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RESEARCH ARTICLE

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Experimental verification of chopper fed DC series motor with ANN controller

Abstract In this article an artificial neural network (ANN) has been designed for the control of DC series motor through a DC chopper (DC-DC buck converter). The proportional-integral-derivative (PID)-ANN speed controller controls the motor voltage by controlling the duty cycle of the chopper thereby the motor speed is regulated. The PID-ANN controller performances are analyzed in both steady-state and dynamic operating condition with various set speeds and various load torques. The rise time, maximum overshoot, settling time, steady-state error, and speed drops are taken for comparison with conventional PID controller and existing work. The training samples for the neuron controller are acquired from the conventional PID controller. The PID-ANN controller performances are analyzed in respect of various load torques and various speeds using MATLAB simulation. Then the designed controllers were experimentally verified using an NXP 80C51 based microcontroller (P89V51RD2BN). It was found that the hybrid PID-ANN controller with DC chopper can have better control compared with conventional PID controller.

Keywords DC series motor, proportional-integral-derivative (PID) controller, artificial neural network (ANN) controller, DC chopper, speed control, MATLAB simulink

1 Introduction

DC series motor drives are engaged with a wide range of applications, such as lifts, cranes, hoist, electric traction, robotic manipulators, and battery operated electric vehicles. Such high performance applications require the motor drive with minimal steady-state error, overshoot and undershoot in its speed commands. The application of DC series motor in industrial environment has increased due to the high performance and high starting torque as suitable drive system [1,2]. Recently, the artificial neural network (ANN) has been widely utilized for various control applications including motor control. The neural network controller can give robust performance of a nonlinear parameter varying system with load disturbance. This controller has made the control of complex nonlinear systems with uncertainty or un-modeled dynamics as simple as possible [3,4].

Earlier, the conventional controllers like proportional-integral (PI) and proportional-integral-derivative (PID) controllers were widely used for chopper control and motor control applications. However, it failed to give satisfactory results when control parameters, loading conditions, and the motor itself are changed. Hence, the tuning and optimization of these controllers are a challenging and difficult task, particularly under varying load conditions, parameter changes, and abnormal modes of operation. 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 PID-ANN controller. Intelligent control techniques involving ANN are found to be simpler for implementation and powerful in control applications [3]. Yousef and Khalil [5] reported 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 which has improved the performance. It is also reported that the settling time and maximum overshoot can be reduced. Due to the inherent limitations, AC to DC converter fed drive introduces unwanted harmonic ripples in the output, and the computation time of fuzzy controller is also high.

Senthil Kumar et al. [6] utilized the ANN controllers for speed control of DC motor, 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

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proposed neuron controller was studied using simulation studies. The designed controller was implemented in a low cost 8051 based embedded system, and the results are documented. DC separately excited motor limits high torque applications. Yildiz and Zeki Bilgin [7] explained the realization of the speed control of a separately excited DC motor driven by DC-DC converter by using neuro-PID controller. A self-tuning PID neuro-controller was developed for speed control on this model. The PID gains are tuned automatically by the neural network in an online way. The controller developed in this work, based on neural network (NN), offers inherent advantages over conventional PID controller for DC motor drive systems.

Buja and Todesco [8] explained that the fuzzy logic suffers from complex data processing; this problem is reduced by implementing a fuzzy logic controller (FLC) on an NN. From the FLC design, an NN is trained by supervision to learn the input-output relationship of FLC. This demonstrates that implementing an FLC on an NN is an effective solution to simplify the data processing required by the fuzzy logic while maintaining its human-like approach and control capabilities. A trained NN is promising, as it requires less computation time and memory. Senthil Kumar et al. [9] demonstrated the design of a low-cost fuzzy controller for closed-loop control of DC drive fed by four-quadrant chopper, and the fuzzy controller was implemented in a low-cost 8051 micro-controller based embedded system. The simulated closed-loop performance of the fuzzy controller in respect of load variation and reference speed change has been reported. Further, the dynamic response of DC motor with fuzzy controller was tested and found to be satisfactory. Muruganandam and Madheswaran [10,11] enlightened the design of a fuzzy controller for closed-loop control of DC series motor drive fed by DC-DC converter. The performance in respect of load variation and speed changes has been reported. The performance of the proposed controller was compared with the reported results and found that the fuzzy based DC-DC drive can have better control. However, it has the limitation of more computation time due to fuzzy controller.

In this proposed work, the DC series motor is controlled by DC-DC buck converter. The equation model of the DC series motor and the DC-DC converter was developed for simulation [4]. A PID controller is designed as a speed controller to extract the training data. Then, an ANN controller is designed, and it is trained with the training patterns obtained from the PID controller. The designed PID-ANN controller is used to reduce the steady-state error, overshoot, and settling time. The closed-loop operation is simulated with the trained PID-ANN controller to achieve the desired performance of DC series motor. This paper is arranged as follows. Section 2 describes the proposed system of DC series motor control. Section 3 describes the mathematical modeling and simulation of DC series motor and DC-DC converter. The design of conventional PID controller and the structure of artificial neuron controller are discussed in Section 4. Section 5 gives the simulation results and discussion of the proposed work. Section 6 explains the experimental implementation of the system. Section 7 clarifies the conclusions made out of the current work.

2 Hybrid PID-ANN controller based DC drive

Process sequence of the whole system with hybrid PID-ANN controller is depicted in Fig. 1. Figure 2 shows the block diagram of the system with hybrid PID-ANN

