Speed Sensorless Control Based Artificial Neural Network for Direct Current Motor

Dr. Adel M. Dakhil [*], Dr. Basil H. Jasim [**].

[*]Department of Electrical Engineering, College Of Engineering.

Misan University

Dr.adelmanaa@yahoo.com

[**]Department of Electrical Engineering, College Of Engineering.

University of Basra

Abstract

In this paper, A robust adaptive speed sensorless by a neural network approach of a separately excited (DC) motor without the use of speed sensors is presented. The simulation carried out by Matlab backage. The actual speed is estimated using a feed-forward neural network, the neural estimator have three inputs which are armature current, armature voltage, and the speed in the previous step of time; and one output which represents the estimated speed. The obtained results are presented to show the validity and efficiency of sensorless control scheme, which in turn obtains high performances.

الخلاصة

في هذا البحث متحسس تم دراسة سرعة لمحرك تيار مستمر منفصل الأثارة متأقلم قوي باستخدام منظومة عصبية. منظومة المحاكاة صممت باستخدام برنامج Matlab. السرعة الحقيقية خُمنت باستخدام منظومة عصبية ذات الارتجاع المسبق. هذه الشبكة العصبية لها ثلاث مدخلات (تيار المنتج ، فولتية المنتج، والسرعة عند الخطوة الماضية من الزمن)؛ و أخراج واحد يمثل السرعة المخمنة ، النتائج المستخلصة أظهرت بيان مصداقية وكفاءة مخطط سيطرة متحسس السرعة لاستخراج خصائص جيدة

I. Introduction

Because of their high reliabilities, flexibilities and low costs, DC motors are widely used in industrial applications such as electric vehicles, steel rolling mills, electric cranes, robotic manipulators, and home appliances where speed or/and position control of motor are required. Generally, a high performance motor drive system must have good dynamic speed command tracking and load regulating response[1].

Therefore, the control of the position or/and speed of a DC motor is an important issue and as been studied since the early decades in the last century [2-3]. DC motors are customarily modeled linearly to enable the application of linear control theory in controller design[4].

Artificial Neural Network (ANN_s), which is based on the operating principle of human being nerve neural. This method is applied to control the motor speed [2]

The key of Artificial Intelligence Control (AIC) is how to construct inverse model of controlled system accurately [5 - 9]. The purpose of this study is to estimate and control the speed of a separately excited DC motor with Artificial Neural Network (ANN) controller using MATLAB software application. Among different kinds of neural networks, the most widely used ones are multilayer neural networks and recurrent networks[10].

weerasoory S. and al-sharkawi M.A, 2009 [2] presents new concepts of Artificial Neural Networks (ANN) in estimating speed and controlling the separately excited DC motor. Vince T., 2009 [10] this research presents regulation possibilities of DC motor via Internet and deals with artificial neural network utilization in such a regulation. In [4] Fielat EA, Ma'aita EK, 2012 , a neural network approach for the identification and control of a separately excited direct (DC) motor (SEDCM) driving a centrifugal pump load is applied. In this application, two radial basis function neural networks (RBFNN) are used to control the machine.

Simulation results are presented to demonstrate the effectiveness and advantage of estimating the speed of DC motor with ANNs in comparison with the conventional estimating schemes.

The organization of this paper is as follows. In section II, the mathematical modeling for a separately excited DC motor. The basic concept of AIC is briefly reviewed in section III. Section IV presents some simulation results on a separately excited DC motor with the new proposed technique. The last section V contains the conclusion.

II. Mathematical Model of DC Motor

The DC machine are characterized by their versatility. By means of various combinations of shunt, series, separately excited field windings they can be designed to display a wide variety of volt-amper or speed torque characteristics for both dynamics and steady state operation [9, 11].

The separated excitation DC motor model is chosen in this paper due to its good electrical and mechanical performances as compared with the other dc motor models.

