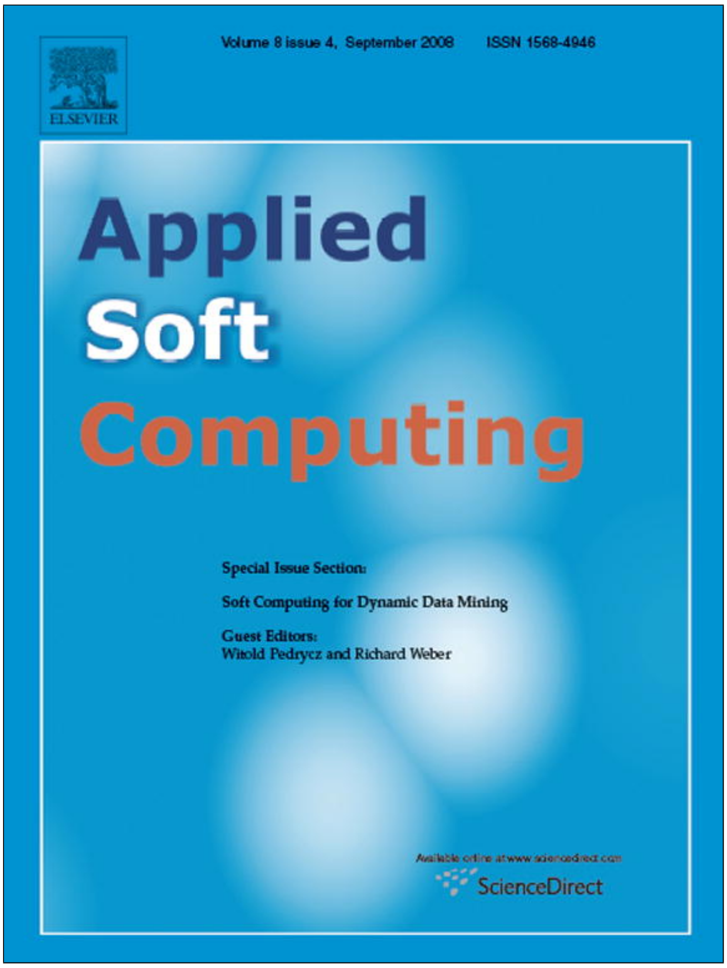
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Design of low cost universal artificial neuron controller for chopper fed embedded DC drives

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Abstract

Artificial neural network (ANN) has become very popular in many control applications due to their high computation rate and ability to handle nonlinear functions. This paper proposes an artificial neuron controller for closed loop speed control of DC drive fed by DC chopper. Neuron control is used to reduce the steady state error, overshoot and settling time. The signal corresponding to the motor speed error and change in speed error are used as inputs to ANN Controller. The controller outputs the required change in duty cycle of pulse width modulated gating signal applied to DC chopper. Thus the voltage fed to the armature of the DC motor is adjusted for achieving the desired speed response. The training patterns for the neuron controller are obtained from the conventional PI controller and the effectiveness of the proposed neuron controller is studied using simulation studies.

The designed controller was implemented in a low cost 8051-based embedded system and the results are documented. Two-loop control system was implemented with an inner ON/OFF current controller and an outer ANN speed controller.

A conventional controller has heavy computation burden whereas a trained neural network requires less computation time. The artificial neural network has the ability to generalize and can interpolate in between the training data. This advantage of ANN makes the ANN controller universal. The ANN controller designed was tested on two different motors and found to work effectively on driving both of them.

Keywords: DC chopper; DC motor drives; Pulse width modulation; Artificial neural networks; PI controller

1. Introduction

DC motor drives have occupied a wide spectrum of applications in industries. DC motors are used in machine tools, printing presses, conveyors, fans, pumps, hoists, cranes, paper mills, textile and rolling mills. Small DC motors are used primarily as control devices and servomotors for positioning and tracking. Separately exited DC motor finds many applications in industries where precise speed control over wide range is required.