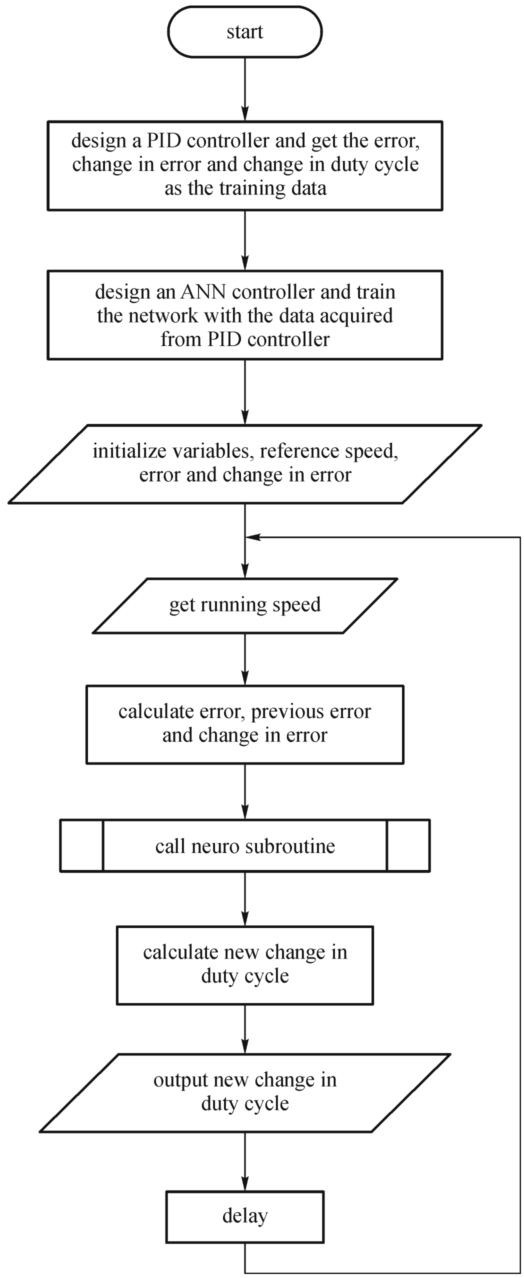

Fig. 1 Flow chart for the proposed hybrid PID-ANN controller

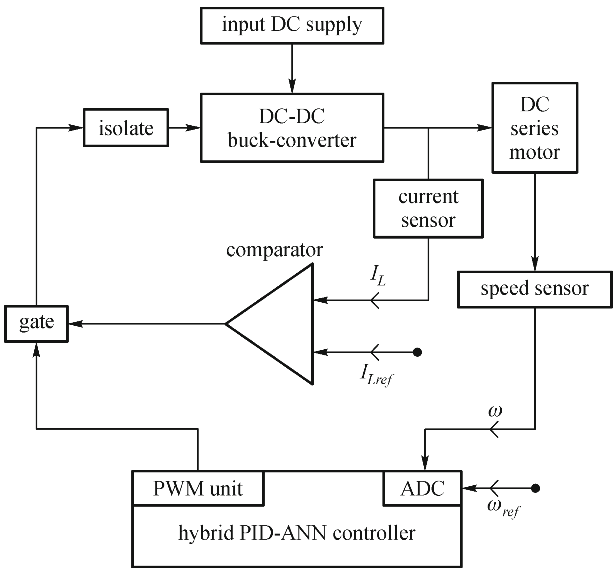

Fig. 2 Block diagram of hybrid PID-ANN controller based DC drive

controller. The system consists of DC-DC buck converter to drive the DC series motor. A tacho generator or a speed sensor is used to sense the speed and is used for speed feedback, i.e., actual speed (ω). The pulse-width modulation (PWM) signal is generated by comparing the carrier signal and the duty cycle of the controller output. During the implementation of the proposed system, a microcontroller or a digital signal processor may be used to generate the PWM signal to switch the DC-DC buck converter [9–11].

The system has two loops, namely, an outer PID-ANN speed control loop and an inner ON/OFF current control loop. The current control loop is used to blocks the PWM signal whenever the motor current exceeds the reference current (I_{Lref}). In outer speed control loop, the actual speed $\omega(k)$ is sensed by tacho generator. The error signal $e(k)$ is obtained by comparing actual speed $\omega(k)$ with reference speed $\omega_{ref}(k)$. The change in error $\Delta e(k)$ can be calculated from the present error $e(k)$ and previous error $e_{previous}(k)$.

In the proposed system, a two-input PID-ANN controller is used. The error and change in error are given as inputs to the controller. The output of the controller is denoted as duty cycle $dc(k)$. The change in duty cycle $\Delta dc(k)$ can be calculated from the new duty cycle $dc(k)$ and previous duty cycle $dc_{previous}(k)$. The DC-DC converter is used to change the input voltage applied to the DC series motor whose speed is to be controlled. The output voltage of the DC-DC buck converter is varied from zero to the input voltage applied; thus, wide range of speed control is possible from zero to the rated speed. The DC series motor with different specifications may also possible to control the speed by artificial neuron controller due to the inner current controller. The input and output gains of the PID-ANN controller can be estimated by simulation. The artificial neuron controller can reduce the error to zero by changing the duty cycle of the switching signal [6].

3 Mathematical modeling of DC series motor and DC-DC converter

The analysis of controller was done using equation model of the motor and buck converter [5].

3.1 DC series motor model

Figure 3 shows the equivalent circuit of DC series motor. From the equivalent circuit the voltage and torque equations are obtained, which are given in Eqs. (1) and (2), respectively.

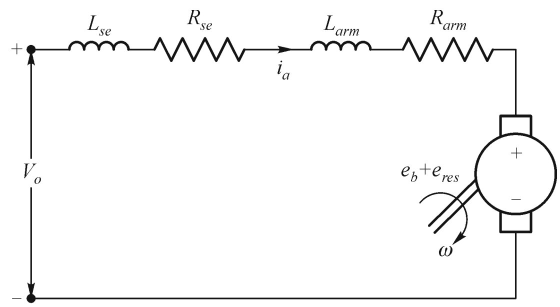

Fig. 3 Equivalent circuit of DC series motor

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

$$V_o = i_a R_a + L_a \frac{\mathrm{d}i_a}{\mathrm{d}t} + e_b + e_{res}, \tag{1}$$

$$T = J\frac{\mathrm{d}\omega}{\mathrm{d}t} + B\omega + T_L. \tag{2}$$

$$\therefore e_b \propto i_a \omega,$$

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

$$\omega = \frac{\mathrm{d}\theta}{\mathrm{d}t} = Angular\ Speed.$$

Similarly,

$$e_{res} \propto \omega,$$

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

$$\therefore e_{res} = K_{res}\frac{\mathrm{d}\theta}{\mathrm{d}t}.$$

Rearrange Eq. (1) by replacing e_b and e_{res},

$$V_o = R_a i_a + L_a \frac{\mathrm{d}i_a}{\mathrm{d}t} + K_{af} i_a \frac{\mathrm{d}\theta}{\mathrm{d}t} + K_{res} \frac{\mathrm{d}\theta}{\mathrm{d}t}, \quad (3)$$

$$\frac{\mathrm{d}i_a}{\mathrm{d}t} = \frac{1}{L_a}\left[V_o - R_a i_a - K_{af} i_a \frac{\mathrm{d}\theta}{\mathrm{d}t} - K_{res}\frac{\mathrm{d}\theta}{\mathrm{d}t}\right]. \quad (4)$$

Similarly, the torque equation is also derived as follows:

$$T \propto \varphi i_a \text{ and } \varphi \propto i_a \text{ (before saturation)}.$$

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

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

$$\omega = \frac{\mathrm{d}\theta}{\mathrm{d}t} = Angular\ Speed.$$

Rearrange Eq. (2) by replacing T:

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

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

(or)

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

The DC motor has been modeled with the modeling Eqs. (4) and (6). The equation modeling is more effective than the transfer function model. In transfer function model, it is required to develop different models for every input and output parameter changes. Whereas in equation model the voltage and load torque are the input parameters, the output parameters are speed, current, deflecting torque, etc.

3.2 DC-DC converter model

The DC-DC converter switch can be a power transistor, SCR, GTO, IGBT, power MOSFET, or similar switching device. To get high switching frequency (up to 100 kHz) the power MOSFET may be taken as a switching device. Normally on state drop in the switch is small and it is neglected [1,2].

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-DC converter are shown in Fig. 4.

The model equation for DC-DC converter is given by

$$V_o = \delta V_s, \quad (7)$$

$$\delta = \frac{T_{ON}}{T}, \quad (8)$$

$$T = T_{ON} + T_{OFF}, \quad (9)$$

where

V_o — output voltage,

V_s — input voltage,

T_{ON} — ON time,

T_{OFF} — OFF time,

T — total time,

δ — duty cycle.

The simulation operation of DC-DC converter is given in Table 1.

4 Simulation of the system using MATLAB simulink

4.1 Conventional controller (PID)

To train the ANN controller, the training data are required.