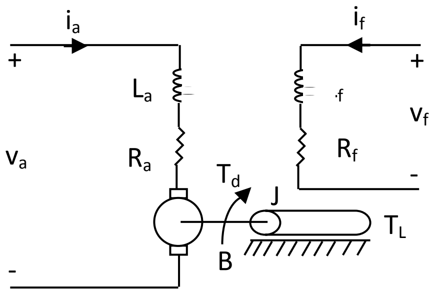

Fig.(1) The equivalent circuit of DC motor with separate excitation

The resistance of the field motor winding and its inductance used in this work are represented by R_f and L_f respectively. The resistance of the armature and its inductance are shown by R_a and L_a respectively.

Armature reactions effects are ignored in the description of the motor, The voltage V_f which applied to the field has constant value. A linear model of a simple DC motor consists of mechanical equation and electrical equation as determined in the following equation

$$J_m \frac{dw_m}{dt} = k_m \phi I_a - b w_m - T_{load} \qquad (1)$$

$$k_b w = v_a - R_a I_a - L \frac{di}{dt} \tag{2}$$

Where R_a is armature resistance (Ω)

L_a is the armature inductance (Ω)

J_m moment of inertia

$k = k_b \phi$ =motor constant (Nm/Amp.)

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b is the damping ratio of mechanical system (Nms)

Thus from eq.(2), the rotor speed can be estimated.

In this work a feed forward back propagation neural network is presented which is trained to approximate eq.(2)

Table (1)

Motor Parameters Value

Parameters	Definition	Value
V_a	Terminal voltage (V)	240
I_a	Armature current (Amp.)	16.2
T_l	Load torque	15
J	Rotor inertia (J/Kg.M^2)	1
B	Viscous friction coefficient	0
R_a	Armature resistance (Ω	0.6
L_a	Armature inductance (H.)	0.012
N	Rotor speed (R.p.m.)	1220

The dynamics model of the system is formed using these differential equation and the matlab simulink as shown in Fig.(2)

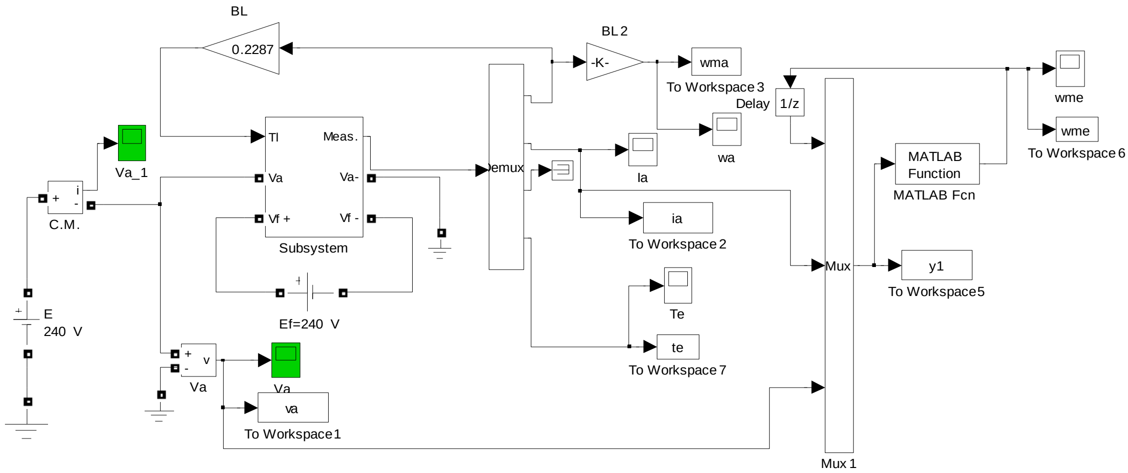

Fig.(2) Simulink model for DC Motor with neural network

III. Artificial Neural Network (ANN)

The approach of neural network basically works on the provided priories information and makes a suitable decision for a given testing input based on the provided training information [1]. The signals activation of nodes either attenuate or amplify, when transmitted to next layer. ANNs are trained to emulate a function by a presenting it with representive set of input/ output functional technique adjusts the weights in all connecting links and thresholds in the nodes so that the difference between the actual output and target output is minimized for all given training patterns [2]. The number of inputs and outputs are the only fixed parameters for a designing and training an ANN to emulate a function, which are based on the input / output variables of the function. It is also widely accepted that maximum of the two hidden layers are sufficient to learn any arbitrary non linearity [12]. First and second layer is the hidden layers, Third layer is the output layer.

