High Performance of Nonlinear DC Motor Speed Control using Backpropagation Neural Network

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Abstract— Conventional PID of controllers for nonlinier DC motors have poor performance when changes of the motor or load dynamics take place. To make improve the performance, an adaptive neural speed controller of a nonlinier dc motor is proposed. BackPropagation neural network (BPNN) is used to appoximate the unknown dynamics. BPNN is trained by the online backpropagation algorithm. The output of the BPNN gives the control voltage applied to the dc motor. The difference between the reference and the actual rotor speed of the nonlinier motor is backpropagated through the BPNN at each step of the control process for updating the connection weights of the BPNN. The control scheme requires neither a knowledge of any motor parameters, nor preferential training of the BPNN. The performance of the controller is simulated and then it is compared with conventional controller or PID in fluctuation disturbance.

Keywords-component; Nonlinier DC Motor; BPNN;

I. INTRODUCTION

DC motors are widely used in industrial systems, such as robotic manipulators, because their control is relatively simple and they are reliable for a wide range of operating conditions. DC motors are usually modelled as linear systems and then linear control approaches are implemented. However, most linear controllers have unsatisfactory performance due to changes of the motor/load dynamics and due to nonlinearities introduced by the armature reaction. Neglecting the impact of external disturbances and of nonlinearities may risk the stability of the closed-loop system. For the aforementioned reasons DC motor control based on conventional PID or model based feedback controllers can be inadequate and more effective control approaches are needed. If the nonlinearities of the motor are known functions, then adaptive tracking control methods with the technique of input–output linearization can be used [1,2]. However, when these nonlinearities or disturbances are unknown, neural or fuzzy control is more suitable for succeeding satisfactory performance of the closed-loop system [3–7]. Results on the successful application of neural identification and control to dc motor drives have been given in [8–10], were neural network controllers for a dc motor were introduced. the unknown nonlinear dynamics of the motor and the external load torque were approximated by a multi-layer neural network.

This paper proposes a method for the control of DC motors, To make high performance an adaptive neural speed controller of a nonlinier dc motor is proposed. The Back Propagation neural network (BPNN) is used to appoximate the unknown dynamics. BPNN is trained by the online backpropagation algorithm. The output of the BPNN gives the control voltage applied to the dc motor. The difference between the reference and the actual rotor speed of the nonlinier motor is back propagated through the BPNN at each step of the control process for updating the connection weights of the BPNN. The control scheme requires neither a knowledge of any motor parameters, nor preferential training of the BPNN. The performance of the controller is simulated and then it is compared with conventional control or PID in fluctuation disturbance.

II. THE DC MOTOR MODEL

A direct current (DC) motor model converts electrical energy into mechanical energy. There are two main ways in controlling a DC motor: the first one named *armature control* consists of maintaining the stator magnetic flux constant, and varying (use as control input) the armature current. Its main advantage is a good torque at high speeds and its disadvantage is high energy losses. The second way is called *field control*, and has a constant voltage to set up the armature current, while a variable voltage applied to the stator induces a variable magnetic flux. Its advantages are energy efficiency, inexpensive controllers and its disadvantages are a torque that decreases at high speeds [11]. A linear model that approximates the dynamics of the DC motor is derived as follows: the torque developed by the motor is proportional to the stator's flux and to the armature's current thus one has

$$\Gamma = k_f \psi K_\alpha I \qquad (1)$$

Where Γ is the shaft torque, ψ is the magnetic flux in the stator field, I is the current in the motor armature. Since the flux is maintained constant the torque of Eq. (1) can be written as

$$\Gamma = k_T I \ , \quad \text{where} \quad k_T = k_f \Psi K_\alpha \qquad (2)$$

