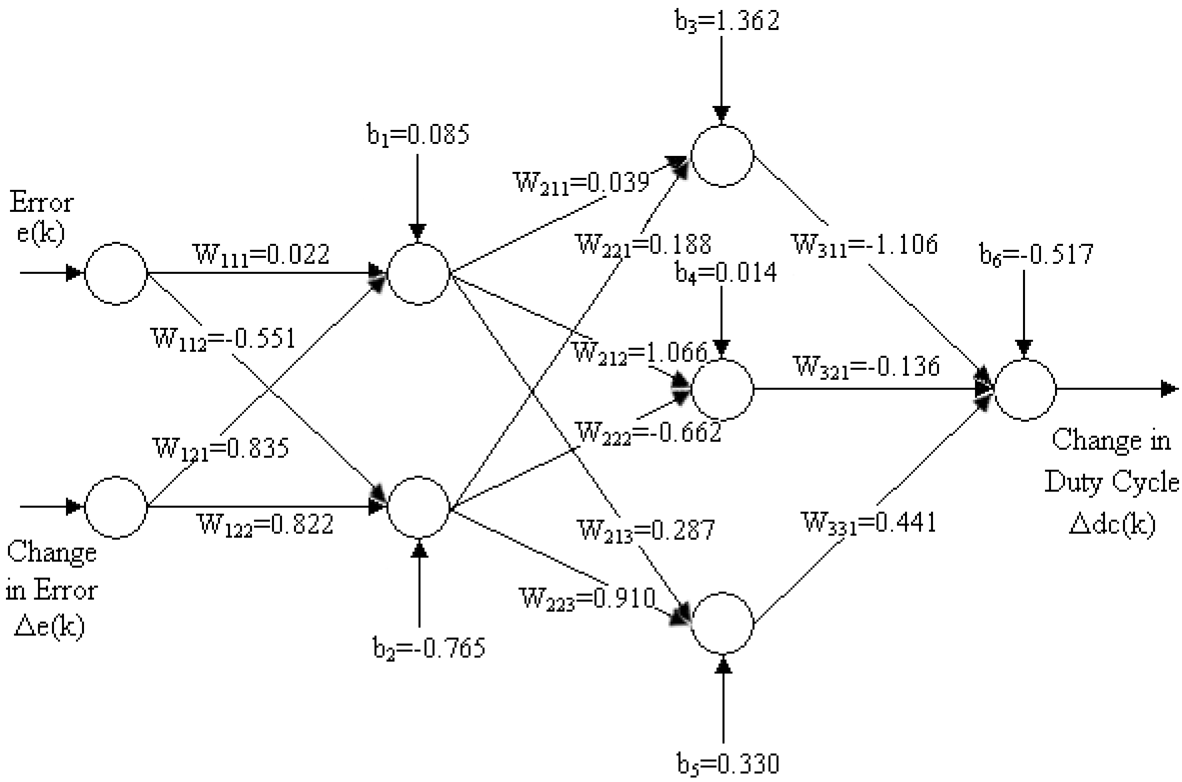

Fig. 10. Configuration of trained Neural Network

The simulation of DC-DC converter fed dc series motor is simulated based on equation modeling technique, using MATLAB/Simulink toolbox. The change in duty cycle is obtained from the FNC and which is given to the PWM generation unit. The PWM unit produces the pulse at 1 KHz of switching frequency. The current controller allows the pulses to the chopper if the actual motor current is below the rated current. The complete Simulink model developed is given in Fig. 11.

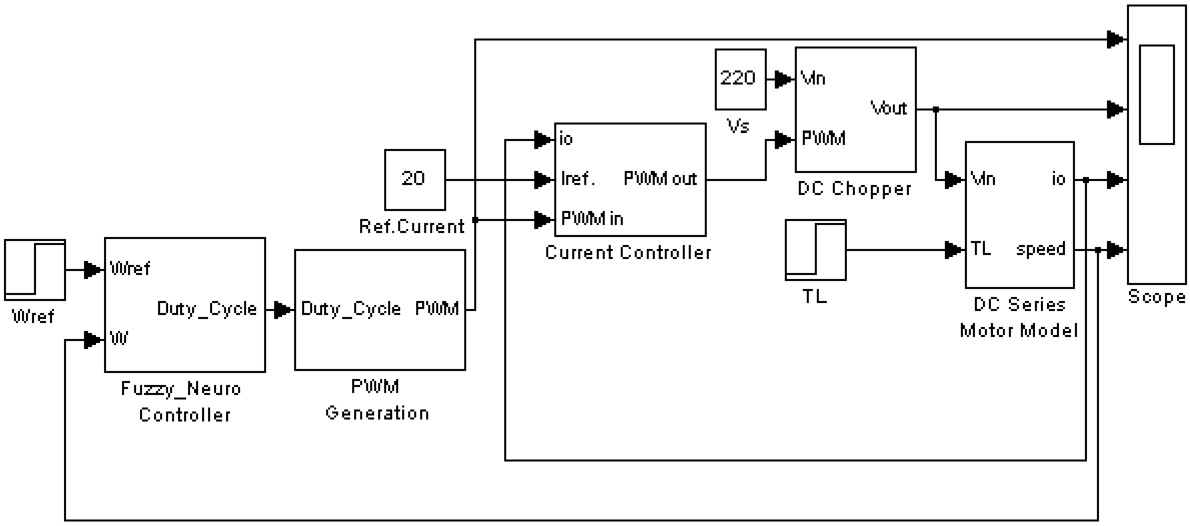

Fig.11. Simulink Model of the developed system

V. Results and Discussion

The proposed models have been simulated using MATLAB Simulink toolbox. The designed FLC and FNC was tested through DC-DC converter with DC series motor and DC separately excited motor. The simulated waves of motor speed with respect to time for rated speed with FLC and FNC for DC series motor and DC separately excited motor are shown in Fig. 12 and 13 respectively. The magnified view of settling part is also shown in the same figures. The specification of DC series motor and DC separately excited motor used for simulation is given in Table III.