The most common feed forward neural network is shown in Fig.(3), the basic component of the network, called neurons. The network consists of three layers : input layer, the hidden layer, and the output layer, each of the input is connected to each neurons in the hidden layer, and in turn, each of the hidden layer neurons is connected to the output, each single neurons can be represented as shown in Fig.(4)

However the hidden neurons and the values of learning parameters, which are equally critical for a satisfactory learning, are not supported by such well established selection criteria. The choice is usually based on experience. The ultimate objective is to find a combination of parameters which gives a total error of required tolerance a reasonable number of training sweeps [2,3]. The structure and the process of learning ANNs for estimation and control a speed for D.C. motor is shown in Fig.(3)

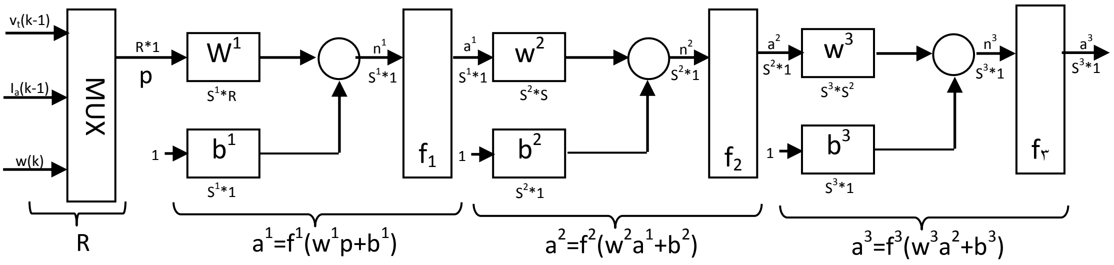

Fig.(3) Three layer network for the presented estimator

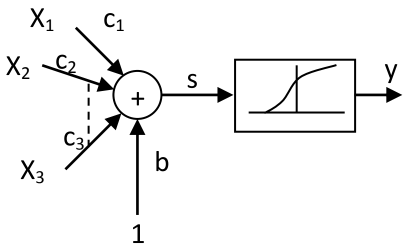

Fig.(4) Single neuron structure

Typically, a sigmoided squashing function is used, that is,

$$y = \frac{1}{1 + e^{-ks}} \tag{3}$$

Where k is constant and if $-\infty < s < \infty$ then $o < y < 1$

Nonlinearity of the squashing function allows the neural network to model nonlinear phenomena, the argument, s, of the squashing function is given by

$$s = b + \sum_{i=1}^{j} c_i x_i \tag{4}$$

Where x_i , i=1,2,…j, are neurons input signals, c_i are respective connection weights, and b is the bais weight.

To work properly, a neural network must be trained, that is, its weights must be set to values resulting in the required quality of operation. The training process consists of sequential application of various sets of inputs, evaluating the difference between the outputs and their reference values, and adjusting the weights to minimize that difference. The training process is usually based on the efficient back propagation algorithm [13]. The training is automated and preformed prior to employing the network in the simulated circuit.

IV. Simulation Results

To study the performance of speed estimator by using the artificial neural network (ANN) for DC motor (DC motor parameters shown in Table 1), the simulation of the system was conducted using Simulink/ Matlab program with the toolbox of neural network is used. The DC motor has the parameter listed in Table(1).

