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Design of Nonlinear PID Neural Controller for the Speed Control of a Permanent Magnet DC Motor Model based on Optimization Algorithm

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Abstract

In this paper, the speed control of the real DC motor is experimentally investigated using nonlinear PID neural network controller. As a simple and fast tuning algorithm, two optimization techniques are used; trial and error method and particle swarm optimization PSO algorithm in order to tune the nonlinear PID neural controller's parameters and to find best speed response of the DC motor. To save time in the real system, a Matlab simulation package is used to carry out these algorithms to tune and find the best values of the nonlinear PID parameters. Then these parameters are used in the designed real time nonlinear PID controller system based on LabVIEW package. Simulation and experimental results are compared with each other and showed the effectiveness of the proposed control algorithm in terms of fast and smooth dynamic response for the speed control of the real DC motor.

Keywords: *Nonlinear PID Controller, DC Motor, Particle Swarm Optimization, Neural Networks, MATLAB, LabVIEW.*

1. Introduction

Direct current (DC) motors have been widely used in many industrial applications such as electric vehicles, steel rolling mills, electric cranes, fans, pumps, hoists, printing presses and robotic manipulators due to precise, wide, simple and continuous control characteristics based armature control method for the speed control [1].

Many industrial applications use PID control to maintain constant process variable. The output of PID controllers (Proportional- Integrative-Derivative controllers) is a linear combination of the input, the derivative of the input and the integral of the input therefore it is widely used and enjoys significant popularity, because of its simplicity, effectiveness and robustness [2].

However, PID controller is sensitive to plant parameter variations and the controller gains must be carefully selected for a desired response. In order to overcome these problems, many control techniques, include the adaptive control, variable structure control and robust control have been applied in DC motor speed [3].

Several years ago, the neural networks are used in a speed control loop applied to a DC motor and the learning capability of neural networks implemented an auto-adaptive control structure to learn the dynamic behavior of the Silicon-Controlled Rectifier (SCR)-driven DC motor [4].

A novel improved PID algorithm based on recurrent wavelet neural network was proposed in [5], which combines the capability of artificial neural networks for learning the process and the capability of wavelet decomposition for identification and control of dynamic systems.

In [6] a novel adaptive neuro-fuzzy controller was applied on transverse flux linear motor for controlling its speed where the proposed controller presented Fuzzy Logic Controller (FLC) with self tuning scaling factors based on artificial neural network structure.

Also, a direct nonlinear adaptive state regulator was derived based on dynamic neural networks and it was applied to control the speed of a nonlinearized DC motor and the control algorithm was that it covers the situation where the magnetic flux continuously varies was presented in [7].

In addition to that, DC series motors were preferred for mechatronic applications requiring high torque/speed ratios. The design and implementation of an open loop DC motor speed control that was based on a micro-controller and Insulated-Gate_Bipolar_Transistor (IGBT) drive stage that can predict the dynamic behavior of systems consisting of mechanical and electronic modules was very desirable as explained in [8].

There is other technique for speed control of the DC motor, a new method of tuning Proportional Integral (PI) coefficients for a permanent magnet DC motor drives was explained in [9], where artificial neural network was used to identify the whole system using maximum overshoot and settling time.

The fundamental essence of the motivation of this work is that the tuning of the nonlinear PID controller in the real time requires a great effort and needs more time; therefore, the nonlinear PID controller is first carried out using the Matlab simulation package which is very time saving and gives close parameter approximation for application in the real time system based on LabVIEW package at the end.

In this paper, experimental investigation is carried out for the appropriate tuning parameters of the nonlinear PID neural controller that controls the speed of a DC motor using two techniques: trial and error method and PSO to obtain the best speed response achievable based on a Matlab simulation package. These parameters are then applied in the designed real time nonlinear PID controller based on LabVIEW package and the results obtained are compared against those of the simulation.

The remainder of this paper is organized as follows: section two, describes the mathematical model of the DC motor speed system. In section three, the proposed nonlinear PID neural controller approach and tuning algorithm are derived. The simulation results (MATLAB) of the proposed controller are presented in section four. Hardware design and real time results based on LabVIEW package are presented in section five and the conclusions are drawn in section six.

2. Permanent Magnet DC Motor Model

A permanent magnet DC motor model can be derived using the linear dynamic equations with a two mass model equivalent system [10]:

$$v_a = R_a i_a + L_a \frac{di_a}{dt} + K_b \omega_m \qquad \ldots(1)$$

$$J_m \frac{dw_m}{dt} + B_m \omega_m = \tau_m = K_t i_a \qquad \ldots(2)$$

where

R_a, L_a, K_b, K_t are the DC motor parameters.

v_a, i_a are the DC motor voltage and current respectively.