The performances comparison of FLC with FNC for both the motors with rated speed and 10% load are given in Table IV. It is seen from Table 4 that the developed Fuzzy-Neuro controller gives more accurate performance than the Fuzzy Logic Controller. In FNC the Maximum overshoot and steady state error is zero and the rise time and settling time is also less than FLC for both the DC motors.

TABLE IIIII
Specifications of DC Motor

Motor Parameters	DC Series Motor	DC Sep. Ext. Motor
Motor Rating	5HP	3HP
Dc supply voltage	220 V	220V
Inertia constant J	0.0465 Kg-m^2	0.011 Kg-m2
Damping constant B	0.005 N.m.Sec./rad	0.004 Nm.Sec./rad
Armature resistance R_a	1Ω	0.6Ω
Armature inductance L_a	0.032 H	0.008 H
Motor Speed	1800 rpm	1800rpm
Armature voltage constant K_{af}	0.027 H	0.55 H
Residual magnetism voltage const. K_{res}	0.027 V.Sec./rad	-

The Fig. 14 shows the speed variations of DC series motor for the step change in reference speed from 500rpm to 1000rpm at 4 sec and 1000rpm to 1800rpm at 7 sec with 10% load torque with FLC and FNC. It is seen from figure that when the speed is increased from 500rpm to 1000rpm the motor takes 0.32 sec with FLC and 0.30 sec with FNC whereas in the initial stage it took almost 0.35 sec with FLC and 0.33 sec with FNC to reach 500rpm. This may be due to the inertia in the beginning.

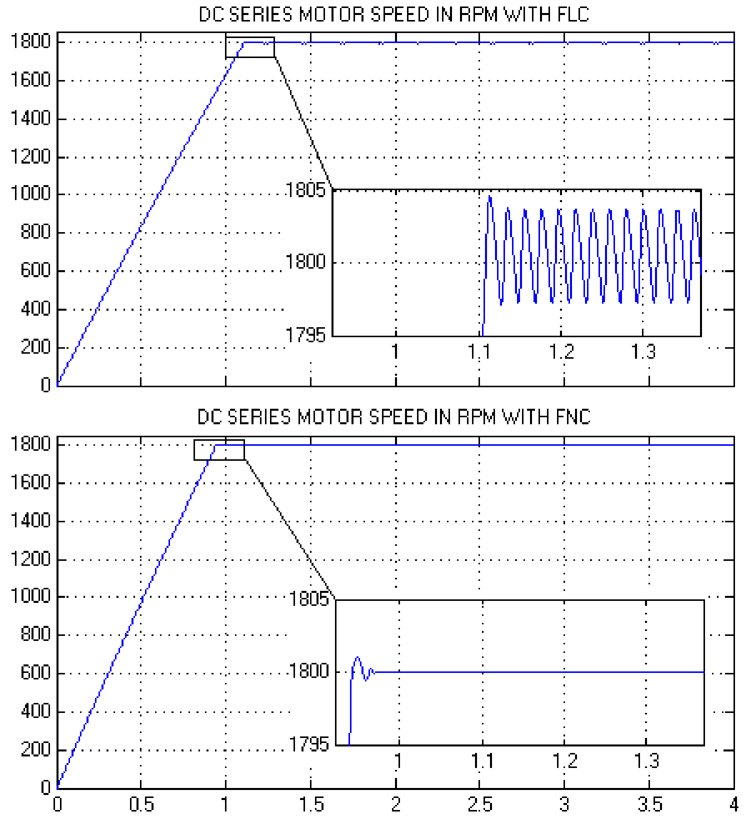

Fig. 12. Motor Speed variation with respect to time response for ω_r=1800rpm for FLC and FNC with magnified view of settling part for DC series motor

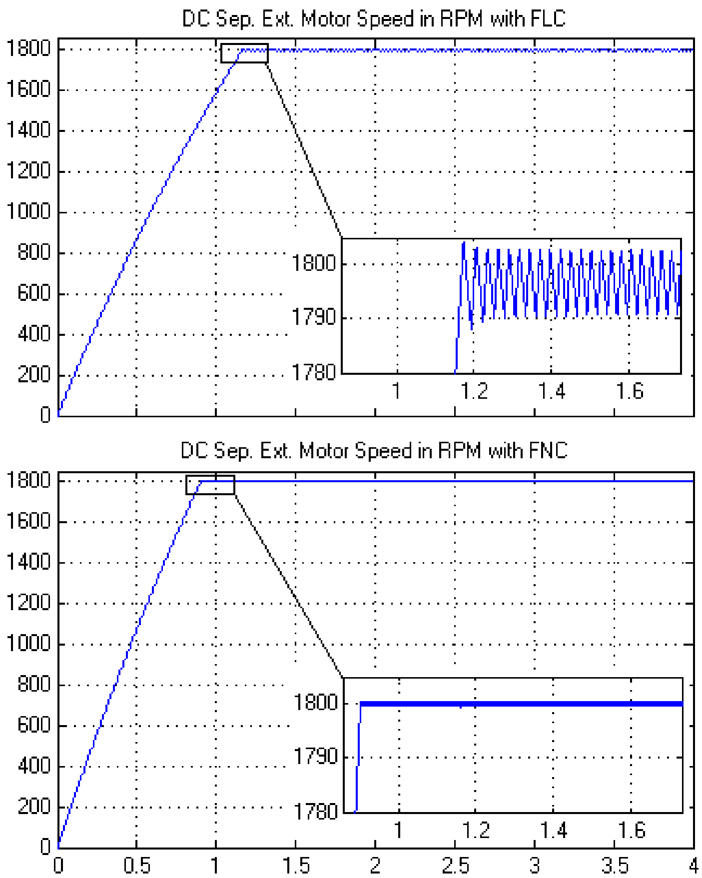

Fig.13 Motor Speed variation with respect to time response for ω_r=1800rpm for FLC and FNC with magnified view of settling part for DC separately excited motor