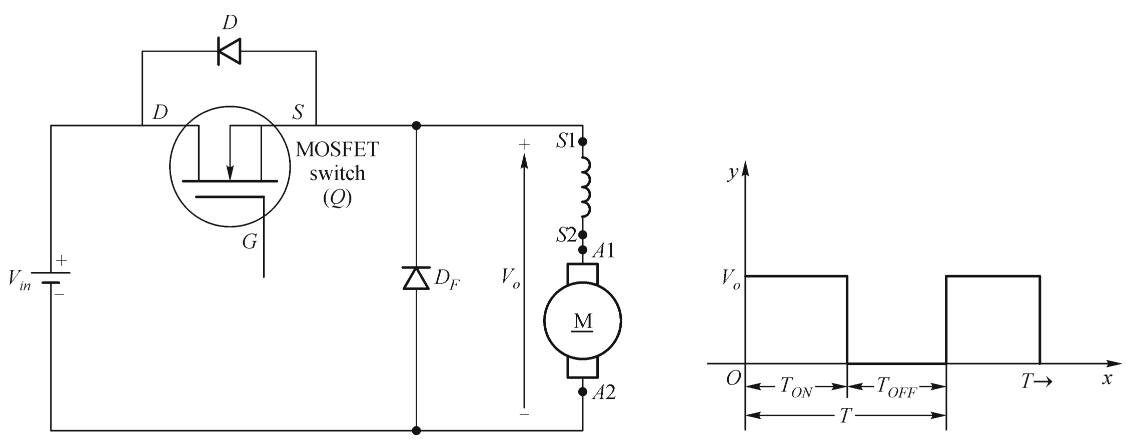

Fig. 4 DC-DC converter circuit and waveform

Table 1 DC-DC converter switching operation

operating mode	switch position		converter output voltage V_o		load current i_o
	motoring (Mode 1)	freewheeling (Mode 2)	Mode 1	Mode 2	
forward motoring	MOSFET (Q) ON	diode (D_F) ON	V_s	0	$+v_e$

A conventional PID controller is designed and simulated with the drive system for extracting the training data. PID controller needs tuning in order to work properly. The PID controller parameters are determined by Ziegler-Nichols method. According to Ziegler-Nichols method, the controller has to run by taking only P value, increase the P value of the controller until the system is self oscillating with constant amplitude, then take the controller gain. According to Ziegler-Nichols procedure the P, I, and D values are determined. The determined values are $P = 88$, $I = 26$, and $D = 0.1$. In the determined P, I, and D values, the D value is very small, in order to reduce the settling time. If the D value increases then the settling time will increase [12–15]. From the nonlinear Eqs. (3) and (6), the simulink model of DC series motor is obtained and given in Fig. 5. A nonlinear controller is desired to control the speed of the modeled DC series motor. The ANN controller is the one of the best suited nonlinear controller, to control the DC motor [15–20].

The simulink model developed based on the mathematical model of the motor, buck converter, and the conventional PID controller is given in Fig. 6.

The PID controller input and output parameters are error and change in duty cycles, respectively. The ANN requires error and change in error as input and the change in duty cycle as the output. Therefore, the change in error is calculated from the error by simulation which is sown in Fig. 6. The above model is simulated for 5 s with the sampling time of 0.0001 s. Totally 50001 data are obtained from the system with PID controller. Out of 50001 only 1200 data are taken for training the ANN controller by removing the same value of data. Some of the sample data are given in Table 2.

4.2 PID based ANN controller (PID-ANN)

Data processing in PID controller is not accurate and it will produce error result, which means that overshoot, undershoot, steady-state error, etc. The neural network is based on nonlinear control algorithm that can be worked out because of its mathematical nature [6]. In this section, the solution of implementing conventional PID controller in a neural network is discussed. The ANN controllers designed in most of the work use a complex network structure. 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. In the proposed work a two-layer feed forward neural network is created with two

