An Online Artificial Neural Network Speed Estimator for Sensorless Speed Control of Separately Excited DC Motor

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***Abstract*—This paper presents a speed estimator for sensorless speed control of separately excited DC motor by using artificial neural network. To estimate the speed, a coefficient, which concerns with the speed in the armature current estimation equation, is adjusted accordingly to an artificial neural network learning principle until the difference between the actual and the estimated armature current is minimal. Widrow-Hoff learning rule is adopted to perform this task. The consequence of using this algorithm leads to the ability of online speed estimation and simple artificial neural network structure. The simulation and experimental results have verified the effectiveness of the introduced method.**

Keywords—speed sensorless; artificial neural network; speed estimation; DC motor

I. Introduction

Separately excited DC motors are still widely used in the industrial applications such as steel rolling mills, lathes, weaving machines, electric cranes, electric traction, etc., because of their low cost, inexpensive maintenance, simple construction and simple controlling methodologies [1-2]. To control speed of a separately excited DC motor, there are two broadly methods, namely open loop control and closed loop control. The closed loop control is more attractive than open loop control in accuracy, performance and reliability aspects when the parameter variations and external disturbances emerge. However, it demands the speed signal that feedback from tachogenerator or the encoder. The use of mechanical speed sensors leads to requirement of the periodic maintenance, increment of the system complexity, reduction of the system reliability and raising the cost of the system. To overcome these drawbacks, the speed estimation strategies are proposed. Back electromotive force based speed estimation approach is presented in [1]. The ripple component of the armature current is analyzed by using support vector machines to estimate the speed of brushed DC motor is introduced in [3]. In [4], the speed of permanent magnet DC brushed motor is estimated by considering the effect of commutation and armature teeth-slots on the armature current. The rise time or duration of the inductive spike, which is generated when the motor is turned off, is used to estimate speed for PWM driven brushed DC motor [5]. Speed estimation of DC motor using Kalman filter is proposed in [6]. In [7-8], the designs of observer-based speed estimation are described.

Recently, artificial neural network (ANN) are extensively used for identification and controlling the nonlinear systems because of its strong learning and fast optimization feature. The offline or online learning can be applied for its training. Moreover, it can approximate the nonlinear functions in wide range with any required preciseness [9]. However, the uncomplicated design, simple structure and easy computation are required for ANN that is used as speed estimator. To ensure that it is suitable for real time implementation.

An online speed estimator for sensorless speed control of separately excited DC motor by using ANN is offered in this paper. Widrow-Hoff learning rule [10] is applied to adjust a coefficient, which concerns with the speed, of the armature current estimation equation until the difference between the actual and the estimated armature current is minimal. By simple calculation from this coefficient, the estimated speed is achieved. As a result of using this algorithm causes the proposed speed estimator can estimate speed online with easy structure. The huge data for training, like offline ANN, are not employed; result in the introduced speed estimation method is appropriate for real time application. The simulation and experimental results have verified the effectiveness of the proposed ANN speed estimator.

II. Dynamic Model of Separately Excited DC Motor

In this paper, the speed control method only focuses on the armature voltage control that the field excitation is kept constant at the rated value and the speed variable lower rated speed can be succeeded by changing the armature voltage. Hence, the differential equations that explain the dynamic behavior of the separately excited DC motor are given as

$$v_a(t) = R_a i_a(t) + L_a \frac{di_a(t)}{dt} + e_b(t) \tag{1}$$

$$e_b(t) = K\omega(t) \tag{2}$$

$$T_m(t) = Ki_a(t) \tag{3}$$

$$\frac{d\omega(t)}{dt} = \frac{T_m(t) - T_L(t)}{J} \tag{4}$$

where $v_a(t)$ and $i_a(t)$ are the armature voltage and current, respectively, $e_b(t)$ is the back electromotive force, $\omega(t)$ is the speed, $T_m(t)$ and $T_L(t)$ are the electromagnetic and load torque, respectively, R_a and L_a are the armature resistance and inductance, respectively, J is the moment of inertia, and K is the constant.