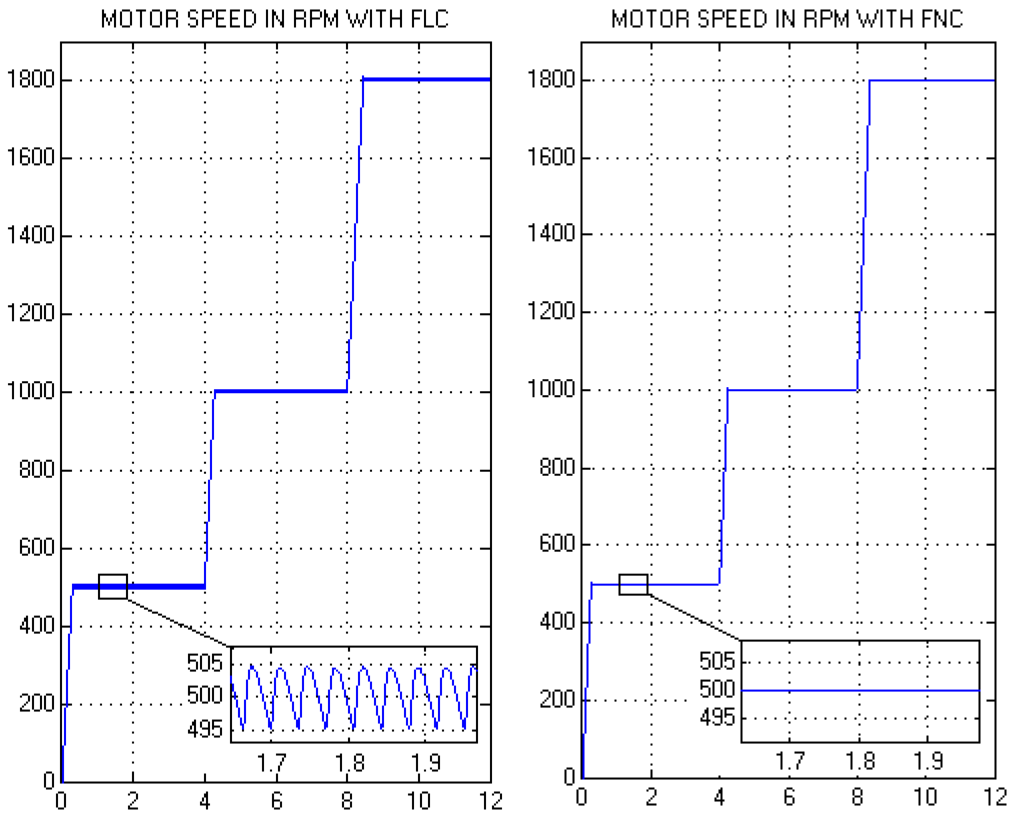

Fig. 14. Speed variation for the step change in reference speed at different interval with 10% load torque for DC series motor

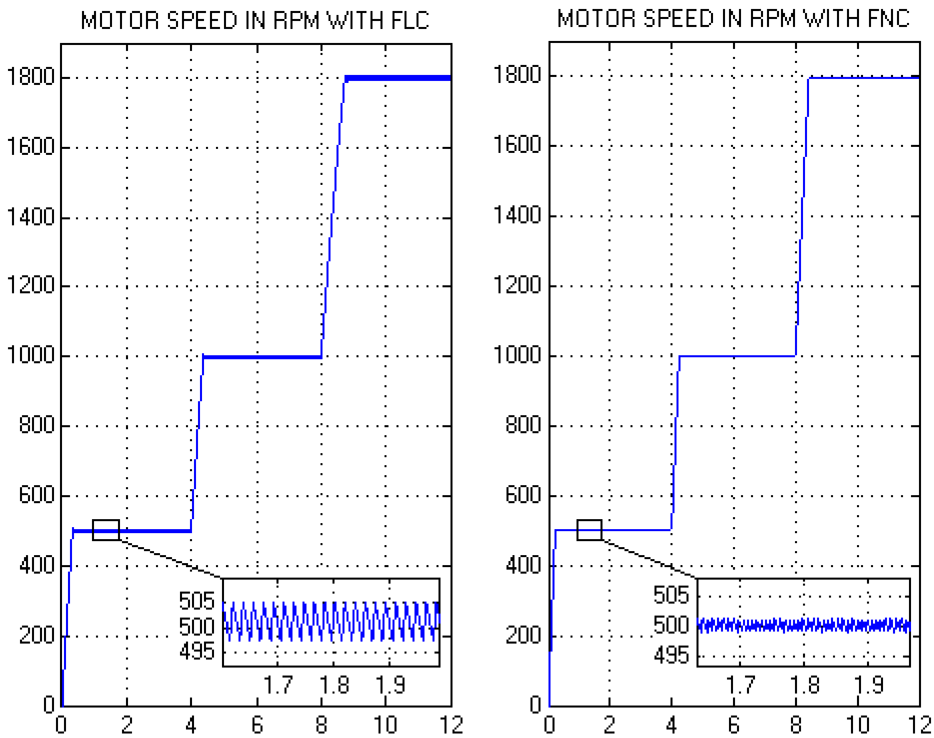

Fig. 15. Speed variation for the step change in reference speed at different interval with 10% load torque for DC Sep. Ext. Motor

TABLE IVV
Performance comparison of FLC with FNC for both the motors with rated speed and 10% load