A part from this, when a current carrying conductor passes through a magnetic field, a voltage V_b appears corresponding to what is called electromagnetic force (EMF)

$$V_b = K_e\omega \tag{3}$$

Where ω is the rotation speed of the motor shaft. The constants k_T and k_e have the same value. Kirchoff's law yields the equation of the motor (Fig. 1) :

$$V - V_{res} - V_{coi} - V_b = 0 \tag{4}$$

Where V is the input voltage, V_{res} = RI is the armature resistor voltage (R denotes the armature resistor), V_{coil} = LI is the armature inductance voltage. The motor's electric equation is then

$$L\dot{I} = -k_e\omega - RI + V \tag{5}$$

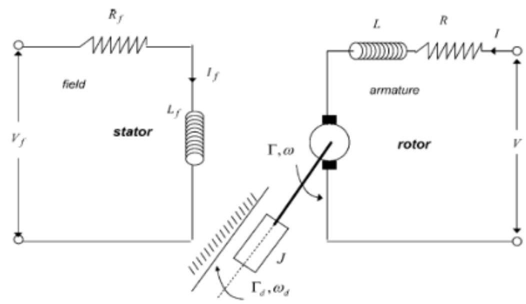

Fig. 1. Parameters of the DC motor model.

From the mechanics of rotation it holds that

$$J\dot{\omega} = k_e I - k_d\omega - \Gamma_d \tag{6}$$

The DC motor model is finally

$$\begin{aligned} L\dot{I} &= -k_e\omega - RI + V \\ J\dot{\omega} &= k_e I - k_d\omega - \Gamma_d \end{aligned} \tag{7}$$

With the following notations

Notation	Significance
L	armature inductance
I	armature current
k_e	motor electrical constant
R	armature resistance
V	input voltage, taken as control input
J	Motor inertia
ω	rotor rotation speed
k_d	mechanical dumping constant
Γ_d	disturbance torque

Where the armature designates the iron cored rotor wound with wired coils. Assuming $\Gamma_d = 0$ and denoting the state vector as $(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3)^T = (\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}})^T$ a linier model of the DC motor is obtained :

$$\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & \dfrac{-k_e^2 - k_d R}{JL} & \dfrac{-JR - k_d L}{JL} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ \dfrac{k_e}{JL} \end{pmatrix} V \tag{8}$$

Usually the DC motor model is considered to be linear by neglecting the effect of armature reaction or by assuming that the compensating windings remove this effect. Introducing the armature reaction leads to a nonlinier system and in that case a nonlinier model may be appropiate. In that case the dynamic model of the DC motor model can be written as [5]:

$$\dot{x} = f(x) + g(x)u \tag{9}$$

With denoting the derivative of the motor's state vector, $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3]^T = [\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \mathbf{i}_a]^T$. The functions f(x) and g(x) are vector field functions defined as :

$$f(x) = \begin{pmatrix} x_2 \\ k_1 x_2 + k_2 x_3 + k_3 x_3^2 + k_4 T_1 \\ k_5 x_2 + k_6 x_2 x_3 + k_7 x_3 \end{pmatrix}, \quad g(x) = \begin{pmatrix} 0 \\ 0 \\ k_8 \end{pmatrix} \tag{10}$$

Where $k_1 = -F/J$, $k_2 = A/J$, $k_3 = B/J$, $k_4 = -1$

$k_5 = -A/L$, $k_6 = -B/L$, $k_7 = -R/L$, $k_8 = -1/L$

A block diagram of nonlinier DC motor is shown in Fig. 2. with speed variable as output.