An intelligent control based on fuzzy logic or artificial neural network, can give robust performance of a nonlinear parameter varying system with load disturbance, and design of such a system may not require mathematical model [1].

General PI and PID controllers are widely used for chopper control and motor control applications [2]. But it does not give satisfactory results when control parameters, loading conditions and the motor itself are changed. The disadvantage with the conventional control system is the high computation time.

It has been found that the computation burden in FLC can be reduced if FLC can be implemented in ANN [3,4]. Intelligent control techniques based on (ANN) has been tremendously growing for industrial applications [5]. Intelligent control techniques involving ANN are found to be simpler for implementation and powerful in control applications [6–8]. The speed of the DC motor has been successfully controlled by using an ANN controller with a hidden layer having nine neurons [9]. Neural network adaptive control along with a reference model has been implemented for a DC drive [10]. A multi-layer feed-forward neural network using a Levenberg Marquardt back propagation-training algorithm has been applied for a DC motor control [11].

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It has been proved that neural controllers are better than fuzzy controllers for microprocessor implementation [12]. ANN for DC drive application is becoming popular due to their high computation rate [13,14].

A trained neural network is promising, as it requires less computation time and memory [15,16]. So, from the designed PI controller, training patterns are generated and these are used to train the Artificial Neural network to be used as a controller. The trained neural network outputs the appropriate control signals for achieving the desired speed response.

The implementation of PI controller in a neural network is presented in this paper. The neuron controller is designed to reduce the steady state error, overshoot, settling time.

Initially, MATLAB/simulink model of the DC motor with the DC chopper was developed and simulated. A PI controller is designed for the inner current controller and the outer speed controller and then the closed loop operation is simulated. Then a neuron controller is designed by using neural network toolbox and it is trained with the patterns obtained from the conventional controller. The closed loop operation is simulated with the trained neural network to achieve the desired performance.

2. Proposed system

Fig. 1 shows the block diagram of the proposed system. The system consists of buck converter type DC–DC power converter or chopper for driving the separately excited DC motor. A micro controller is used to generate the PWM waveform which is required to switch the DC chopper.

The performance of the DC drive will be based on the choice of controllers. The closed loop control designed has two loops. One is the outer speed control loop and the other is the inner current control loop. The current controller is selected as simple on-off controller. A gating circuit is used to switch off the PWM signal from the microcontroller whenever the motor current exceeds the reference current I_{LREF} [17,18]. In outer speed control loop, the motor speed is sensed by a speed sensor and is fed back to the microcontroller unit through an ADC. In the microcontroller unit, the sensed speed signal is compared with the reference speed. The error and the change in error are given as input to neuron controller. The neuron controller attempts to reduce the error to zero by changing duty cycle of switching signal. The DC chopper is used to change the armature voltage applied to the separately excited DC motor whose speed is to be controlled.

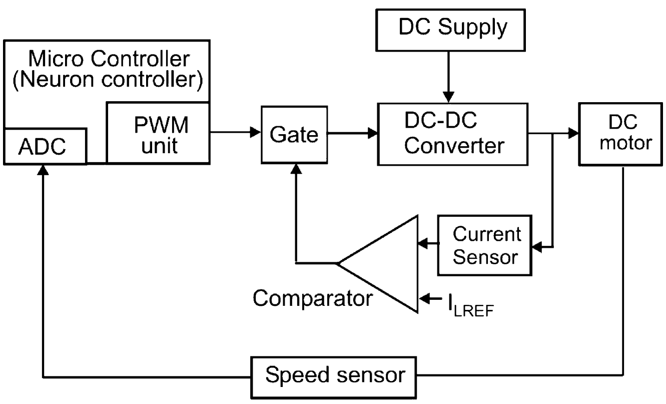

Fig. 1. Block diagram of the proposed system.