Controller	DC Series Motor		DC Sep. Ext. Motor	
	FLC	FNC	FLC	FNC
Rise time in seconds	0.8	0.76	0.89	0.68
Settling time in Seconds	1.1	0.97	1.2	0.89
Max. over Shoot in %	0.28	0.05	0.25	0.03
Steady state error in RPM	±2	±0.3	±12	±1.2

The Fig. 15 shows the speed variations of DC separately excited motor for the step change in reference speed from 500rpm to 1000rpm at 4 sec and 1000rpm to 1800rpm at 7 sec with 10% load torque with FLC and FNC. From the Fig. 15 the speed variation is large in FLC due to its characteristics which are negligible in FNC. The FNC provides proper speed regulation for all the speed changes than FLC. The comparative time domain parameters of speed variation for various set speed changes with 10% load for FLC and FNC with both the motors are depicted in Table 5.

TABLE V
Time domain specifications of Fuzzy controller and Fuzzy-Neuro controller for different set speed change with 10% load

Time Domain Specifications	Set Speed Change from 0 to 500rpm		Set Speed Change from 500 to 1000rpm		Set Speed Change from 1000 to 1800rpm	
	FLC	FNC	FLC	FNC	FLC	FNC
DC series motor						
Max. over Shoot in %	1.00	0.5	0.77	0.38	0.61	0.21
Settling time in Sec.	0.35	0.33	0.32	0.30	0.47	0.42
DC separately excited motor						
Max. over Shoot in %	0.94	0.09	0.83	0.07	0.55	0.05
Settling time in Sec.	0.34	0.33	0.33	0.31	0.60	0.42

The simulated result of speed regulation of DC series motor for step change in the load torque from 10% to 25%, 25% to 50% and 50% to 100% applied at 2 sec, 4 sec and 6 sec respectively are shown in Fig. 16 for both FLC and FNC. The FNC gives proper response to the system for the load changes from 10% to 100%. At 100% load there is a small dip in the speed response with FLC and it is recovered the speed with in 1.1 sec whereas in FNC the speed dip is very less and it is negligible. The expanded part for different load changes is also given in the Fig. 16 for comparison.

The simulated result of speed regulation of DC separately excited motor for step change in the load torque from 10% to 25%, 25% to 50% and 50% to 100% applied at 2 sec, 4 sec and 6 sec respectively are shown in Fig. 17 for both FLC and FNC. During each load change there is a negligible amount of distortion in speed response with FNC. The FNC gives appropriate response to the system for the load changes from 10% to 100%. Even at 100% load the drop in the speed is very less than it is present in FLC. It can be seen from the Table 6 the steady state error increases when the load increases in the case of FNC but vice-versa for FLC. However the recovery time and maximum speed drop of FNC is very less compared with the FLC. From this analysis it is seen that comparatively, the FNC provides superior performance in all the aspects.

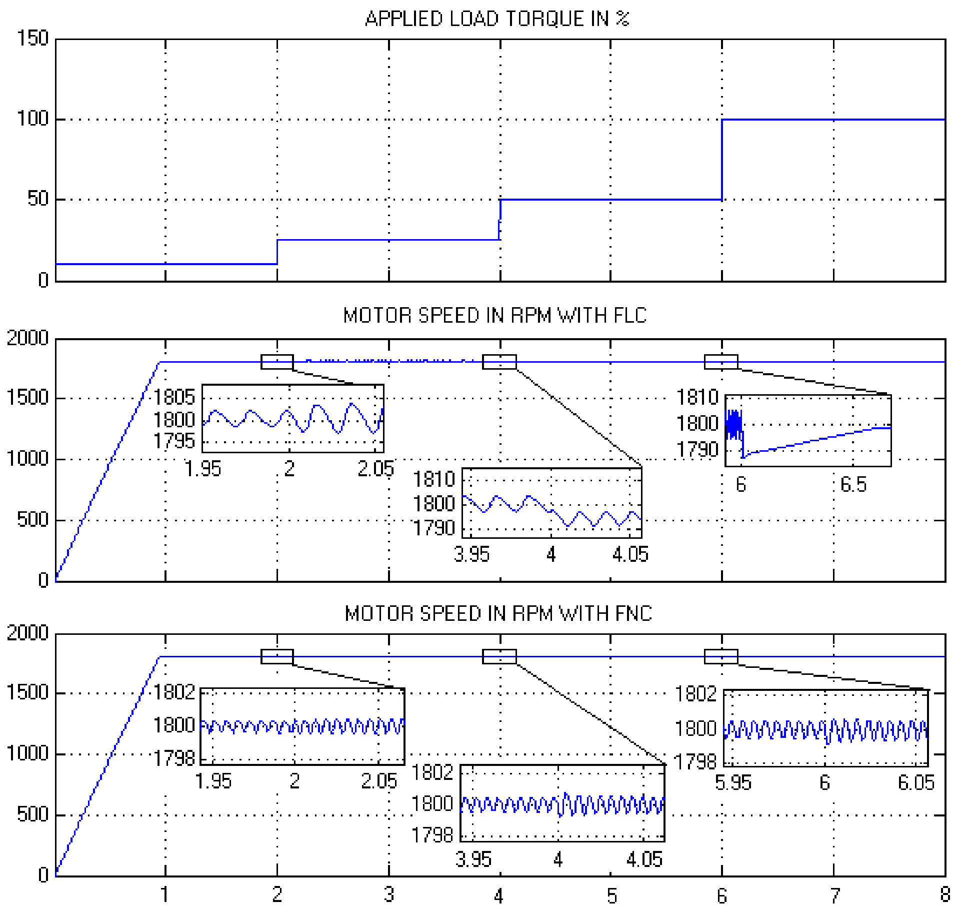

Fig. 16. Controller performance for load variation at different interval
for rated speed with FLC and FNC for DC series motor