ω_m is motor speed.

τ_m the motor torque.

J_m the motor inertia.

B_m the damping coefficient.

By taking the Laplace transformation of the equations (1 and 2).

$$V_a(s) = R_a I_a(s) + L_a S I_a(s) + K_b \omega_m(s) \qquad \ldots(3)$$

where

$K_b \omega_m(s)$ is e.m.f.

$$V_a(s) - K_b \omega_m(s) = I_a(s)(R_a + L_a S) \qquad \ldots(4)$$

$$J_m S \omega_m(s) + B_m \omega_m(s) = \tau_m(s) = K_t I_a(s) \qquad \ldots(5)$$

$$\omega_m(s)(J_m S + B_m) = \tau_m(s) \qquad \ldots(6)$$

The block diagram of the DC motor model is shown in Fig. 1.

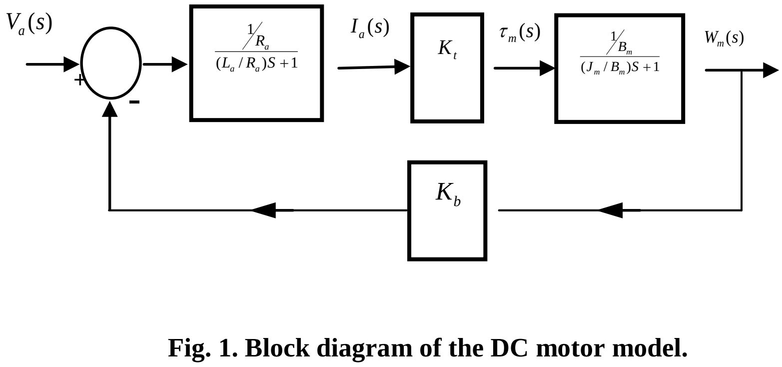

Fig. 1. Block diagram of the DC motor model.

The parameters of the permanent magnet DC motor implemented in the designed system are shown in Table (1) [11].

Table 1,
Parameters of the DC motor.

Real Parameter of DC Motor	**Values**
Armature Resistance R_a	0.56 Ω
Armature Inductance L_a	0.023H
Inertia Constant J	0.083 Nm/(rad/s^2)
Damping Constant B	0.006 Nm/(rad/s)
Torque Constant K_t	0.43 Nm/A
Back emf Constant K_b	0.43 V/(rad/sec)
Speed	250 rpm or 26 rad/sec
DC supply	12 volt
Armature Current i_a	0.4 A

3. Control Methodology Based on Optimization Algorithms

The feedback PID neural controller is very important because it is necessary to stabilize the tracking error of the DC motor speed when the speed of the DC motor is drifted from the desired speed.

The proposed structure of the nonlinear PID neural controller can be given in the form of block diagram, as shown in Fig. 2. The trial and error method and particle swarm optimization will generate the optimal parameters for the nonlinear PID neural controller in order to obtain best control signal that will minimize the tracking error of the DC motor speed.

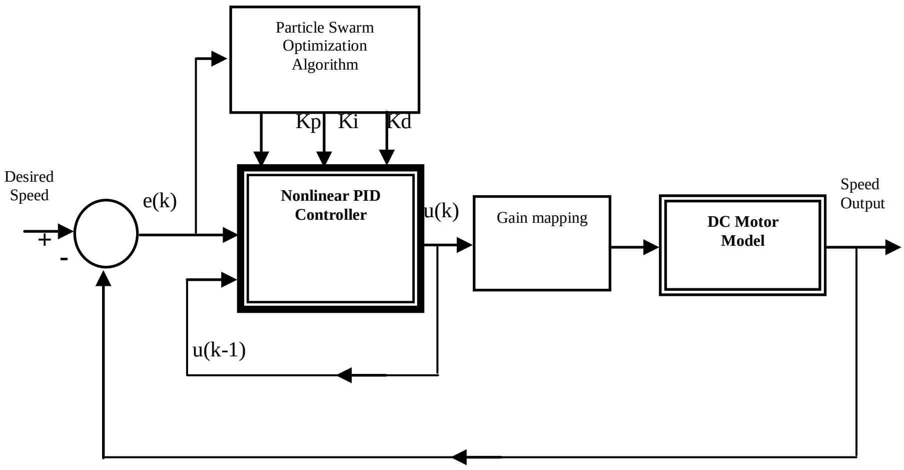

Fig. 2. The proposed block diagram of nonlinear PID Controller.