The controller implemented on neural network with an inner current control has the advantage of using any motor with any specification. The controller is designed to work with buck converter type DC chopper and so the speed can be controlled over a wide range from zero to the rated speed. Changing I_{LREF} in Fig. 1 can change the operation and limit the motor current to I_{LREF}. The changing I_{LREF} can be easily done by hardware using a potentiometer connected to the comparator unit.

3. Model of DC motor and buck converter

The simulation and design of the controller was done using equation models of the motor and buck converter [2]. The DC motor has been modeled with the modeling Eqs. (1) and (2).

$$\frac{\mathrm{d}^2\theta}{\mathrm{d}t^2} = \frac{1}{J}\left[K_{\mathrm{T}} i_{\mathrm{o}} - B\frac{\mathrm{d}\theta}{\mathrm{d}t} - T_{\mathrm{L}}\right] \tag{1}$$

$$\frac{\mathrm{d}i_{\mathrm{o}}}{\mathrm{d}t} = \frac{1}{L}\left[V_{\mathrm{o}} - R i_{\mathrm{o}} - K_{\mathrm{b}}\frac{\mathrm{d}\theta}{\mathrm{d}t}\right] \tag{2}$$

where J: moment of inertia of the motor (kg m^2); B: friction coefficient of the motor (Nm/rad/s); K_{T}: torque constant of the motor (Nm/A); K_{b}: motor back emf constant (V/rad/s); T_{L}: load torque applied (Nm); i_{o}: Armature current (A); V_{o}: Armature voltage applied (V); R: Armature resistance (ohms); L: Armature inductance (mH).

The DC chopper is modeled with a supply voltage of V_{s} and DC motor as load using Eqs. (3)–(6). Mode 1 is when the MOSFET switch of the chopper is ON and Mode 2 is when the MOSFET switch of the chopper is OFF.

Mode 1: (Switch ON)

$$V_{\mathrm{s}} = R_{\mathrm{a}} i_{\mathrm{a}} + L_{\mathrm{a}}\frac{\mathrm{d}i_{\mathrm{a}}}{\mathrm{d}t} + K\omega \tag{3}$$

$$K i_{\mathrm{a}} = J\frac{\mathrm{d}\omega}{\mathrm{d}t} + B\omega + T_{\mathrm{L}} \tag{4}$$

Mode 2: (Switch OFF)

$$0 = R_{\mathrm{a}} i_{\mathrm{a}} + L_{\mathrm{a}}\frac{\mathrm{d}i_{\mathrm{a}}}{\mathrm{d}t} + K\omega \tag{5}$$

$$K i_{\mathrm{a}} = J\frac{\mathrm{d}\omega}{\mathrm{d}t} + B\omega + T_{\mathrm{L}} \tag{6}$$

The above two states of the converter can be averaged using the fact that the switch is in position 1 for a period of ($D \times$ Ts) over the switching period Ts, where D is the duty cycle. The averaged small signal model is formulated by assuming perturbations $\overline{v_s}, \bar{d}$ in the steady state values of supply voltage V_{s} and the duty cycle D respectively [2]. The small signal model for the chopper fed DC drive is given by Eqs. (7) and (8).

$$L_{\mathrm{a}}\frac{d\bar{i}_{\mathrm{a}}}{\mathrm{d}t} = D\bar{v}_{\mathrm{s}} + V_{\mathrm{s}}\bar{d} - R_{\mathrm{a}}\bar{i}_{\mathrm{a}} - K\bar{\omega} \tag{7}$$

$$J\frac{d\bar{\omega}}{dt} = K\bar{i}_a - B\bar{\omega} - T_L \tag{8}$$

Considering duty cycle $\bar{d}(s)$ as control signal and speed $\bar{\omega}(s)$ as the output signal, the motor speed transfer function is calculated as

$$\frac{\bar{\omega}(s)}{\bar{d}(s)} = \frac{\bar{\omega}(s)}{\bar{i}_a(s)} \times \frac{\bar{i}_a(s)}{\bar{d}(s)} \tag{9}$$