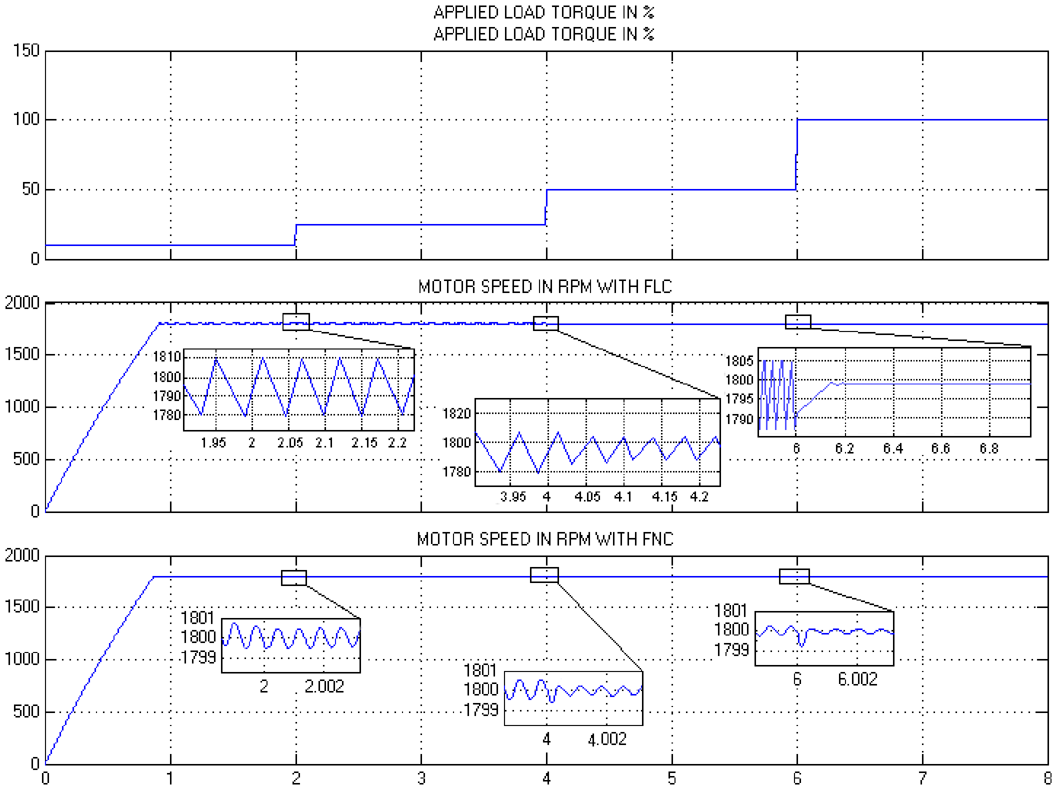

Fig. 17. Controller performance for load variation at different interval
for rated speed with FLC and FNC for DC separately excited motor

TABLE VI
Time domain specifications of FNC for load changes with rated speed

Time Domain Specifications	**Load Changes from 10% to 25%**		**Load Changes from 25% to 50%**		**Load Changes from 50% to 100%**	
	FLC	**FNC**	**FLC**	**FNC**	**FLC**	**FNC**
DC series motor						
Max. Speed Drop in %	0.31	0.02	0.47	0.04	0.72	0.05
Recovery time in Seconds	0.025	0.002	0.030	0.005	1.1	0.015
Steady State Error in rpm	±10	±0.5	±9	±0.75	+3.3	±1
DC separately excited motor						
Max. Speed Drop in %	1.05	0.016	0.77	0.027	0.50	0.047
Recovery time in Seconds	0.060	0.004	0.075	0.005	0.18	0.006
Steady State Error in rpm	±12	±0.2	±8	±0.4	+2.5	±0.6

VI. EXPERIMENTAL IMPLEMENTATION

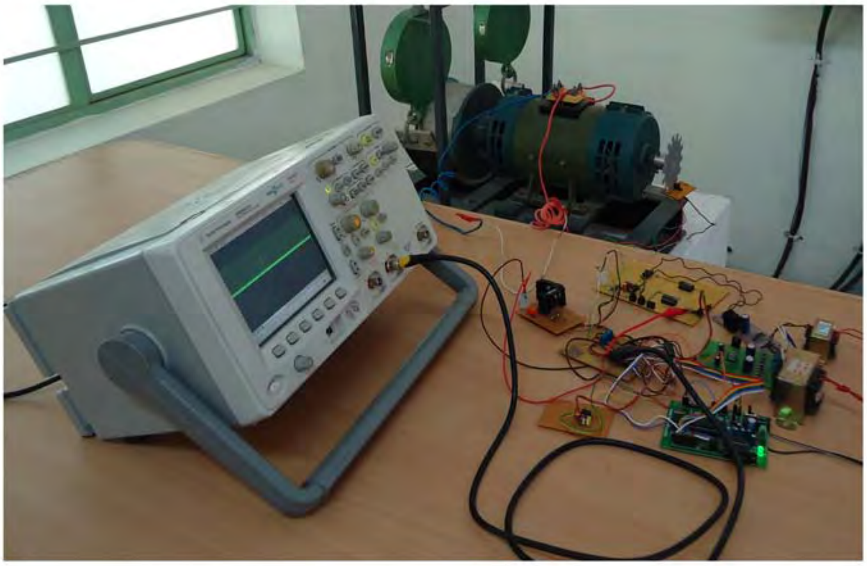

Fig 18. Experimental setup of the proposed system

The designed FLC and FNC are implemented by using a NXP 80C51 based microcontroller (P89V51RD2BN). A DC-DC buck converter is built with the MOSFET using IRFP450, and the controllers were tested with DC series motor and DC separately excited motor. The speed of the motor is sensed by a pulse type digital speed sensor and fed back to the controller. The Fig. 18 shows the experimental setup of the proposed system with DC series motor. The microcontroller (P89V51RD2BN) has an 80C51 compatible core with the following features: 80C51 Central Processing Unit, 5 V Operating voltage from 0 to 40 MHz, 64 kB of on-chip Flash program memory. PCA (Programmable Counter Array) with PWM and Capture/Compare functions. The PWM is generated at a frequency of 10 kHz.