The proposed nonlinear PID neural controller has the characteristics of control agility, strong adaptability, good dynamic characteristic and robustness because it is based on a conventional PID controller that consists of three terms: proportional, integral and derivative where the standard form of a PID controller is given in the s-domain as equation (7) [12].

$$Gc(s) = P + I + D = K_p + \frac{K_i}{s} + K_d s \qquad \ldots(7)$$

where K_p, K_i and K_d are called the proportional gain, the integral gain and the derivative gain respectively.

The proposed nonlinear PID neural controller scheme is based on the discrete-time PID as equation (8).

$$u(k) = u(k-1) + Kp[e(k) - e(k-1)] + Ki[e(k)] + Kd[e(k) - 2e(k-1) + e(k-2)] \qquad \ldots(8)$$

Therefore, the tuning PID input vector consists of $e(k)$, $e(k-1)$, $e(k-2)$ and $u(k-1)$, where $e(k)$ and $u(k-1)$ denote the input error signals and the PID output signal respectively.

The nonlinear PID neural controller for speed of DC motor system can be shown in Fig. 3.

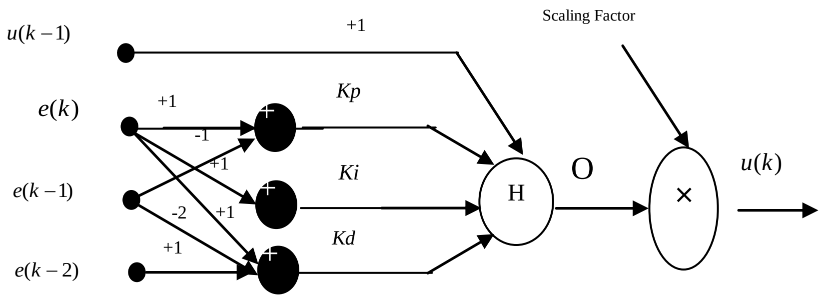

Fig. 3. The nonlinear PID neural feedback controller structure.

The proposed control law of the feedback control signal (u) can be proposed as follows:

$$u(k) = 5O \quad \ldots(9)$$

o is the output of the neural network that can be obtained from non-linear sigmoid activation function and multiple by scaling factor that is equal to 5. The nonlinear relationship of the sigmoid function can be presented in the following equation:

$$o = \frac{2}{1+e^{-net}} - 1 \quad \ldots(10)$$

net is calculated from this equation:

$$net(k) = Kp[e(k) - e(k-1)] + Kie(k) + Kd[e(k) - 2e(k-1) + e(k-2)] \quad \ldots(11)$$

The control parameters Kp, Ki and Kd of the nonlinear PID neural controller are adjusted using trial and error method and particle swarm optimization.

3.1. Learning Particle Swarm Optimization Algorithm

Particle Swarm optimization (PSO) is a kind of algorithm to search for the best solution by simulating the movement and flocking of birds. PSO algorithms use a population of individual (called particles) "flies" over the solution space in search for the optimal solution [13].

Each particle has its own position and velocity to move around the search space. The particles are evaluated using a fitness function to see how close they are to the optimal solution [14]. The previous best value is called as *pbest*. Thus, *pbest* is related only to a particular particle. It also has another value called *gbest*, which is the best value of all the particles *pbest* in the swarm.

The nonlinear PID neural controller with nine weights parameters and the matrix is rewritten as an array to form a particle. Particles are then initialized randomly and updated afterwards according to equations (12, 13, 14, 15, 16 and 17) in order to tune the PID parameters:

$$\Delta Kp_m^{k+1} = \Omega(\Delta Kp_m^k) + c_1 r_1 (pbest_m^k - Kp_m^k) + c_2 r_2 (gbest^k - Kp_m^k) \quad \ldots(12)$$

$$Kp_m^{k+1} = Kp_m^k + \Delta Kp_m^{k+1} \quad \ldots(13)$$

$$\Delta Ki_m^{k+1} = \Omega(\Delta Ki_m^k) + c_1 r_1 (pbest_m^k - Ki_m^k) + c_2 r_2 (gbest^k - Ki_m^k) \quad \ldots(14)$$

$$Ki_m^{k+1} = Ki_m^k + \Delta Ki_m^{k+1} \quad \ldots(15)$$

$$\Delta Kd_m^{k+1} = \Omega(\Delta Kd_m^k) + c_1 r_1 (pbest_m^k - Kd_m^k) + c_2 r_2 (gbest^k - Kd_m^k) \quad \ldots(16)$$

$$Kd_m^{k+1} = Kd_m^k + \Delta Kd_m^{k+1} \quad \ldots(17)$$

$$m = 1,2,3,.....pop$$

where
pop is number of particles.
K_m^k is the weight of particle *m* at k^{th} iteration.
c_1 and c_2 are the acceleration constants with positive values equal to 1.55.
r_1 and r_2 are random numbers between 0 and 1.
$pbest_m$ is best previous weight of m^{th} particle.
$gbest$ is best particle among all the particle in the population.
Ω is the inertia weight factor and it is equal to 0.75.