From the above equation, the speed gain is given by Eq. (10) assuming the load torque is constant.

$$\frac{\bar{\omega}(s)}{\bar{i}_a(s)} = \frac{K}{Js + B} \tag{10}$$

Similarly, when the supply voltage is kept constant, the current gain is given by Eq. (11).

$$\frac{\bar{i}_a(s)}{\bar{d}(s)} = \frac{V_s(Js + B)}{(L_a s + R_a)(Js + B) + K^2} \tag{11}$$

So, the final transfer function of the chopper fed DC motor under the assumed conditions is calculated as in Eq. (12).

$$\frac{\bar{\omega}(s)}{\bar{d}(s)} = \frac{KV_s}{(L_a s + R_a)(Js + B) + K^2} \tag{12}$$

4. Design of conventional controller

The current controller $H_i(s)$ and the speed controller $H_s(s)$ are to be designed. The inner current controller is designed based on the current gain. The frequency response of the transfer function is low and it has to be improved, so a PI controller is designed in the form given by Eq. (13).

$$H_i(s) = \frac{s + \omega_L}{s} \tag{13}$$

ω_L is selected as the corner frequency of the motor current transfer function. The inner compensated closed loop for current will have unity gain for low frequency signals.

Table 1
110 V DC Motor parameters

DC motor parameters	Value
DC supply voltage	110 V
Armature resistance (R_a)	1 Ω
Armature inductance (L_a)	46 mH
Inertia constant (J)	0.093 Nm/(rad/s^2)
Damping constant (B)	0.008 Nm/rad/s
Torque constant (K_t)	0.55 Nm/A
Back emf constant (K_b)	0.55 V/(rad/s)
Speed	1500 rpm

The outer speed controller is designed in the form of Eq. (14).

$$H_s(s) = \frac{K_s(\omega_m + s)}{s} \tag{14}$$

ω_m is selected as the corner frequency of the motor speed transfer function. The value of K_s is selected as 5 to achieve a bandwidth of 500 rad/s [2]. The values for ω_L, ω_m are selected as 15 and 0.086 rad/s respectively for the DC motor parameters given in Table 1. The simulink model developed based on the mathematical model of the motor and buck converter and the basic control blocks is given in Fig. 2.

5. Neural network implementation of conventional controller

Data processing in PI controller is a complex task that requires heavy computation time. The neural network is a nonlinear algorithm that can be worked out because of its mathematical nature [15]. In this section, the solution of implementing conventional PI controller in a neural network is discussed.

The ANN controllers designed in most of the work use a complex network structure for the controller. The aim of this work is to design a simple ANN controller with as low neurons as possible while improving the performance of the controller.