The PWM from the microcontroller is then amplified for a level through the open collector optocoupler CYN 17-1 and fed to the DC–DC power converter through an isolator and driver chip IR2110. The DC-DC buck converter output is given to the DC series motor whose speed is to be controlled. The speed sensor connected to the motor shaft gives the pulsed output which is again converted in to voltage using f/v converter and this DC voltage is fed to the ADC available in the microcontroller.

Fig. 19 shows the speed response with set speed of 1800rpm through FNC for DC series motor, it is taking almost 4.5 sec to settle at the set speed also seen that it has lesser speed variations due to the Hybrid controller nature. The DC series motor with FLC is taking almost 6 sec to settle the set speed also it has more oscillations present in the response due to Fuzzy Logic Controller nature. The Fig. 20 shows the speed response with the set speed of 1800rpm through FNC for DC separately excited motor. From the Fig. 19 and 20 it is observed that there is no overshoot, zero steady state error and the settling time also less than FLC. The Table 7 exposes the performance comparison of experimental setup of FNC with FLC for both the motor.

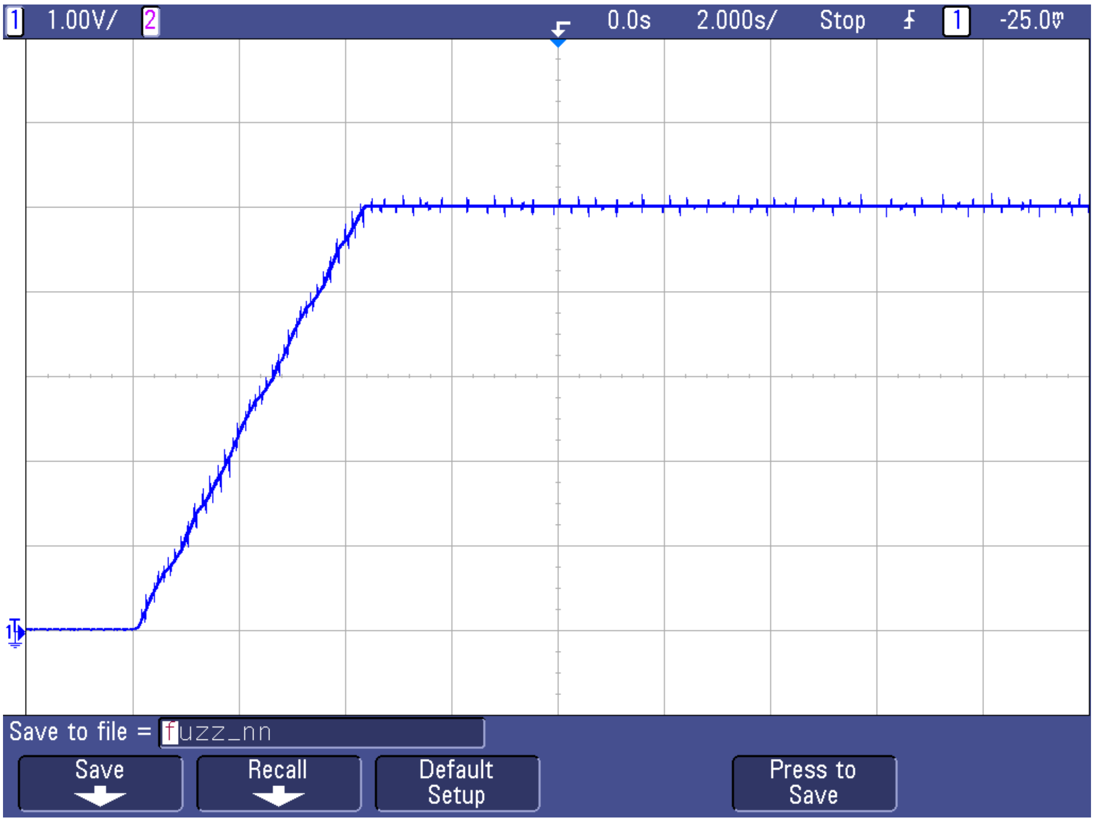

Fig.19. Experimental graph of speed variation for rated set speed using FNC for DC series motor