Mean square error (MSE) function for DC motor speed system is chosen as criterion for estimating the model performance and an objective function to be minimized as equation (18):

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(desiredSpeed(j) - SpeedOutput(j))^2 \quad \ldots(18)$$

where N is the number of samples and equal to 1000.

The number of dimension in particle swarm optimization is equal to three because the nonlinear PID has three parameters. The mean square error function is chosen as criterion for estimating the model performance as in equation (18).

The steps of PSO for nonlinear PID neural controller can be described as follows:

Step1 Initial searching points $Kp^0, Ki^0, Kd^0, \Delta Kp^0, \Delta Ki^0$ and ΔKd^0 of each particle are usually generated randomly within the allowable range. Note that the dimension of search space consists of all the parameters used in the nonlinear PID neural controller, as shown in Fig. 2. The current searching point is set to *pbest* for each particle. The best-evaluated value of *pbest* is set to *gbest* and the particle number with the best value is stored.

Step2 The objective function value is calculated for each particle by using equation (18). If the value is better than the current *pbest* of the particle, the *pbest* value is replaced by the current value. If the best value of *pbest* is better than the current *gbest*, *gbest* is replaced by the best value and the particle number with the best value is stored.

Step3 The current searching point of each particle is updated using equations (12, 13, 14, 15, 16 and 17).

Step4 If the current iteration number reaches the predetermined maximum iteration number, then exit. Otherwise, return to step 2.

4. Simulation Results

This section discusses the mapping between the real process and the simulation carried out using Matlab package. The proposed nonlinear PID neural controller in conjunction with the input voltage to the DC motor unit which has a linear relationship with saturation transfer function has a slope equal to (12/5). This slope is used as a mapping gain to limit the motor drive voltage to 12Volts which is chosen in accordance with the DC motor modeling description.

To investigate the open loop response of the DC motor system, the open loop step response of the speed of the DC motor is shown in Fig. 4. When applying a step change in the input voltage of the motor equal to (0.438) volt, it will increase the motor speed by 1 rad/sec with reference to its speed at the initial condition which is equal to zero rad/sec. The settling time for the speed of the DC motor is equal to 1.2sec and the time constant is equal to 0.082sec. Therefore the sampling interval for the DC motor speed control is chosen to be 0.01sec using Shannon theory.

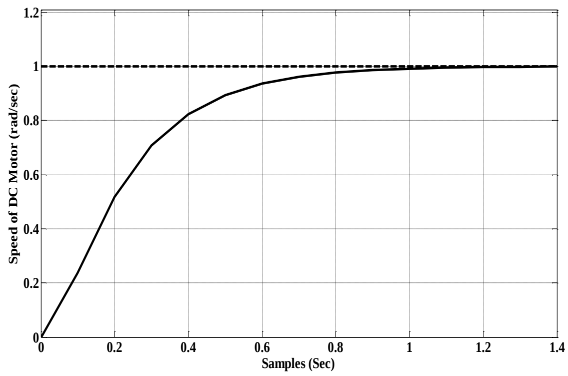

Fig. 4. Step response of open loop DC motor system.

The proposed nonlinear PID neural controller scheme as in Fig. 2, is applied to the DC motor model and it used two algorithms for tuning the parameters of the controller; first algorithm is trial and error method where executing many trial runs to find the well system response by varying the parameters of the PID controller and it has taken a long time to produce the achievable system response. But the second algorithm is PSO and applying the steps of the proposed learning algorithm for tuning PID controller's parameters to find the best system response at only one run where the PSO algorithm is set to the following parameters:

Population of particle is equal to 25.

Number of iteration is equal to 100.

Number of weight in each particle is equal to 3 because there are three parameters of PID controller.

The nonlinear PID neural controller parameters that are obtained from the simulation package that give the best system responses are shown in table (2).

Table 2,
PID controller parameters.

Tuning Algorithm	K_P	K_I	K_D
Trial and Error	35	2.1	3.2
PSO	42.8047	1.6147	0.9996

From the simulation results, the closed loop time response of the DC motor speed control system with nonlinear PID neural controller based on PSO algorithm is illustrated in Figs. 5a, 5b and 5c for the initial speed of zero rad/sec.