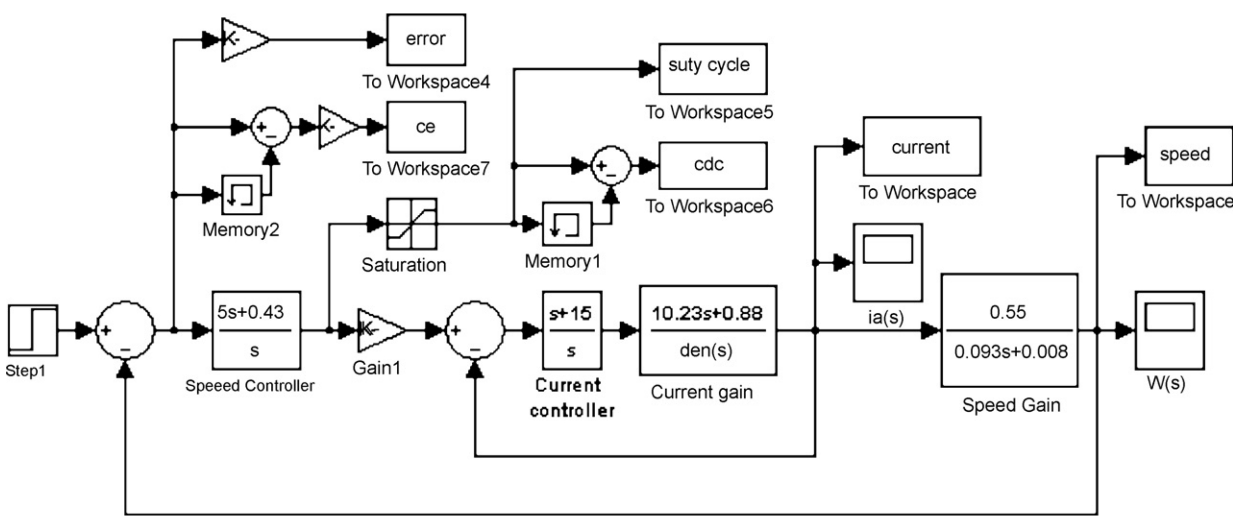

Fig. 2. Simulink model of the conventional controller.

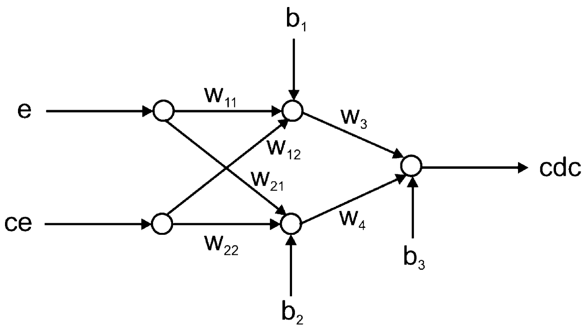

Fig. 3. Neural network implementation of PI controller.

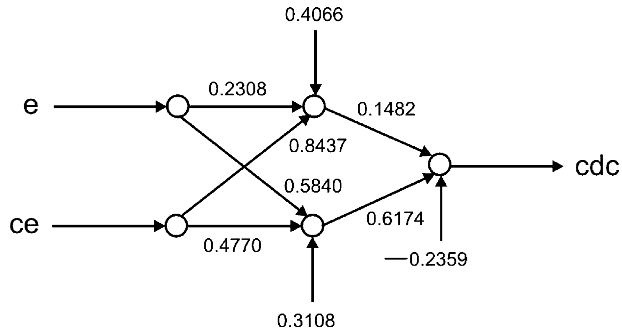

Fig. 4. Details of the trained network.

A two layer feed forward neural network is constructed with two neurons in the input layer and one neuron in the output layer. The structure of the neural network used to implement PI controller is shown in Fig. 3. As the inputs to the neuron controller are the error and the change in error, two neurons are used for input layer. The neurons are biased. The activation functions used for the input and output neurons are pure linear and tangent sigmoid respectively. The network is trained for the set of inputs and desired outputs [19]. The training patterns are extracted from the conventional controller designed. Supervised back propagation training algorithm is used [20]. A back propagation neural network-training algorithm is used with a fixed error goal. The network is trained for an error goal of 0.0005.

The error (e) and change in error (ce) are the inputs to the controller. The output corresponds to the change in the duty cycle for the motor control. The details of the trained network are shown in Fig. 4.

6. Hardware implementation

The neuron controller was implemented using Cygnal 8051 based processor (C8051F005) and by programming it. A buck converter was built and the neuron controller with the buck converter was tested on the DC motor. A tacho-generator was used to sense the speed and to achieve closed loop control.

The micro controller (C8051F005) has 8051 compatible core with the following features: 12-bit eight channels ADC; Two 12-bit DACs, 2KB data RAM and 32KB Flash – in system programmable. It also has an in built PWM waveform generator available as a programmable counter array. The PWM is generated at a frequency of 14 kHz.