The neural network was trained using four sets of input/ target pairs, each pair corresponding to excitation case, the training process of the ANN is shown in Fig.(5) the performance is (0.00010287) with (100) epochs

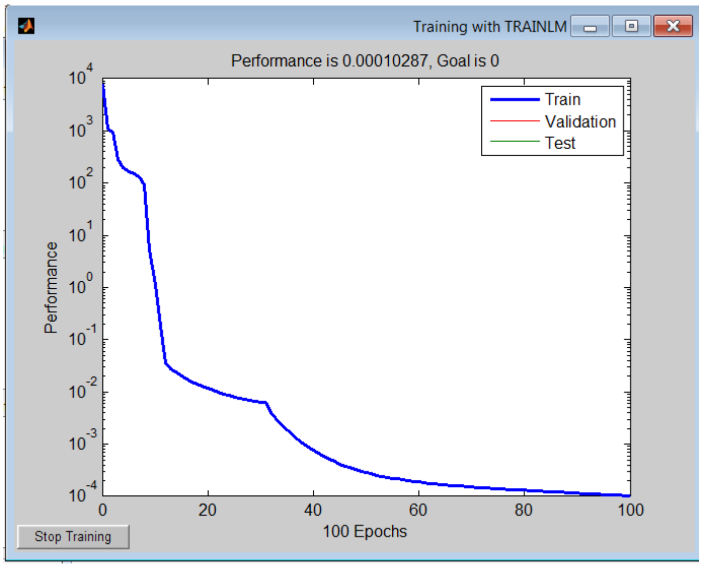

Fig.(٥) Error of the Neural Network

Now the ANN is used to estimate the speed of the motor, the corresponding actual speed, estimated speed, armature voltage and current with the developed torque is shown in Fig.(6) –Fig.(8)