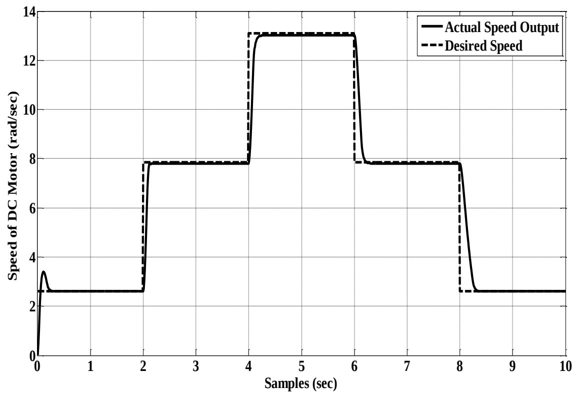

Fig. 5a. The speed output of the DC motor.

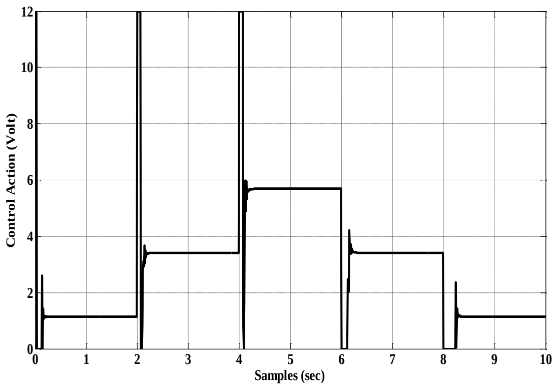

Fig. 5b. The control action.

Figure 5a shows the response of the DC motor speed output to a steps change, it had small over shoot at first step (2.82) rad/sec and no over shoots in the other steps as well as the steady-state error is equal to zero in each steps when the desired change in speed is (25, 75, 125, 75 and 25) r.p.m as (2.84, 8.52, 14.2, 8.52 and 2.84) rad/sec respectively.

The nonlinear PID neural control action response is shown in Fig. 5b that it had few spikes in response to the desired step change in motor speed with very small oscillation in order to keep the speed output of the DC motor within desired range.

The error between the desired speed and the actual speed output of the DC motor is shown in Fig. 5c and it is very small in the transient and becomes very close to zero in steady state.

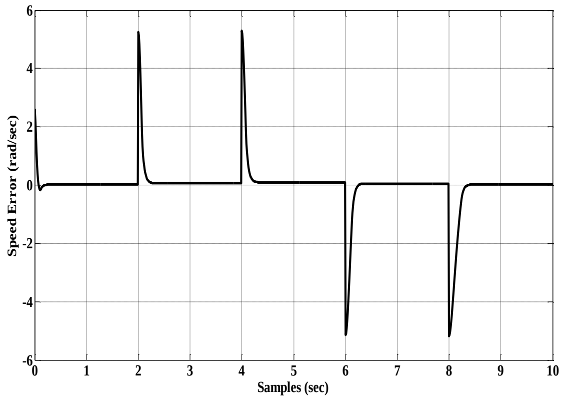

Fig. 5c. The speed error.

The fundamental essence for applying the proposed control algorithm based on PSO is to minimize the tracking speed error and to obtain smoothness of the control signal in comparison with trial and error method in terms of time saving and obtaining an optimal control parameters of the nonlinear PID neural controller with best speed response.

5. Hardware Design and Real Time Results

In this section, the experimental setup for the real-time speed control of the DC motor is shown in Fig. 6. The setup consists of:

- The permanent magnet DC motor and DC Tacho generator with a sensitivity figure equal to 20mV/rad/sec. The motor has a speed range of operation "0 rad/sec to 26 rad/sec".
- DC power supply that provides power to the motor and the rest of the circuitry.
- The data acquisition device from National Instrument NI Company.
- Motor drive board based on LM324 operational amplifiers.