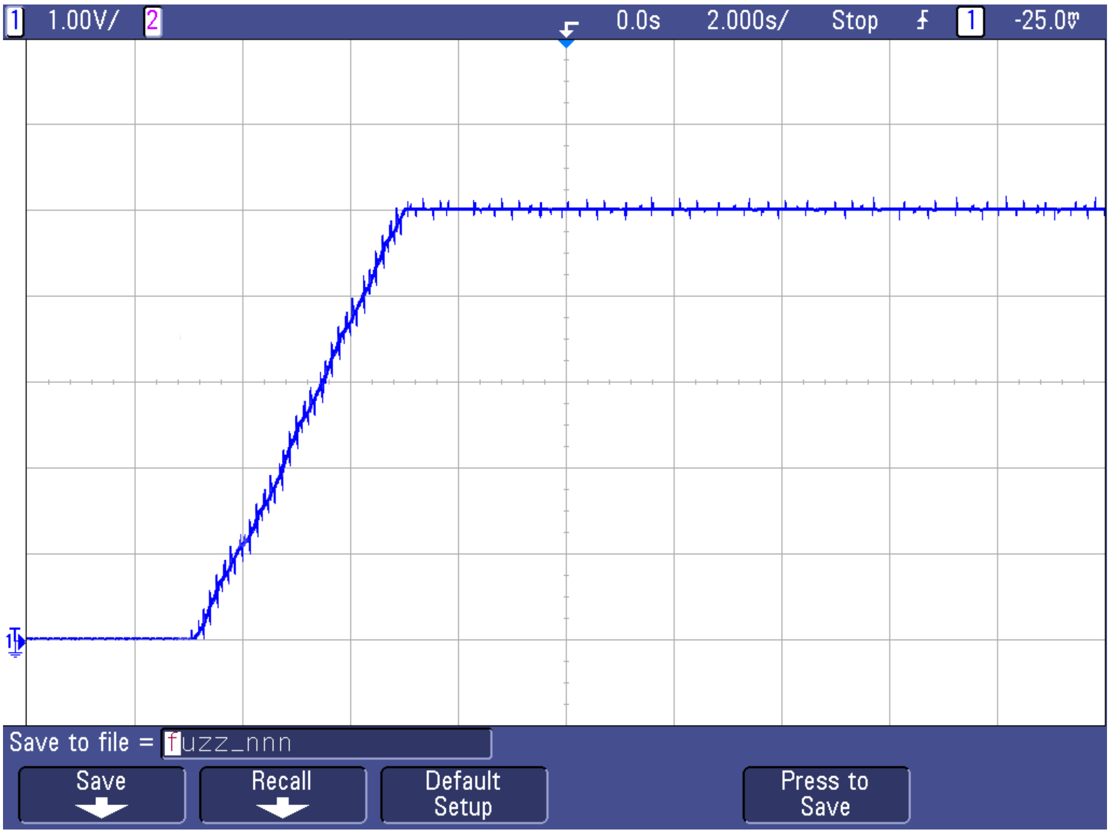

Fig.20. Experimental graph of speed variation for rated set speed using FNC for DC separately excited motor

TABLE VII
Hardware performance comparison of proposed system
with FLC and FNC for the rated speed

Controller	Developed FLC		Developed FNC	
	DC Series Motor	DC Sep. Ext. Motor	DC Series Motor	DC Sep. Ext. motor
Settling Time (sec)	6	3.2	4.5	4
Max. Over Shoot (%)	0.9	0.8	0.2	0.1
Steady State Error (rpm)	±17	±15	±4	±2

VII. CONCLUSION

In this work the performance of Fuzzy Logic and Fuzzy-Neuro controlled DC-DC converter fed DC motors are presented. The dynamic speed response of DC series motor with FNC was estimated for different load torque and different set speed change and found that the speed can be controlled effectively with the FNC. Here the number of neuron used in each layer and the number of layers are reduced. There by the computation time was reduced. The FNC based speed control of DC Motor reduces the peak overshoot, settling time and steady state error. It was implemented with a simple low cost NXP 80C51 microcontroller (P89V51RD2BN) based embedded system, thereby the cost of the system also reduced. The analysis provides the various useful parameters and the information for effective use of developed system.

VIII. REFERENCE

[1] Bose, B.K. "Power electronics and motor drives-recent technology advances", Proceedings of the IEEE International Symposium on Industrial Electronics, 2002. ISIE 2002.pp. 22- 25.

[2] Dimiter Drainkov, Hans Hellendoorn and Michael Reinfrank, An Introduction to Fuzzy Control, Narosa Publishing House, 1996.

[3] Zurada, J. M., Introduction to Artificial Neural Systems, Mumbai: Jaico Publishing House, 1992.

[4] MATLAB, Neural Network Tool Box User's Guide, Version 3, Massachusetts: The Mathworks Inc.

[5] H.A.Yousef,H.M.Khalil"A fuzzy logic-based control of series DC motor drives", Proceedings of the IEEE International Symposium on Volume 2, Issue , 10-14 Jul1995 Page(s):517 – 522.

[6] N.Senthil Kumar, V.Sadasivam, H.M.Asan Sukriya, S.Balakrishnan, "Design of low cost universal artificial neuron controller for chopper fed embedded DC drives", Science Direct, Elsevier B.V., Applied Soft Computing 8 (2008) 1637–1642.

[7] Kumar, N. Senthil, Sadasivam, V. and Asan Sukriya, H.M, "A Comparative Study of PI, Fuzzy, and ANN Controllers for Chopper-fed DC Drive with Embedded Systems Approach", Electric Power Components and Systems,36:7, 2008 Page(s): 680-695

[8] N. Senthil Kumar, V. Sadasivam, M. Muruganandam "A Low-cost Four-quadrant Chopper-fed Embedded DC Drive Using Fuzzy Controller", Inter National Journal of Electric Power Components and Systems, Volume35, Issue 8 August 2007, pages 907 – 920.

[9] M.Muruganandam and M.Madheswaran, "Performance Analysis of Fuzzy Logic Controller Based DC-DC Converter fed DC Series Motor" IEEE international conference, Chinese Control and Decision Conference (CCDC 2009), Pages 1635-1640.

[10] M.Muruganandam and M.Madheswaran, Modeling and Simulation of Modified Fuzzy Logic Controller for Various types of DC motor Drives" IEEE international conference on Control, Automation, Communication and Energy Conservation -2009, 4th-6th June 2009.

[11] Buja, G. S., and Todesco, F., "Neural network implementation of a fuzzy logic controller," IEEE Trans. Indust. Electron., Vol. 41, No. 6, pp. 663–665, December 1994.

[12] Young Im Cho "Development of a new Neuro-Fuzzy hybrid system" Industrial Electronics Society, IECON 2004. 30th Annual Conference of IEEE Volume 3, 2-6 Nov. 2004 Page(s):3184 - 3189 Vol. 3 Digital Object Identifiers 10.1109/IECON.2004.1432322.