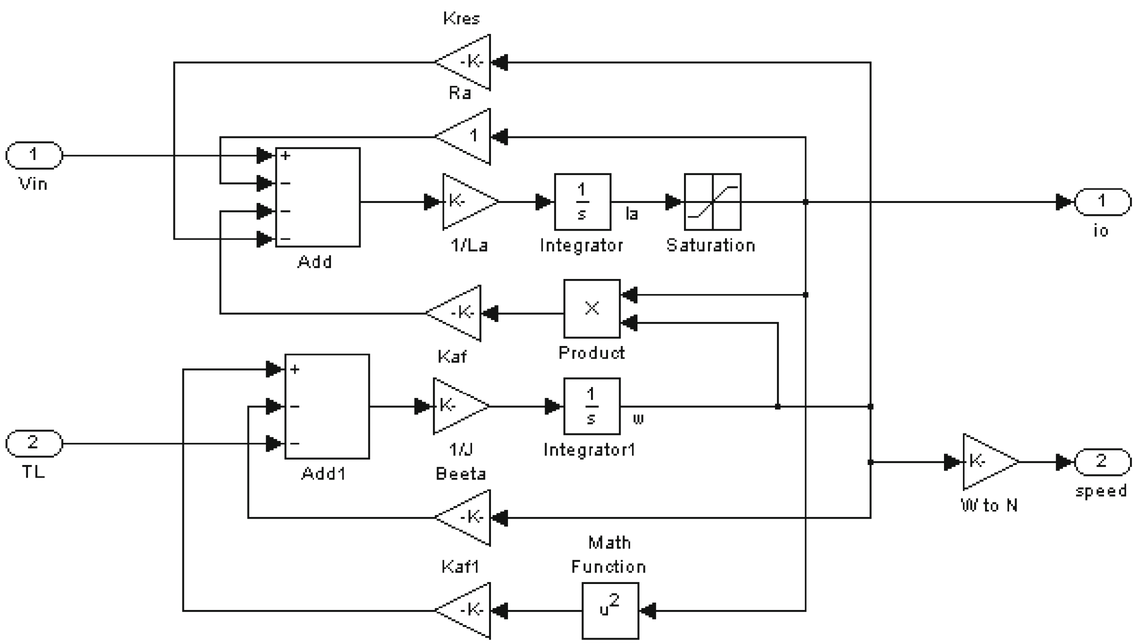

Fig. 5 Simulink model of DC series motor

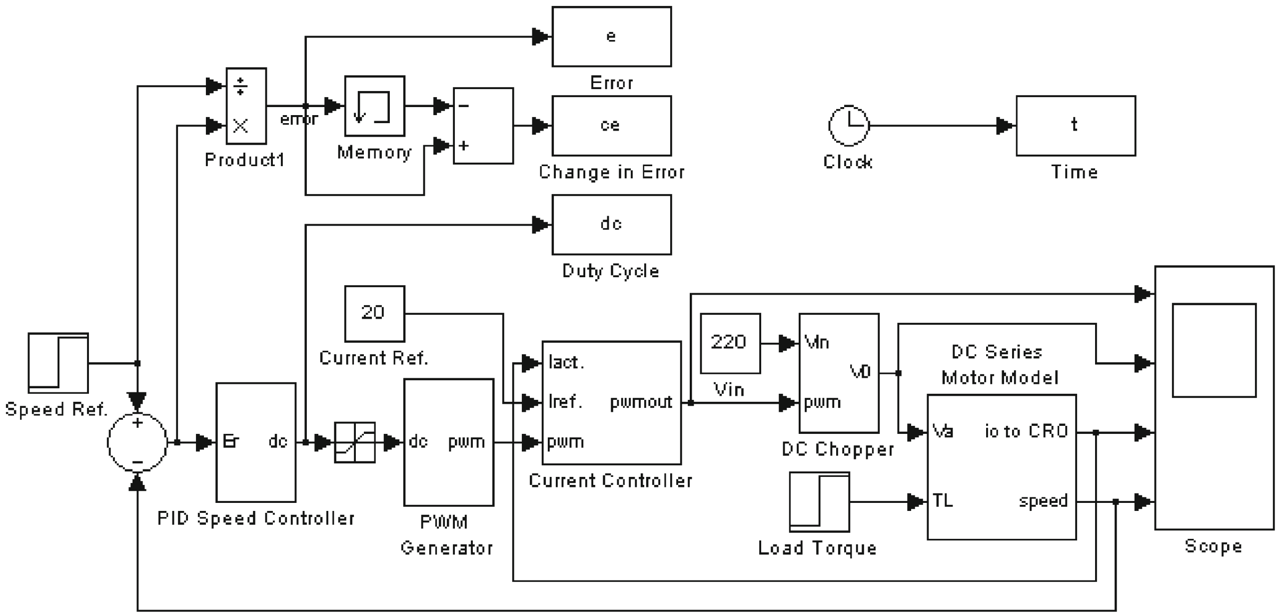

Fig. 6 Simulink model of the system with conventional PID controller

Table 2 Sample data from PID controller

input data		target data
error	change in error	corresponds to δ
1.0000	−0.0005	200020
0.8573	−0.0004	−19160
0.7334	−0.0004	−10409
0.6271	−0.0003	−4932
0.5356	−0.0003	−7337
0.4572	−0.0002	−6190.2
0.3898	−0.0002	239.08

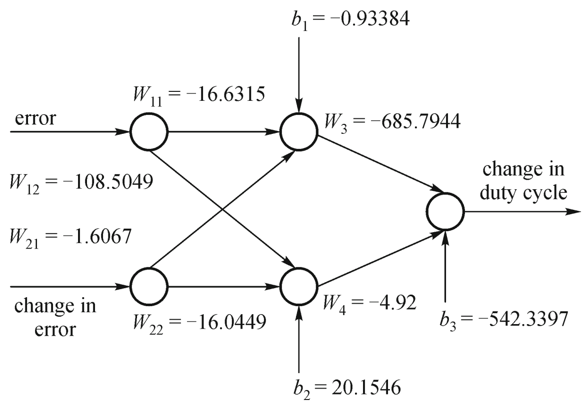

Fig. 7 Structure of trained neural network

neurons in the input layer and one neuron in the output layer.

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 neurons are pure linear, and the tangent sigmoid activation function is used for output neuron. The network is trained for the set of inputs and desired outputs [6]. The training patterns are extracted from the conventional PID controller, and a supervised back propagation neural network training algorithm is used with a fixed error goal. The network is trained with minimum error goal. 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 detail of the trained network is shown in Fig. 7 [6,21–25].

The PID-ANN is trained with the error goal of 0.000086703 in 10 epochs, since this network is not a perceptron type network. The variation of ANN parameter during supervised back propagation training algorithm is graphically shown in Fig. 8.

The structure of the artificial neuron controller using MATLAB simulink is shown in Fig. 9.

The simulation of DC-DC converter fed DC series motor is done based on equation modeling technique using MATLAB simulink toolbox. The complete simulink model developed is given in Fig. 10. The duty cycle is getting from the ANN controller and is given to PWM unit. The PWM unit generates the pulse at 1 kHz of switching frequency. The current controller permits the pulse to the chopper if the motor current is below the reference current.

5 Results and discussion

The proposed model has current controller, and the PID

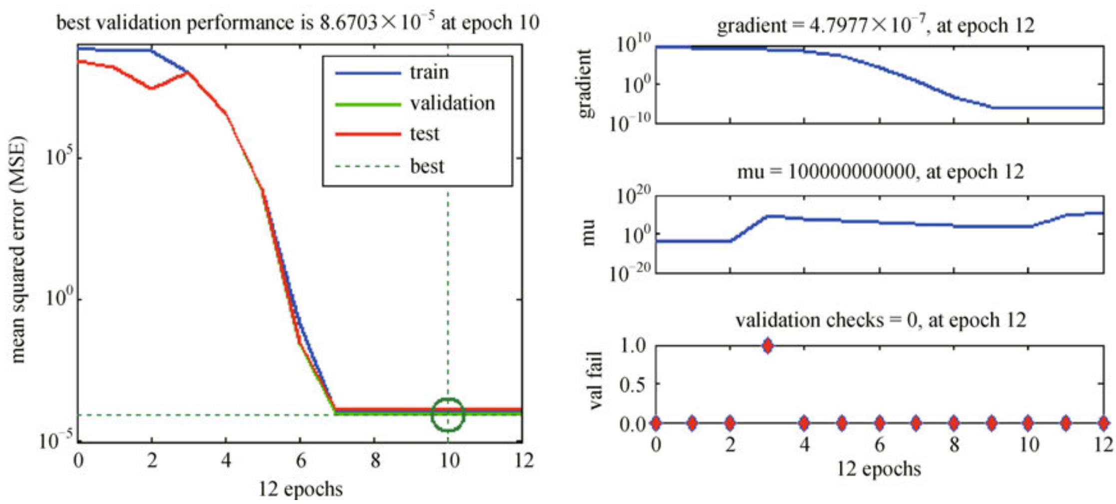

Fig. 8 ANN parameter variation during training

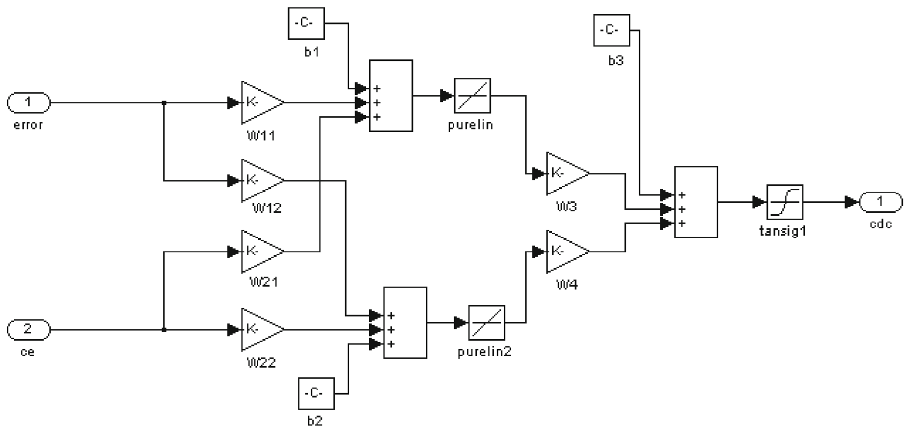

Fig. 9 Structure of the artificial neuron controller using MATLAB

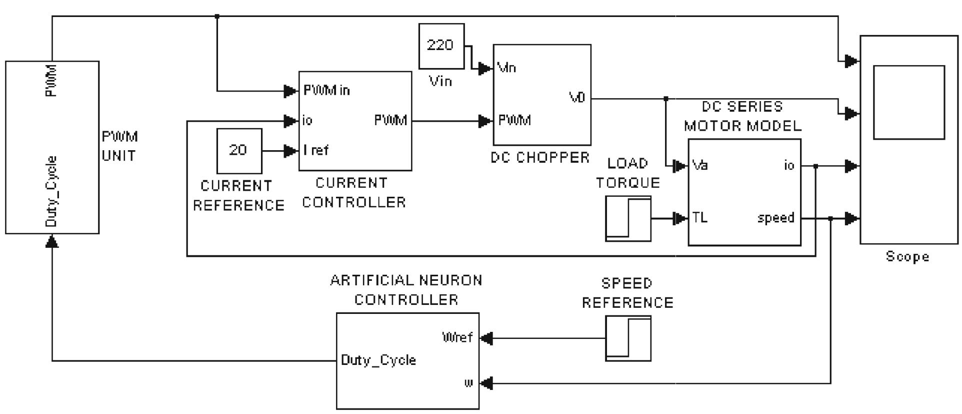

Fig. 10 Simulink model of the proposed system with ANN controller

based ANN speed controller have been simulated using MATLAB simulink. The neuro controller has been designed, and DC-DC converter fed DC series motor performance was tested for the motor specified in Table 3. The simulated waves of gate pulse, output voltage, motor current, and motor speed with respect to time for ω_{ref} = 1800 rpm with 10% load are shown in Fig. 11. The expanded graph in the time interval 1.495 to 1.52 s shows the precise variations of the above parameters.