III. The Proposed Speed Estimator

Design procedures of the ANN based speed estimator are shown as follows:

Using the equations as mentioned above, the armature current equation is shown in (5)

$$\frac{di_a(t)}{dt} = -\frac{R_a}{L_a} i_a(t) - \frac{K}{L_a}\omega(t) + \frac{v_a(t)}{L_a} \tag{5}$$

Applying forward rectangular rule to (5), the discrete time armature current equation is depicted in (6)

$$i_a(k) = \left(1 - \frac{R_a T}{L_a}\right) i_a(k-1) + \frac{T}{L_a} v_a(k-1) - \frac{KT}{L_a}\omega(k-1) \tag{6}$$

where T is the sampling period. From (6), the armature current estimation equation, which has pattern consistent with ANN, is written as

$$\hat{i}_a(k) = w_1 x_1 + w_2 x_2 + w_3 x_3 \tag{7}$$

where $w_1 = \left(1 - \frac{R_a T}{L_a}\right)$, $x_1 = \hat{i}_a(k-1)$

$w_2 = \frac{T}{L_a}$, $x_2 = v_a(k-1)$

$w_3 = \frac{KT\hat{\omega}(k-1)}{L_a}$, $x_3 = -1$

and " ^ " denotes estimated value. The coefficient in (7) that relates to speed is w_3. Therefore, Widrow-Hoff learning rule is adopted to modify this coefficient until the difference of the actual and the estimated armature current is minimal.

The difference of the actual and the estimated armature current at the sampling time k is given by

$$e(k) = i_a(k) - \hat{i}_a(k) \tag{8}$$

From (8), the least square error function can be expressed as

$$E(k) = \frac{1}{2}e^2(k) = \frac{1}{2}\left(i_a(k) - \hat{i}_a(k)\right)^2 \tag{9}$$

The weight adjustment according to Widrow-Hoff learning rule is given as

$$w_3(k) = w_3(k-1) + \Delta w_3 \tag{10}$$

and Δw_3 can be derived as

$$\Delta w_3 = -\mu\frac{\partial E}{\partial w_3} = -\mu\left[\frac{\partial E}{\partial e}\cdot\frac{\partial e}{\partial \hat{i}_a}\cdot\frac{\partial \hat{i}_a}{\partial w_3}\right] = -\mu e(k) \tag{11}$$

The speed can be estimated by substituting (11) into (10) and rearranging as shown in (12)

$$\hat{\omega}(k) = \hat{\omega}(k-1) - \eta e(k) \tag{12}$$

where μ is learning rate and $\eta = \frac{\mu L_a}{KT}$. From (8) and (11), found that the weight w_3 can adjust (learning) online by measuring the actual armature current every sampling time k. As a consequence, the speed can be estimated online.

The diagram of the proposed speed estimator is depicted in Fig. 1.

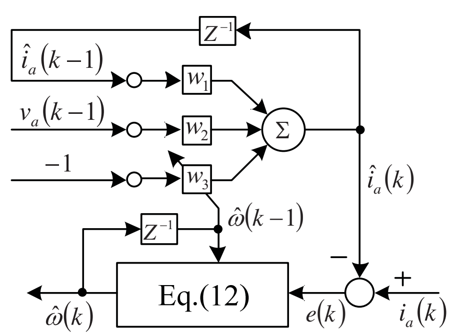

Fig. 1. Diagram of the proposed speed estimator.

IV. Feedforward Control

From (3), the electromagnetic torque can be controlled by control the armature current. The armature current can also be controlled through the armature voltage as seen from (1) and (2) in steady-state operation. As a result, the electromagnetic torque can control by controlling the armature voltage that uses feedforward control as

$$v_a^*(k) = R_a i_a^*(k) + K\hat{\omega}(k) \qquad (13)$$

where " * " denotes reference value. The diagram of the speed control system for separately excited DC motor with the proposed speed estimator and feedforward control is demonstrated in Fig. 2.

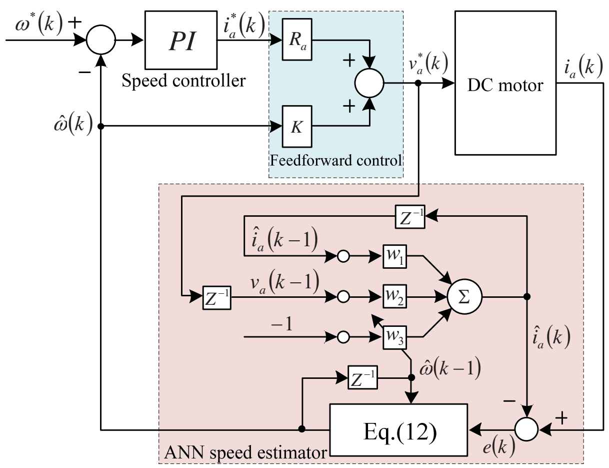

Fig. 2. Diagram of the speed control system with the proposed speed estimator and feedforward control.