A LEM make Hall effect current sensor LTS25NP is used to sense the armature current and it is compared with the reference current using the comparator LM 399. The AND gate is used to allow the PWM waveform when the actual current is less than the reference current. This PWM waveform is then level amplified and fed to the DC–DC power converter through IR2110 isolator chip. The Buck converter output is used as supply to the armature of the DC motor to maintain the speed. The tacho-generator connected to the motor shaft gives a DC voltage proportional to the speed and this DC voltage is fed to the ADC available in the micro-controller.

A pseudo code for the single run of the ANN controller is given below.

- error = (Reference_speed − Actual_speed)/(Reference_-speed);
- change_in_error = (error-previous_error);
- neuron1_output = (0.2308* error) + (0.8437* change_in_error) + 0.4066;

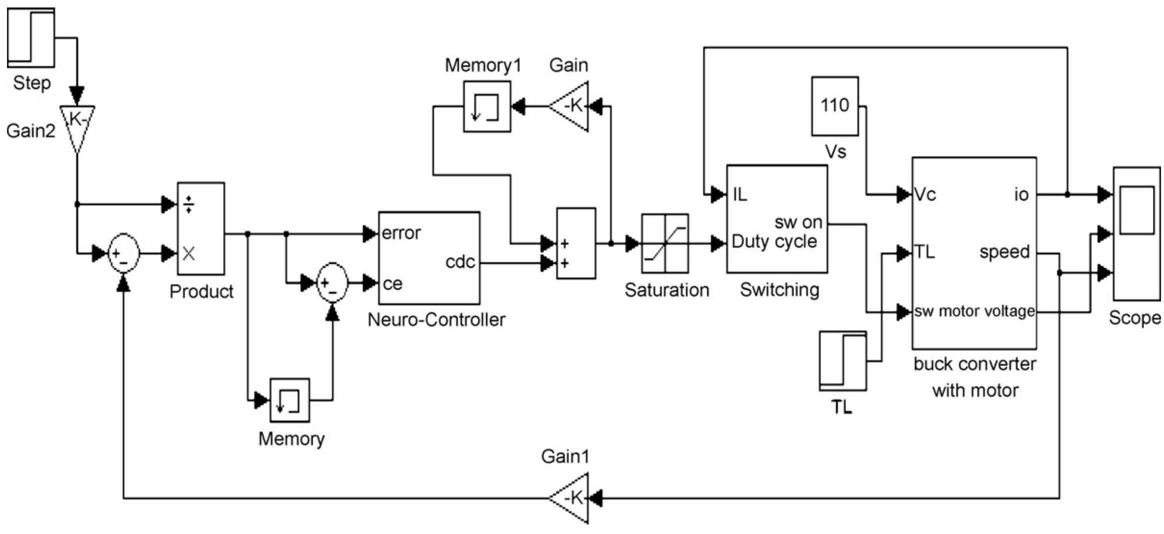

Fig. 5. Simulink model of the proposed system.