The motor speed, deflecting torque, and motor current for various set speed changes having 10% load with respect to time response for PID controller and ANN controller are given in Fig. 12. The comparative time domain specifications corresponding to these set speed changes are depicted in Table 4 for both the controllers. From Table 4, it can be seen that the performance of the designed PID controller is fairly good compared with the reported result in Ref. [5].

Table 3 DC motor specifications

DC motor parameters	value
motor rating	5 HP
DC supply voltage	220 V
motor rated current	18 A
inertia constant J	0.0465 $\mathrm{kg\cdot m^2}$
damping constant B	0.005 $\mathrm{N\cdot m\cdot s/rad}$
armature resistance R_a	1 Ω
armature inductance L_a	0.032 H
motor speed	1800 rpm
armature voltage constant K_{af}	0.027 H
residual magnetism voltage constant K_{res}	0.027 $\mathrm{V\cdot s/rad}$

With respect to Table 4, the overall performance of ANN controller is superior comparing with Ref. [5] and the performance of the designed PID controller during set change in the speed. Hence, it is recommended for all modern industrial and engineering DC series motor drive applications.

The motor speed, deflecting torque, and motor current for various load changes at different time intervals with rated speed with respect to time response for PID controller and ANN controller are given in Fig. 13. The comparative time domain specifications corresponding to these load changes are illustrated in Table 5 for both the controllers.

With respect to Table 5, the overall performance of PID-ANN controller is to be evaluated. Up to 25% of load, the maximum speed drop and the recovery time are negligible