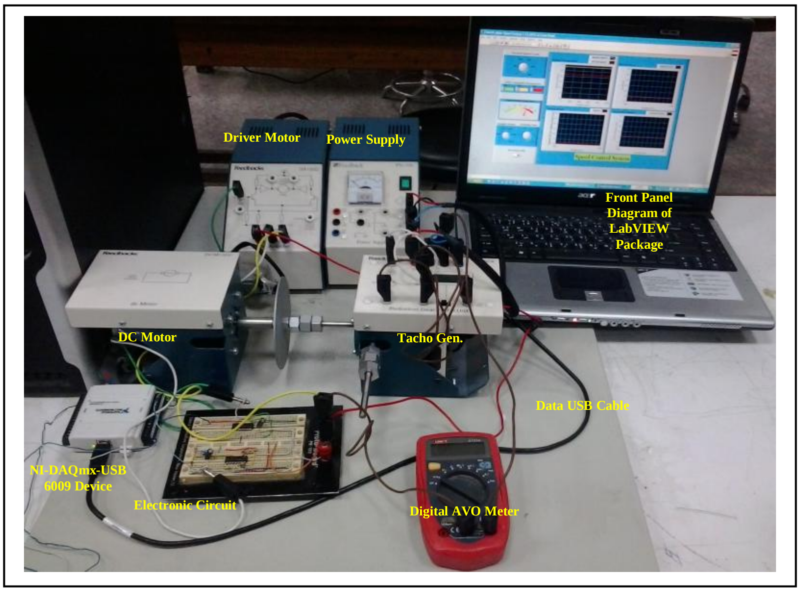

Fig. 6. The experimental work in the real-time speed control.

In the real time computer control system based on LabVIEW package, the fine tuned parameters of the nonlinear PID neural controller that have been obtained from the simulation based on PSO algorithm are applied in the real time computer controller with sampling time equal to 0.01sec. The computer code and front panel diagram of the control algorithm have been written in the LabVIEW, as shown in Fig. 7.

a

b

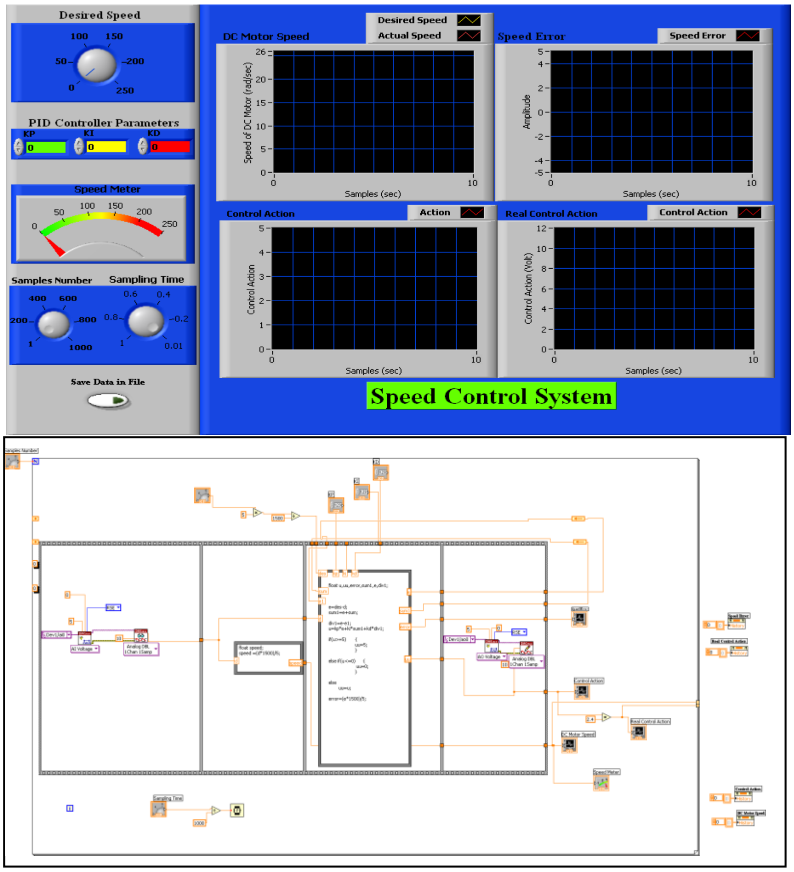

Fig. 7. LabVIEW control algorithm (a) Front panel diagram; (b) Computer code program.

Figure 8 shows the electronic circuit diagram design for the speed control system and it consists of multi-stage as follows: the first stage is signal conditioning circuit that includes a voltage follower with unity gain to avoid the attenuation in the feedback signal of the Tacho generator and the first order low pass filter stage that has a cutoff frequency of 10Hz which will remove noise components possible to occur in the sensor outputs especially within mains supply frequency at 50Hz. This filter removes noise components within mains frequency effectively from the Tacho generator output prior to delivering it to the level conditioning amplifier with unity gain. This amplifier is built using LM324 quad operational amplifier [15].