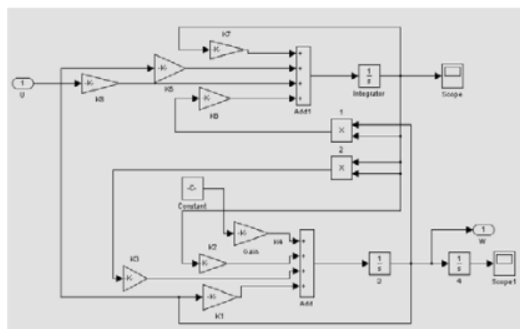

Fig 2. Block scheme of Nonlinier DC Motor

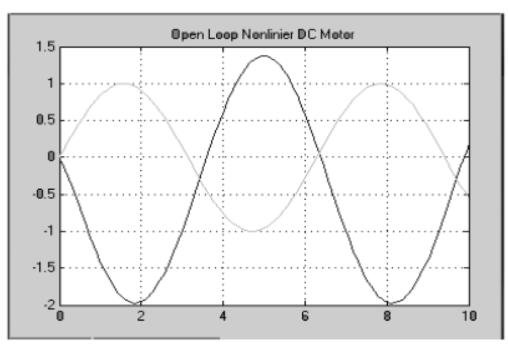

Fig. 3. Effect of nonlinear in open-loop control mode

Fig. 3 shows the effect of these nonlinearities on DC motor system. The speed response of the system to a sinusoidal control voltage is measured in open loop using a tachometer mounted on the load side.

III. BPNN THOPOLOGY

A general structure of a multi-layer NN is shown in Figure 1 [I2]. Such a neural network contains *three* layers: input layer, hidden layer(s) and output layer. Each layer is composed of several neurons. The number of the neurons in the input and output layers depends on the number of the selected input and output variables.

The number of hidden layers and the number of neurons in each depend on the *system* dynamics and the desired degree of accuracy. Usually one layer is adequate in many applications. A trial and error method *can* be used to select a proper number of the hidden neurons.

All the neurons in adjacent layers are interumnected. The strength of the interconnection is determined by the weighting vector of the BPNN.

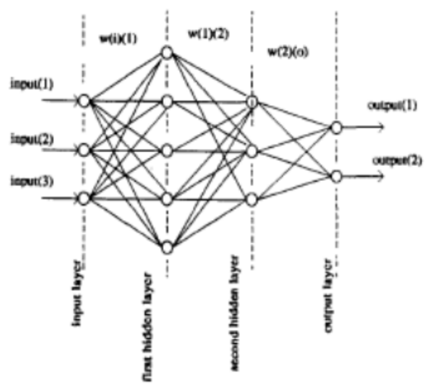

Fig. 4: Multi Layer Neural Network

Each neuron perfinms two functions, as shown in Figure 2. The fust is to sum all the inputs from the upper layer based on their weighting factors as given in equation (11). The second is to process this *sum* by a nonlinear sigmoidal function [I2] as shown in equation (12). The input and output neurons may not contain nonlinear functions.

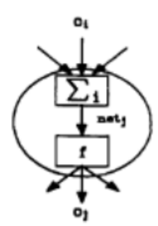

Fig. 5: A Single Neuron

The basic equations describing the dynamics of each neuron are

$net_j = \Sigma_i W_{ij}.O_i$ (11)

0, = f(netj + ej) (12)

where:

Wij weight between the j^{th} neuron and the i^{th} neuron in two adjacent layers;

θ_j threshold of the j^{th} neuron;

O_i output of i^{th} neuron;

O_J output of j^{th} neuron;

f (.) sigmoidal function

The BPNN **has** two phases of operation: training and testing. In the training phase, the weights of the BPNN are adjusted to map the input of the system to its output. In the testing phase, the BPNN should predict the correct system output for a given input, even if the input was not used in training.

Fig. 6 Indicate block diagram of nonlinier DC motor using PID controller. The proportional integral derivative (PID) gains of the closed-loop system are adjusted after obtaining by the Ziegler Nichols method [14]. Fig. 7 Indicate block diagram nonlinier DC motor using BPNN controller .

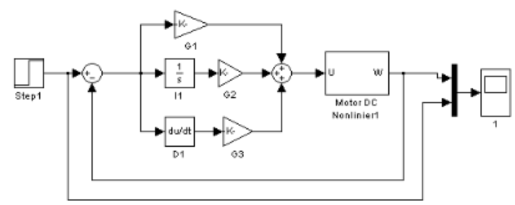

Fig. 6. Block Scheme of nonlinier DC motor with PID controller

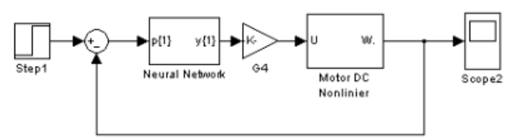

Fig 7. Proposed DC Motor with BPNN controller

IV. SIMULATION RESULT

In this section, we illustrate the efectiveness of the proposed control scheme by computer simulations Figure 8 shows training results of the BPNN controller at the speed control.