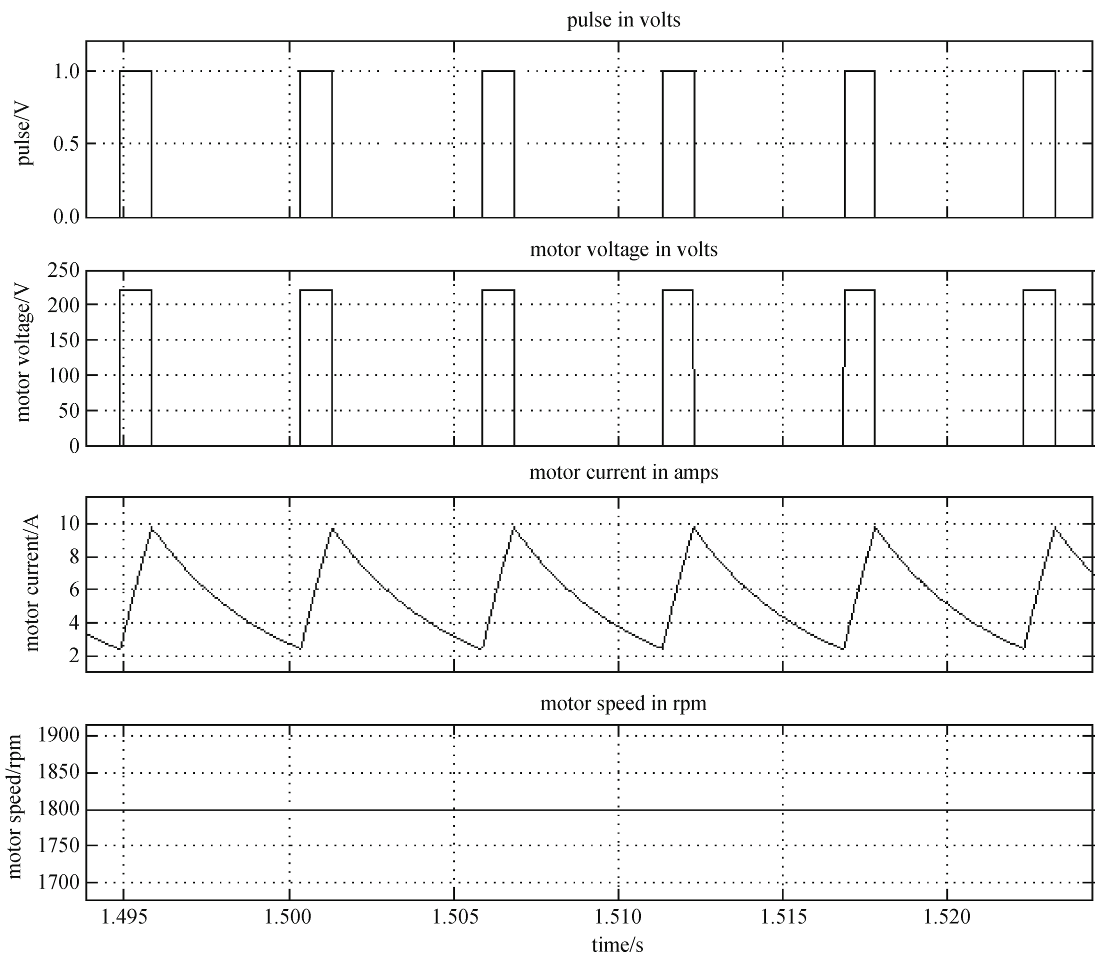

Fig. 11 Pulse, output voltage, motor current, and speed with respect to time

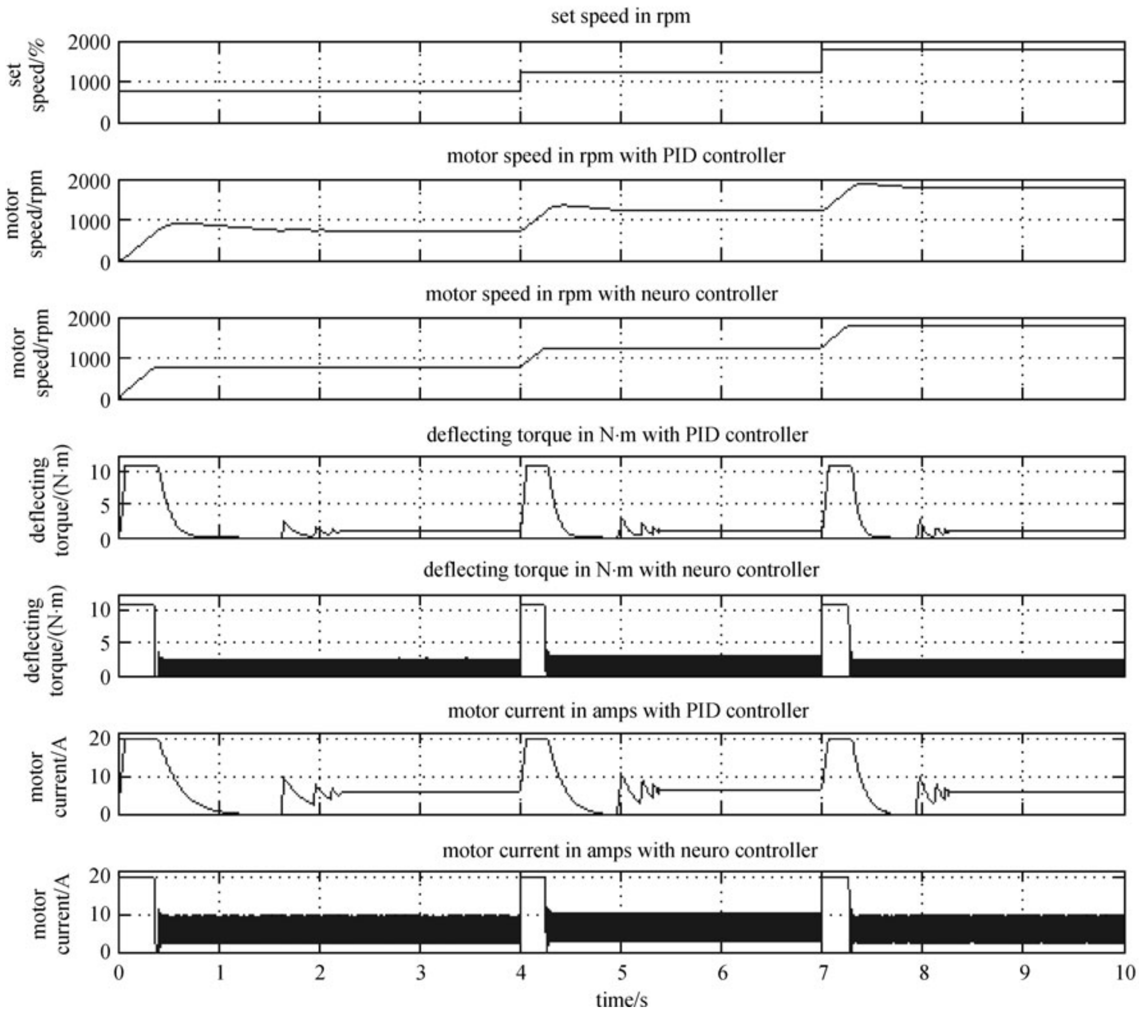

Fig. 12 Performance of controller for speed variation from 750 to 1250 rpm at 4 s and from 1250 to 1800 rpm at 7 s.

Table 4 Time domain specifications of ANN and PID controllers for different set speed changes with 10% load

time domain specifications	set speed change from 0 to 750 rpm		set speed change from 750 to 1250 rpm		set speed change from 1250 to 1800 rpm	
	conventional PID	PID-neuro (proposed system)	conventional PID	PID-neuro (proposed system)	conventional PID	PID-neuro (proposed system)
maximum overshoot/%	8.7	0.31	5.5	0.19	4.3	0.15
settling time/s	2.2	0.4	1.4	0.3	1.2	0.28

in PID-ANN controller. If the load increased from 25% to 100%, its value increased slightly than the conventional PID controller. The steady-state error is also much less in PID-ANN controller than the conventional PID controller. Therefore, the performance of PID-ANN controller is superior comparing with Ref. [5] and the performance of the designed PID controller during load changes from 10% to 100%. Hence, it can be recommended for all modern industrial drive applications using DC series motor.

Figure 14 shows the load variation from 10% to 80% at 4 s for both conventional PID and PID-ANN controllers. It is observed that in conventional PID controller the speed drop is 4% when the load increased from 10% to 80% and it takes 0.4 s. to recover the original speed. In the case of ANN controller the speed drop is negligible for the same case and it recovers the original speed immediately. The time domain performance of set speed change and load disturbance are simulated and compared for both the controllers, as shown in Fig. 15. The set speed is changed from 1000 to 1800 rpm at 4 s. The load disturbance is at 7 s

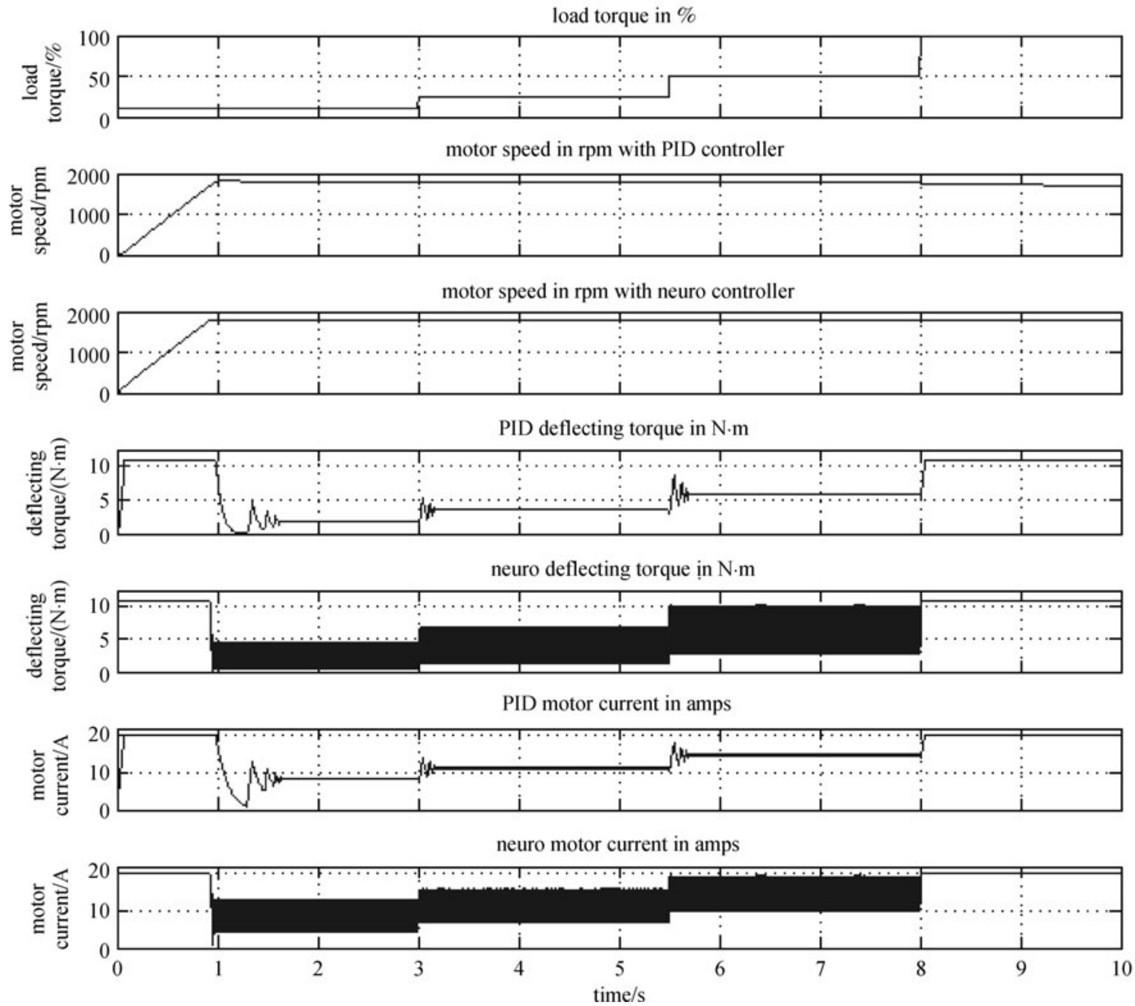

Fig. 13 Performance of controller for load variation from 10% to 25%, 25% to 50%, and 50% to 100% at 3, 5.5, and 8 s, respectively