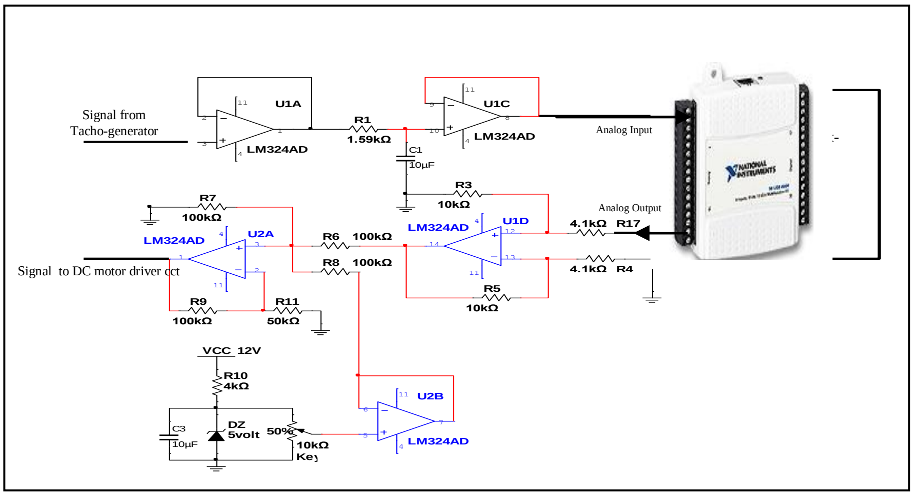

Fig. 8. The schematic diagram of the electronic control circuit.

The output of this amplifier is fed to the analog to digital converter ADC 14 bit high speed low power successive approximation converter of the NI-DAQmx-USB 6009 device with range of input voltage from 0 to 5 volt as second stage.

Inside the personal computer, LabVIEW software instructions compares the sensed speed signal received via this interface with the set point desired speed. The resulting error is given as an input to the nonlinear PID neural controller that has been built in the LabVIEW package.

The nonlinear PID neural controller attempts to reduce the error to zero by changing the control action “input voltage to the DC motor” which is in the form of real data varying within "0 to 5". These data are sent to the motor drive electronics through the USB connector to digital to analog converter DAC 12 bit of the NI-DAQmx-USB 6009 device with range of output voltage from 0 to 5 volt as third stage. The output of this DAC is sent to an op-amp based amplifier that has a gain of "2.4" as fourth stage.

This amplifier is also built using LM324 operational amplifier. To remove the nonlinear effect “dead zone” in the modeling of the DC motor system, a small dc drive voltage is added to the motor in order to minimize its effect as shown in the motor drive electronic circuit design in the fifth stage.

The output of this amplifier is fed to the motor drive stage to furnish the final output required to drive the DC motor as sixth stage. The motor accepts drive voltages ranging from "0V to 12V" which will drive the motor through the speed range of "0 rad/sec to 26 rad/sec".

The speed response of the DC motor in real time is shown in Fig.9a. It can be seen that it is a fast response with oscillation output value in the range of ($\pm 0.02(rad/\sec)$).

The response of the feedback nonlinear PID neural control action is shown in Fig. 9b. It has many spikes during the step change in the desired speed and a small oscillation can also be observed. This action of the controller has kept the speed of the DC motor within the desired value with minimum tracking speed error.

The tracking error between the desired speed and the actual speed output of the DC motor which was very small in the transient state and had steady state value equal to $\pm 0.02(rad/\sec)$), is shown in Fig. 9c.

In fact, there are small differences in results between the real time control action and the simulation control action because in the real time there were accumulation errors such as undesirable characteristics of speed sensor (tacho generator) "non-linearity, drift, and offset", offset in the operational amplifier output, and the quantization error of the analog to digital and digital to analogue converters; therefore, the results in the real time have small oscillation in the actual speed output of the DC motor as it is equal to $\pm 0.02(rad/\sec)$.