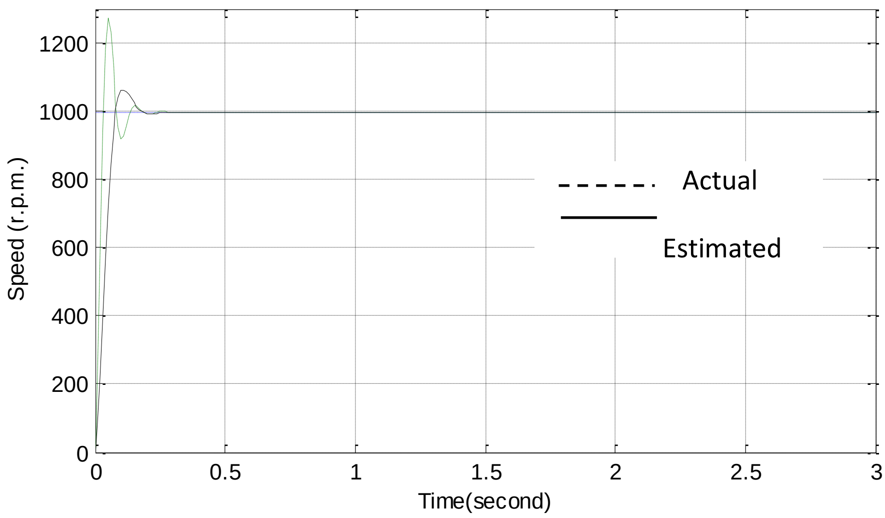

Fig.(6) Actual and estimated speed

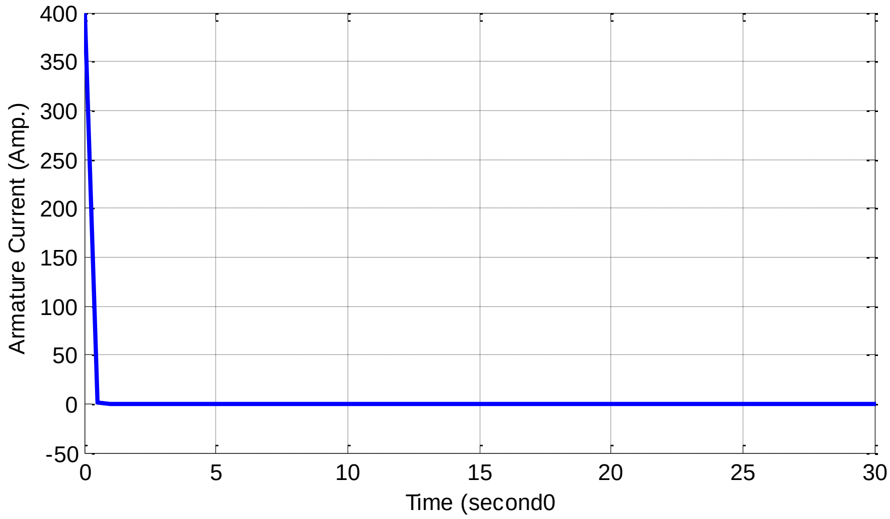

Fig.(7) Armature current waveform for the tested DC Motor

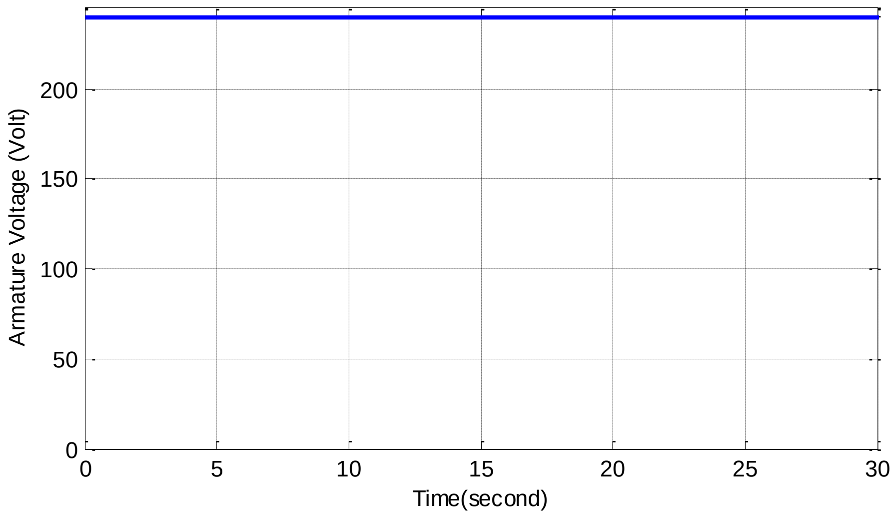

Fig.(8) Armature voltage waveform for the tested DC Motor

Other test for this estimator is done by using a step change of 15 N.m. loads at t= 5 sec and observing the performance of this system.

From results shown in these two tests the estimation process by this Artificial Neural Network (ANN) is robustness the fluctuation of the estimated speed and to the variation of load torque. This network is able to estimate not only the speeds included in the training set, but it also is able to interpolate and extrapolate well.

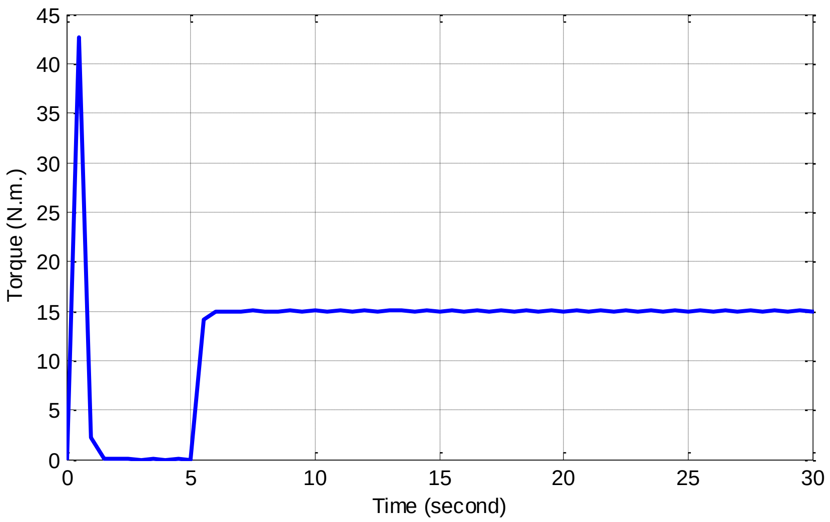

Fig.(9) Torque profile for DC motor with step change in torque equal 15 N.m. at t=5 second