Table 5 Time domain specifications of ANN and PID controllers for different load changes with rated speed

time domain specifications	load change from 10% to 25%		load change from 25% to 50%		load change from 50% to 100%	
	conventional PID	PID-ANN (proposed system)	conventional PID	PID-ANN (proposed system)	conventional PID	PID-ANN (proposed system)
maximum speed drop/%	0.66	—	1.1	0.02	2.8	0.2
recovery time/s	0.17	—	0.68	0.004	1.3	0.035
steady-state error/rpm	−15	±0.5	−20	±0.4	−36	±0.3

between 10% and 50%. From the simulated result, it is inferred that the PID-ANN controller gives better performance during speed change and load disturbances.

Figure 16 shows the motor current versus deflecting torque characteristic. The curve is the same for both conventional PID controller and PID-ANN controller. The curve departs parabolic nature in the starting stage, then it is linear. It shows the general characteristic of DC series motor.

6 Experimental implementation

The designed controllers were implemented by using an NXP 80C51 based microcontroller (P89V51RD2BN). The DC-DC converter was built with the MOSFET of IRFP450, and the controllers were tested with DC series motor. PWM from the microcontroller was then amplified with an optocoupler CYN 17-1 and fed to the DC-DC power converter through an isolator and driver chip

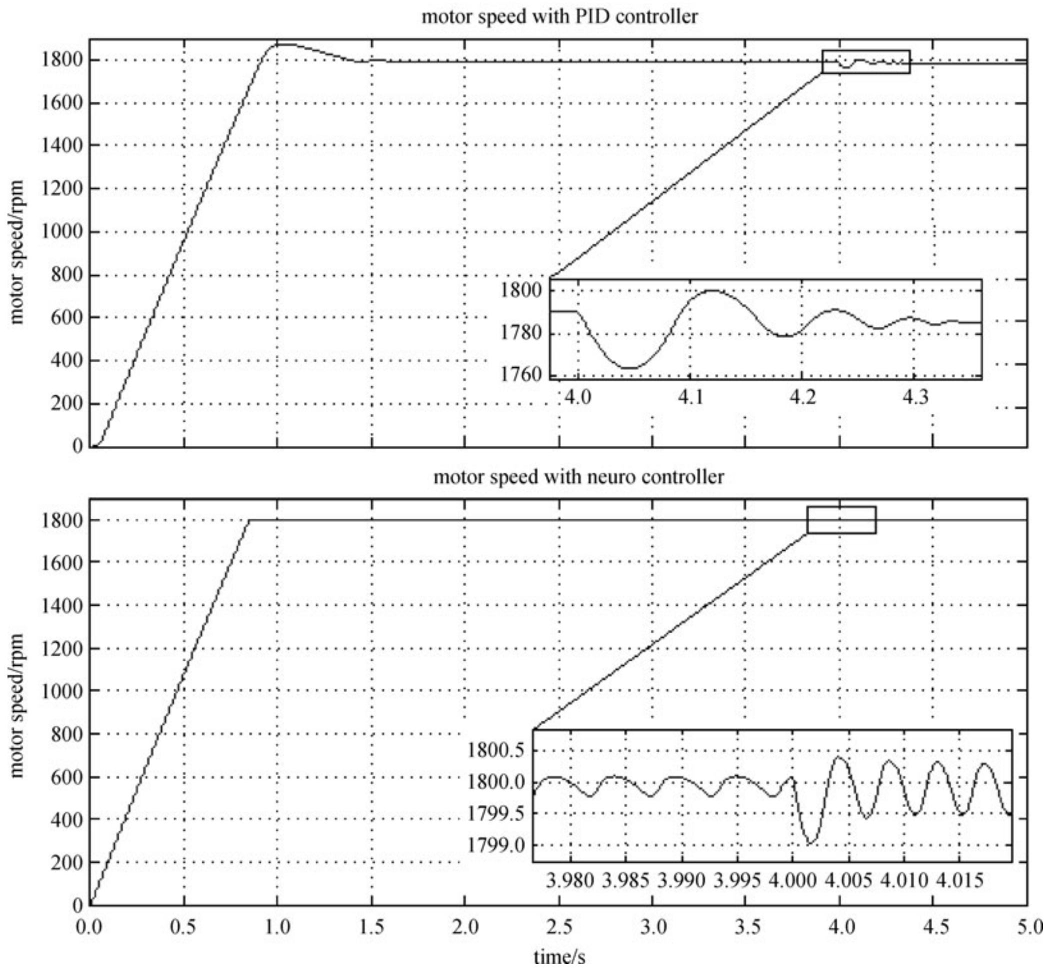

Fig. 14 Load variation form 10% to 80% at 4 s for both controllers

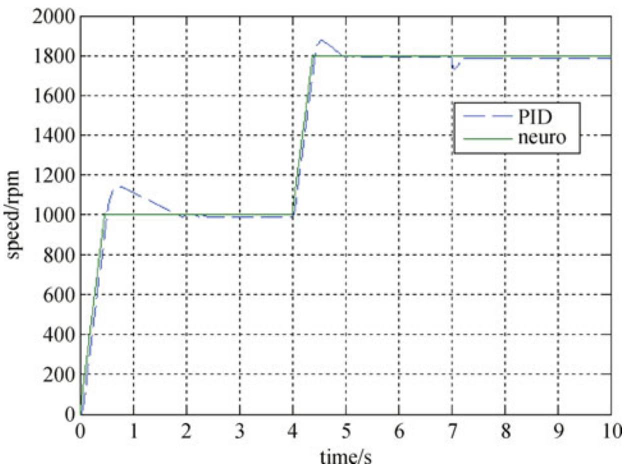

Fig. 15 Controller's performance for speed variation at 4 s and load disturbance at 7 s

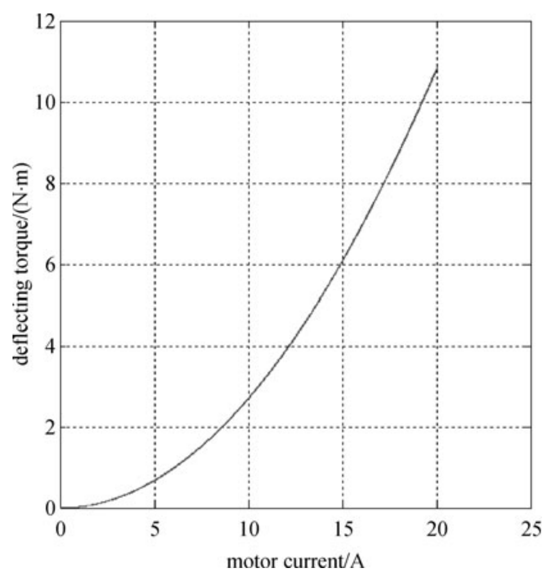

Fig. 16 Deflecting torque with respect to motor current load disturbance

Fig. 17 Experimental graph of speed variation for the step change in reference speed using the conventional PID controller