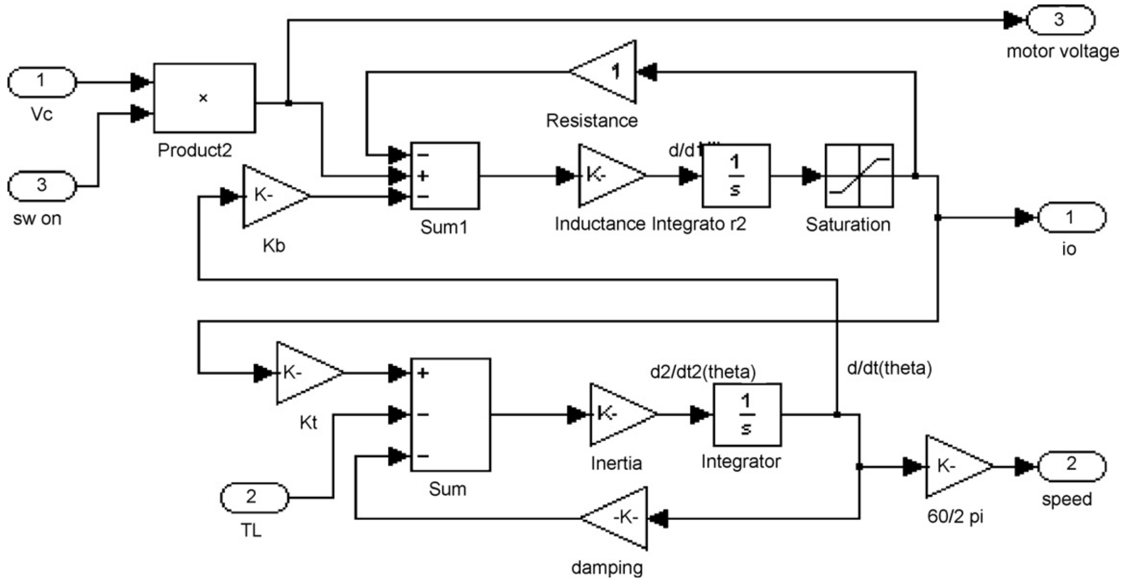

Fig. 6. Simulink model of the motor.

- neuron2_output = (0.584* error) + (0.4770* change_in_error) + 0.3108;
- neuron3_output = (0.1482* neuron1_output) + (0.6174* neuron2_output)-0.2359;
- network_output = (exp(-2* neuron3_output) + 1);
- change_in_duty_cycle = (2/network_output)-1;
- previous_error = error.

7. Simulation, results and conclusion

The simulation of buck converter fed DC motor is done based on equation modeling using MATLAB/simulink toolbox. The simulink model developed is given in Figs. 5 and 6.

The simulation was done for a Buck converter fed DC motor with the neuron controller. The computer simulation was run for a step change in motor reference speed from 60% of the rated speed to the 100% of rated speed applied at 3 s and the actual change in speed is recorded. The step change in load torque from 0 to the rated torque is applied at 6 s to the motor running at rated speed and the corresponding change in the speed is recorded. The simulation results for the conventional controller and the neuron controller are given in Fig. 7. The results show that the neuron controller performance is better in respect of steady state error, overshoot and settling time.

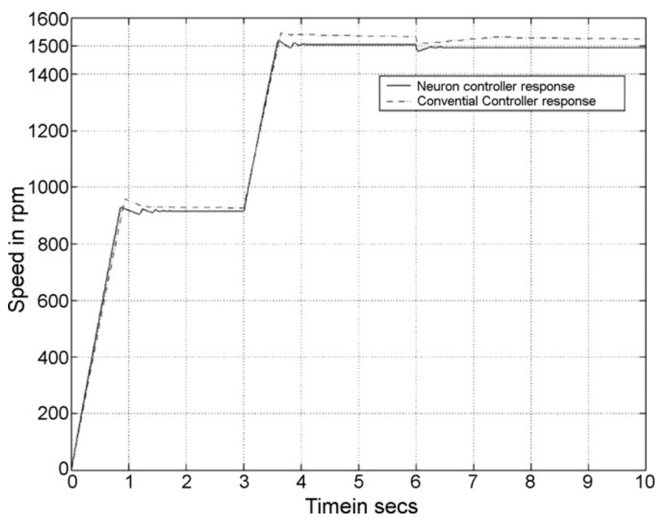

Fig. 7. Graph of speed variation for the step change in reference speed at 3 s and step change in torque applied at 6 s for 110 V motor.

For illustrating the ability of the proposed neuron controller to generalize and to act as a universal controller, the system with the same neuron controller is simulated with a 220 V motor with the parameters given in Table 2. The simulated result for the same conditions is shown in Fig. 8. The results justify that the neuron controller is universal and can be used for any separately excited DC motor drive.