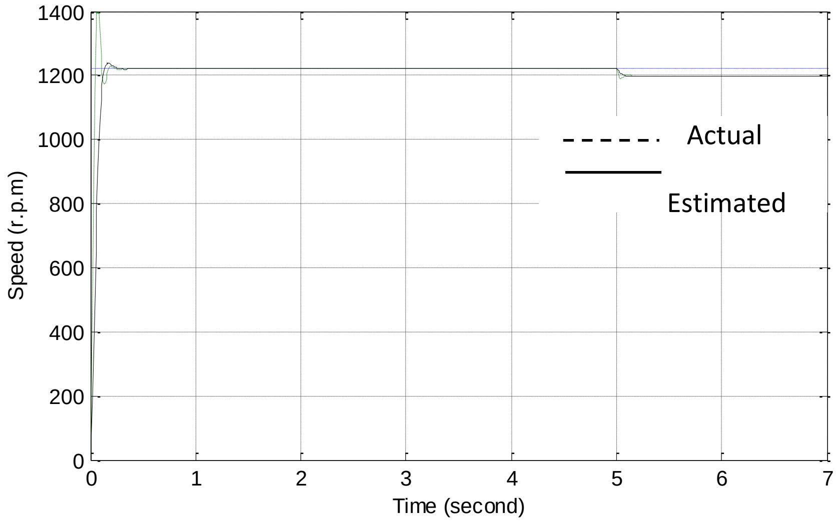

Fig.(10) Actual and estimated speed profile for DC motor with step change in torque equal 15 N.m. at t=5 second

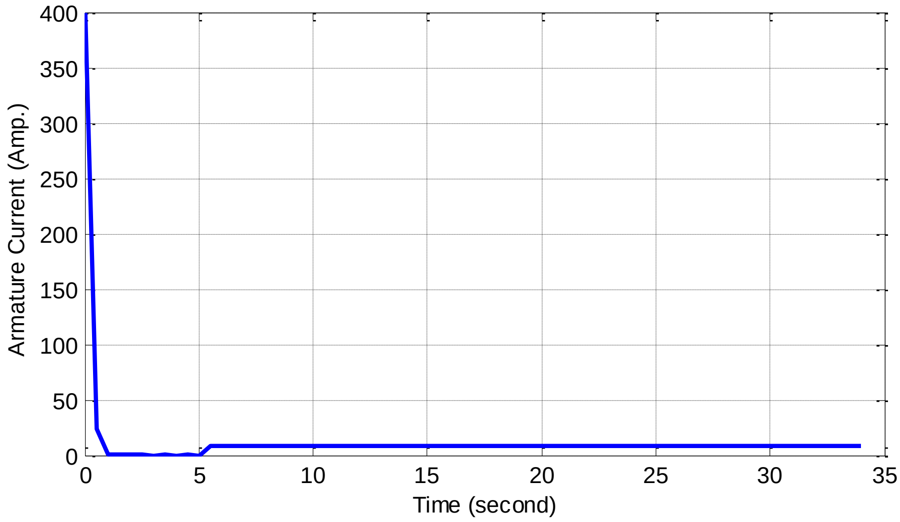

Fig.(10) Armature current waveform for DC motor with step change in torque equal 15 N.m. at t=5 second

V. Conclusion

In this work the speed of DC motor has successfully estimated and controlled using Artificial Intelligence, this work is trained to emulate function, by application such network there is no need to use speed sensors hence the speed estimated by measurement the armature current and voltage. The simulation results demonstrate that this estimator is able to estimate not only the speeds included in the training sets, but it is able to interpolate and extrapolate very well, this estimator also able cover the variation of speed due to load change.

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