[13] Abdulla Ismail, A.M.Sharaf, "An Efficiant Neuro-Fuzzy Speed Controller for Large Industrial DC Motor" IEEE International Conference on Control Applications, September 18-20, 2002 Glasgow, Scotland, U.K Page(s):1027-1031

[14] Y.-H. Kang, L.-K. Kim, Design of Neuro-Fuzzy controller for speed control of DC servomotor, in: (IEEE) Proceedings of the Fifth International Conference on Electrical Machines and Systems-ICEMS, vol. 2, 2001.

[15] Boumediene Allaoua, Abdellah Laoufi, Brahim Gasbaoui, And Abdessalam Abderrahmani, "Neuro-Fuzzy DC Motor Speed Control Using Particle Swarm Optimization" Leonardo Electronic Journal of Practices and Technologies, Issue 15, July-December 2009, pp. 1-18

[16] D. Kukolj, F. Kulic and E. Levi, "Design of the speed controller for sensorless electric drives based on AI techniques: a comparative study" An International Journal of Artificial Intelligence in Engineering, Elsevier, 2000. pp. 165–174.
[17] Hamit Erdem, "Application of Neuro-Fuzzy Controller for Sumo Robot control" An International Journal of Expert Systems with Applications, Elsevier, 2011. pp. 9752–9760.
[18] S. K. Pradhan, D. R. Parhi and A. K. Panda, "Neuro-fuzzy technique for navigation of multiple mobile robots" Springer Science + Business Media, Fuzzy Optim Decis Making, 2006, pp.255–288
[19] M.Madheswaran and M.Muruganandam, "Simulation and Implementation of PID-ANN Controller for Chopper Fed Embedded PMDC Motor" ICTACT International Journal On Soft Computing, APRIL 2012, Volume: 02, Issue: 03, Page(s):319-324.
[20] M.Muruganandam and M.Madheswaran "Stability Analysis and Implementation of Chopper fed DC Series Motor with Hybrid PID-ANN Controller" published in International Journal of Control, Automation and Systems, Springer, Volume 11, Issue 5, October 2013. ISSN: 1598-6446 (Print) 2005-4092 (Online)
[21] Ahmed Rubaai, Marcel J. Castro-Sitiriche, Moses Garuba, and Legand Burge, "Implementation of Artificial Neural Network-Based Tracking Controller for High-Performance Stepper Motor Drives" , IEEE Trans. Ind. Electr. 54 (1) (2007).
[22] Muammer Gokbulut, Besir Dandil, and Cafer Bal, "A Hybrid Neuro-Fuzzy Controller for Brushless DC Motors" Springer-Verlag Berlin Heidelberg 2006. pp. 125-132.
[23] Cetin Gencer, Ali Saygin, Ismail Coskun, "DSP Based Fuzzy-Neural Speed Tracking Control of Brushless DC Motor", Springer-Verlag Berlin Heidelberg 2006. pp. 107-116.
[24] M. Ali Akcayol, "Application of adaptive neuro-fuzzy controller for SRM" An International Journal of Advances in Engineering Software, Elsevier, 2004. pp. 129–137.

Masilamani Muruganandam received his B.E degree in Electrical and Electronics Engineering from the Periyar University Salem, India, in 2003, and his M.E degree Power Electronics and Drives from the Anna University of Chennai, India, in 2005. He is currently working towards his doctoral degree at the Anna University Chennai, India. He has been a member of the faculty at Centre for Advanced Research, Muthayammal Engineering College, Rasipuram, Tamilnadu, India since 2005. His research interests include fuzzy logic and neural network applications to power electronics and drives and machine modelling. He is a life member of ISTE.

Iyyanar Thangaraju received his B.E degree in Electrical and Electronics Engineering from University of Madras, India in 2000 and his M.E degree in Power Electronics and Drives from Anna University-Chennai, India, in 2005. He obtained his Ph.D. degree in Electrical Engineering from Anna University-Chennai, India, in 2013. He started his career as Lecturer and later was promoted as Assistant Professor in Electrical and Electronics Engineering department at Muthayammal Engineering College, Rasipuram, India. Then he was working as Assistant Engineer in Hydro Electric Power Station, TANGEDCO / Tamil Nadu Electricity Board, Mettur Dam, India for 5½ years. At present he is working as Assistant Professor in the department of Electrical and Electronics Engineering at Government College of Engineering, Bargur, Tamilnadu, India. He has published more than ten research papers in International Journals and conferences. His research interests include Intelligent controllers and drives for electrical applications. He is a member of IEEE and life member of ISTE.

Muthusamy Madheswaran received his BE Degree from Madurai Kamaraj University in 1990, an ME Degree from Birla Institute of Technology, Mesra, Ranchi, India in 1992, both in Electronics and Communication Engineering. He obtained his Ph.D. degree in Electronics Engineering from the Institute of Technology, Banaras Hindu University, Varanasi, India, in 1999. At present he is a Principal of Mahendra Engineering College, Mallasamudram West, Tiruchengode, Namakkal Dist. Tamilnadu, India. He has authored over hundred and forty five research publications in international and national journals and conferences. His areas of interest are theoretical modeling and simulation of high-speed semiconductor devices for integrated optoelectronics application, Biooptics and Bio-signal Processing. He was awarded the Young Scientist Fellowship (YSF) by the State Council for Science and Technology, Tamilnadu, in 1994 and Senior Research Fellowship (SRF) by the Council of Scientific and Industrial Research (CSIR), Government of India in 1996. Also he has received YSF from SERC, Department of Science and Technology, Govt. of India. He is named in Marquis Who's Who in Science and engineering in the year 2006. He is a life member of IETE, ISTE and IE (India) and also a senior member of IEEE.