Neuron controller developed in C language was implemented in the embedded system and down loaded in to the flash memory of the micro-controller using in system programming technique. The Fig. 9 shows the experimental response of DC motor for change in reference speed. The response is found to be satisfactory conforming to the simulation results. The speed regulation for various loaded conditions is compared for open loop and for ANN controller in the Fig. 10.

In this paper the use of artificial neural network for the speed control of DC motor is presented. The simulation studies show

Table 2
220 V DC motor parameters

DC motor parameters	Value
DC supply voltage	220 V
Armature resistance (R_a)	0.6 Ω
Armature inductance (L_a)	0.008 H
Inertia constant (J)	0.011 Nm/(rad/s^2)
Damping constant (B)	0.004 Nm/(rad/s)
Torque constant parameter (K_t)	0.55 Nm/A
Back emf constant (K_b)	0.55 V/(rad/s)
Speed	1800 rpm

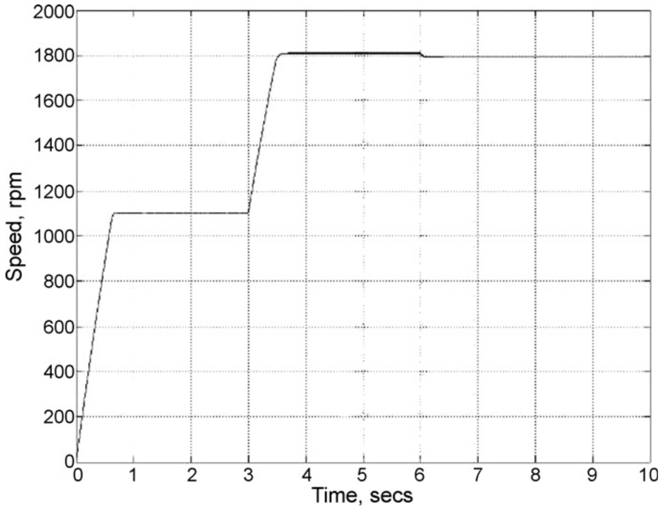

Fig. 8. Graph of speed variation for the step change in reference speed at 3 s and step change in torque applied at 6 s for 220 V motor.

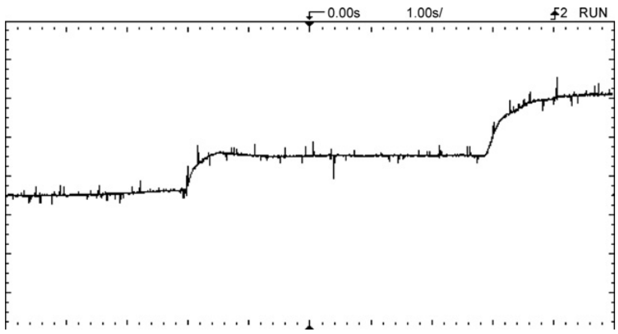

Fig. 9. Experimental result of speed variation for two step reference speed change with neuron controller.

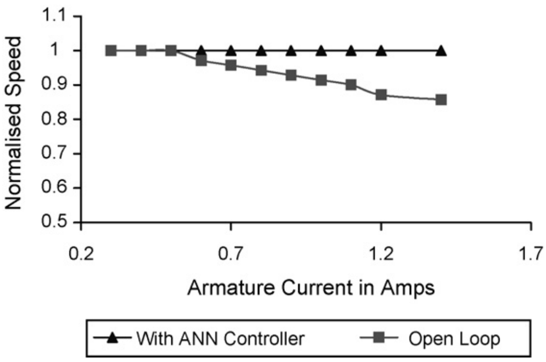

Fig. 10. Experimental result of speed regulation of the motor with neuron controller compared with open loop response.

that the neuron controller provides better dynamic response and can also act as a universal controller for similar systems. The architecture of the neural network is simple and uses only two layers with three biased neurons. The neuron controller is easy to implement and requires less computation burden in an embedded system. The ANN control algorithm developed for real time embedded system implementation has very less code size and occupies less memory space.

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