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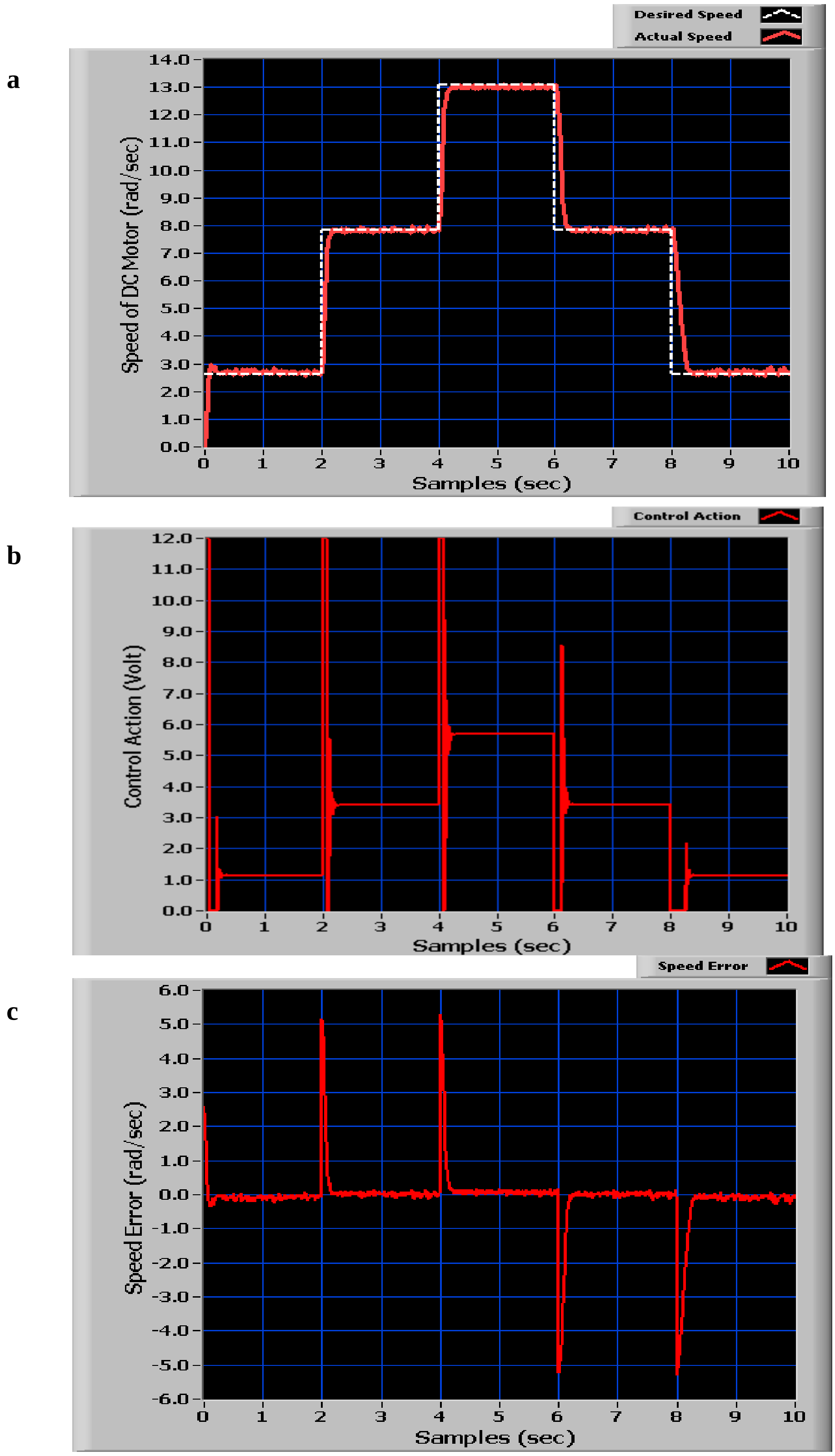

Fig. 9. (a) Actual speed of DC motor; (b) Actual control action; (c) Speed error of DC motor.

6. Conclusions

Nonlinear PID neural speed control methodology for the permanent magnet DC motor model has been presented in this paper. It has been designed and tested using Matlab package and carried out on real DC motor using LabVIEW package.

Simulation results and real time computer control results show evidently that the proposed nonlinear PID neural controller model has demonstrated the capability of tracking desired speed and effective minimization of the tracking speed errors of the real DC motor model as well as it has the capability of generating smooth and suitable voltage control action

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تصميم مسيطر عصبي تناسبي تكاملي تفاضلي لاخطي للسيطرة على سرعة محرك تيار مستمر ثابت المغناطيسية مبنيا على أساس الخوارزمية الأمثلية

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الخلاصة

في هذا البحث تمت السيطرة على سرعة المحرك التيار المستمر بشكل تجريبي باستخدام المسيطر العصبي التناسبي التكاملي التفاضلي اللاخطي. تم استخدام طريقة التجربة والخطأ وتقنية حشد الجسيمات الأمثلية لسهولة وسرعة تنغيم عناصر المسيطر العصبي التناسبي التكاملي التفاضلي اللاخطي لإيجاد أفضل استجابة لسرعة المحرك التيار المستمر.

لتوفير الزمن في النظام الحقيقي, تم استخدام الحقيبة البرمجية (Matlab) لتنفيذ خوارزمية التنغيم لعناصر المسيطر اللاخطي وبعد ذلك تم استخدام هذه العناصر في تصميم المسيطر اللاخطي للنظام في الزمن الحقيقي باستخدام الحقيبة البرمجية (LabVIEW).

لقد تم مقارنة نتائج المحاكاة مع النتائج التجريبية وتبين كفاءة تأثير الخوارزمية المسيطر المقترح من حيث سرعة ونعومة الاستجابة لسرعة المحرك التيار المستمر الحقيقي.