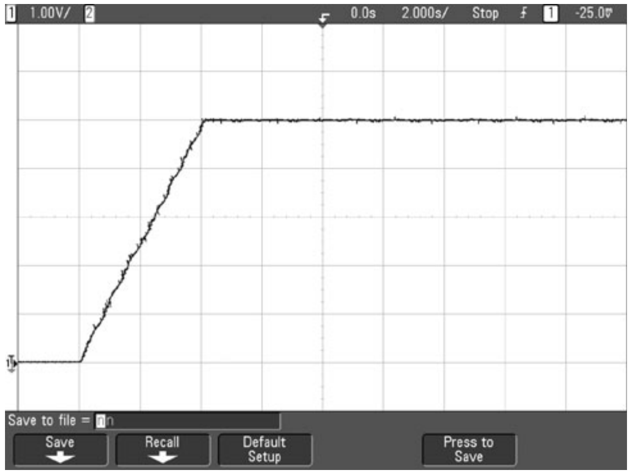

Fig. 18 Experimental graph of speed variation for the step change in reference speed using PID-ANN controller

Table 6 Hardware performance comparison of the proposed system with conventional PID controller for the speed ω_{ref} = 1800 rpm and ΔT_L = 10%

controller	PID		PID-ANN	
	simulation	hardware	simulation	hardware
settling time/s	0.75	10.25	0.5	4
maximum overshoot/%	4.2	5	no overshoot	no overshoot
steady-state error/rpm	−15	−30	±0.5	—

IR2110. The buck converter output was given to the DC series motor whose speed is to be controlled. The speed sensor connected to the motor shaft gives the pulse output which again converted into voltage using f/v converter, and this DC voltage is fed to the ADC available in the microcontroller.

Figure 17 shows the speed response with set speed of 1800 rpm for conventional PID controller, it is taking more time to settle the set speed and also can be seen that it has overshoot present in the waveform due to conventional PID controller and its linear nature. Figure 18 shows the speed response with the set speed of 1800 rpm for PID-ANN controller. From Fig. 18, it is observed that there is no overshoot, no steady-state error, and the settling time also less than the conventional PID controller. Table 6 exposes the hardware performance comparison of the proposed system with conventional PID controller.

7 Conclusion

The performance of the hybrid PID-ANN controlled DC-DC converter fed DC series motor is presented here. The dynamic speed response of DC series motor with PID-ANN controller was estimated for various load disturbances and various speeds, and found that the speed can be controlled effectively. It also verified experimentally that the experimental result also almost follows the simulation results. The hybrid PID-ANN controller gives the proper speed regulation from 10% to 100% load disturbance. Here, the PID-ANN controller reduces the computational time. Also, the memory required for the program is reduced. The implementation cost also reduced due to the availability of low cost microcontrollers. The analysis provides the various useful parameters and the information for effective use of the proposed system.

References

1. Bose B K. Power electronics and motor drives-recent technology advances. In: Proceedings of the IEEE International Symposium on Industrial Electronics (ISIE 2002). 2002, 1: 22–25
2. Krein P T. Elements of Power Electronics. Oxford University Press, 1998
3. Zurada J M. Introduction to Artificial Neural Systems. Jaico Publishing House, 1992
4. MATLAB. Neural Network Tool Box User's Guide. Version 3. The Mathworks Inc.
5. Yousef H A, Khalil H M. A fuzzy logic-based control of series DC motor drives. In: Proceedings of the IEEE International Symposium on Industrial Electronics (ISIE 1995). 1995, 2: 517–522
6. Senthil Kumar N, Sadasivam V, Asan Sukriya H M, Balakrishnan S. Design of low cost universal artificial neuron controller for chopper

fed embedded DC drives. Applied Soft Computing, 2008, 8(4): 1637–1642

7. Yildiz A B, Zeki Bilgin M. Speed control of averaged DC motor drive system by using neuro-PID controller. Lecture Notes in Computer Science, 2006, 4251: 1075–1082
8. Buja G S, Todesco F. Neural network implementation of a fuzzy logic controller. IEEE Transactions on Industrial Electronics, 1994, 41(6): 663–665
9. Senthil Kumar N, Sadasivam V, Muruganandam M. A low-cost four-quadrant chopper-fed embedded DC drive using fuzzy controller. Electric Power Components and Systems, 2007, 35(8): 907–920
10. Muruganandam M, Madheswaran M. Performance analysis of fuzzy logic controller based DC-DC converter fed DC series motor. In: Proceedings of Chinese Control and Decision Conference (CCDC 2009). 2009, 1635–1640
11. Muruganandam M, Madheswaran M. Modeling and simulation of modified fuzzy logic controller for various types of DC motor drives. In: Proceedings of 2009 International Conference on Control, Automation, Communication and Energy Conservation. 2009, 1–6
12. Yuan X F, Wang Y N. Neural networks based self-learning PID control of electronic throttle. Nonlinear Dynamics, 2009, 55(4): 385–393
13. Bilgin M Z, Çakir B. Neuro-PID position controller design for permanent magnet synchronous motor. Lecture Notes in Computer Science, 2006, 4221: 418–426
14. Barsoum N. Artificial neuron controller for DC drive. In: Proceedings of IEEE Power Engineering Society Winter Meeting. 2000, 398–402
15. Ismail A, Sharaf A M. An efficient neuro-fuzzy speed controller for large industrial DC motor. In: Proceedings of the 2002 International Conference on Control Applications. 2002, 2: 1027–1031
16. Gencer C, Saygin A, Coskun I. DSP based fuzzy-neural speed tracking control of brushless DC motor. Lecture Notes in Computer Science, 2006, 3949: 107–116
17. Senthil Kumar N, Sadasivam V, 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, 2008, 36(7): 680–695
18. Rubaai A, Kotaru R. Online identification and control of a DC motor using learning adaptation of neural networks. IEEE Transactions on Industry Applications, 2000, 36(3): 935–942
19. Fallahi M, Azadi S. Adaptive control of a DC motor using neural network sliding mode control. In: Proceedings of the International MultiConference of Engineers and Computer Scientists (IMECS 2009). 2009, 1–5
20. Cho Y I. Development of a new neuro-fuzzy hybrid system. In: Proceedings of the 30th Annual Conference of IEEE Industrial Electronics Society. 2004, 3: 3184–3189
21. Meireles M R G, Almeida P E M, Simoes M G. A comprehensive review for industrial applicability of artificial neural networks. IEEE Transactions on Industrial Electronics, 2003, 50(3): 585–601
22. Rubaai A, Castro-Sitiriche M J, Garuba M, Burge L. Implementation of artificial neural network-based tracking controller for high-performance stepper motor drives. IEEE Transactions on Industrial Electronics, 2007, 54(1): 218–227
23. Baruch I S, Garrido R, Flores J M, Martinez J C. An adaptive neural control of a DC motor. In: Proceedings of the 2001 IEEE International Symposium on Intelligent Control (ISIC'01). 2001, 121–126
24. Kang Y H, Kim L K. Design of neuro-fuzzy controller for the speed control of a DC servo motor. In: Proceedings of the Fifth International Conference on Electrical Machines and Systems (ICEMS 2001). 2001, 2: 731–734
25. Meireles M R G, Almeida P E M, Simoes M G. A comprehensive review for industrial applicability of artificial neural networks. IEEE Transactions on Industrial Electronics, 2003, 50(3): 585–601