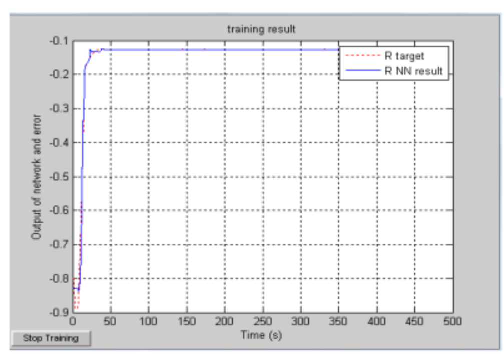

Fig 8. Result training for DC motor speed

The simulation results of the speed control with the step reference signal by the PID controller and by the BPNN controller is in Fig. 9 and Fig. 10. Fig. 11 showed simulation result of the speed control with disturbance by the PID controller and by BPNN.

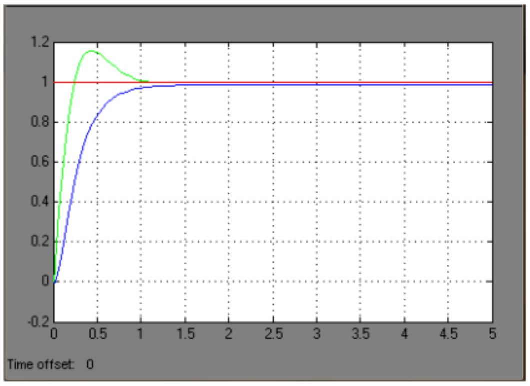

Fig. 9. Simulation results of the speed control with the unit step reference signal (a) by the PID controller and (b) by the BPNN

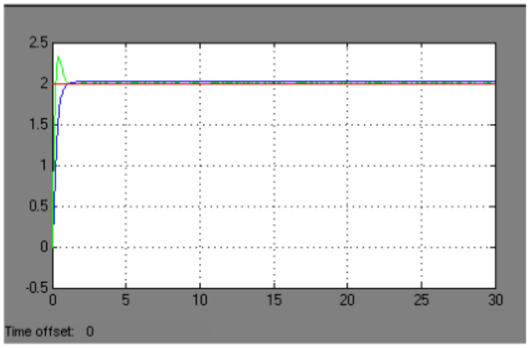

Fig. 10. Simulation results of the speed control with step reference signal (a) by the PID controller and (b) by the BPNN.

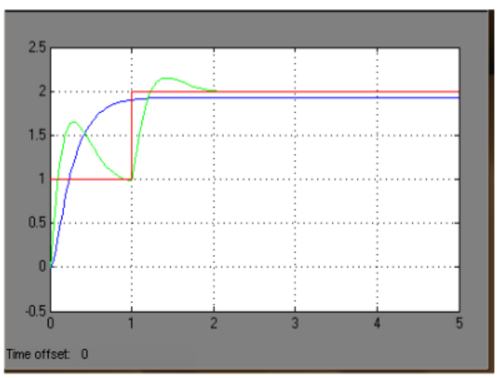

Fig. 11. Simulation results of the speed control with disturbance (a) by the PID controller and (b) by the BPNN

V. Conclusion

In this paper, a model-following adaptive control method is developed for the speed control of a nonlinear DC motor system using Back Propagation neural networks (BPNN). In comparison of simulation results with the PI controller, the proposed BPNN controller system can yield a better dynamic performance with shorter settling time and without overshoot. In comparison of simulation results with give disturbance has showen that system can yield a better dynamic performance than PID controller.

Acknowledgements

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