V. Simulation and Experimental Results

To validate the effectiveness of the introduced speed estimator, the control system in Fig. 2 is developed for simulation in Matlab/Simulink environment and also implemented for practical verification. The PI controller parameters for speed controller are determined by symmetrical optimum method that the details of design are mentioned in [7]. The parameters of separately excited DC motor are given in Appendix. The learning rate μ of the speed estimator is 0.02.

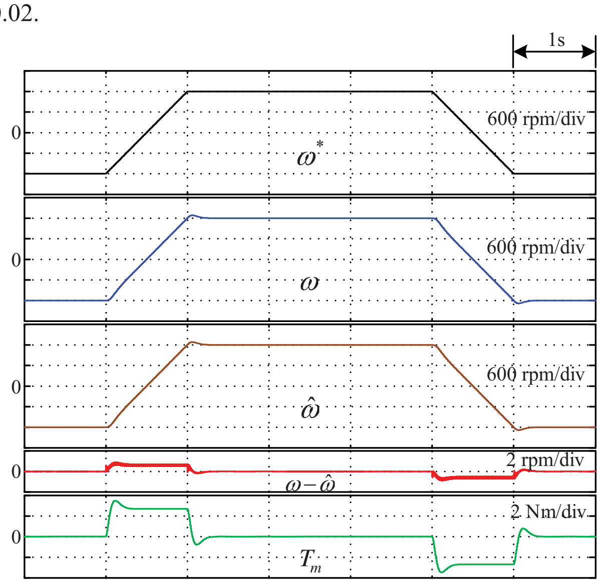

Fig. 3. Simulation results when speed reversal.

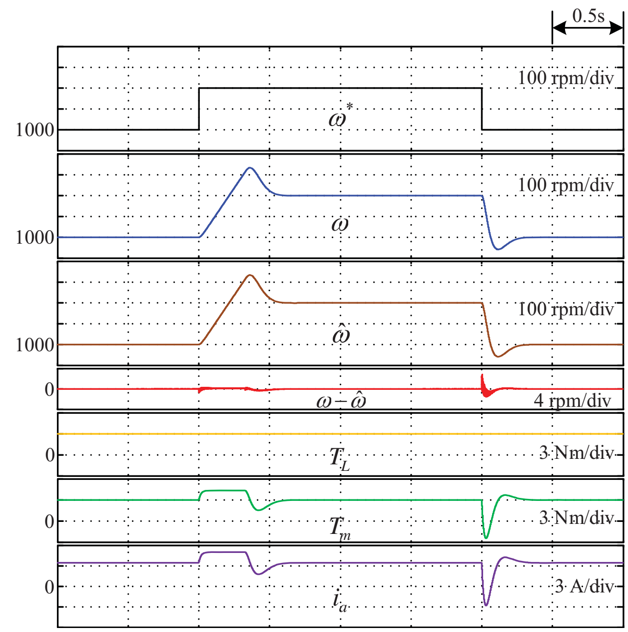

Fig. 4. Simulation results when step speed with full load.

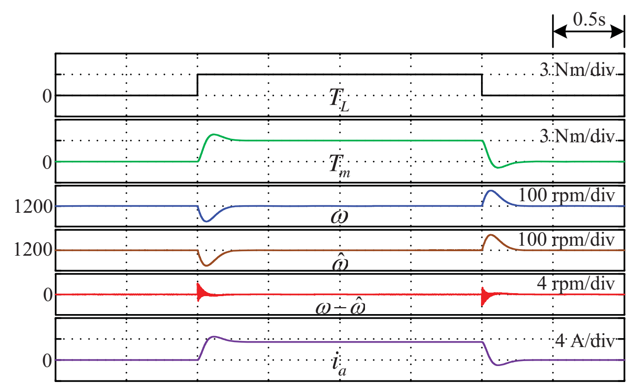

Fig. 5. Simulation results when step load.

The responses at speed reversal during -1200 rpm to 1200 rpm are displayed in Fig. 3. Fig. 4 shows the responses to the changing of the speed reference while full load is connected all time. The responses during step load torque from no load to full load are represented in Fig. 5. As seen from the simulation results, in the transient conditions the different speeds ($\omega - \hat{\omega}$) are very little and reach to zero in steady-state conditions. These results indicate the accuracy of the proposed speed estimation method. The PI speed controller incorporated with feedforward control can precisely respond to the changing of speed reference and load torque.

The experimental results at speed reversal during -1200 rpm and 1200 rpm are shown in Fig. 6. Fig. 7 shows the responses to the changing of the speed reference while full load is connected all time. The responses during step load torque from no load to full load in high speed range and low speed range are represented in Fig. 8 and Fig. 9, respectively.

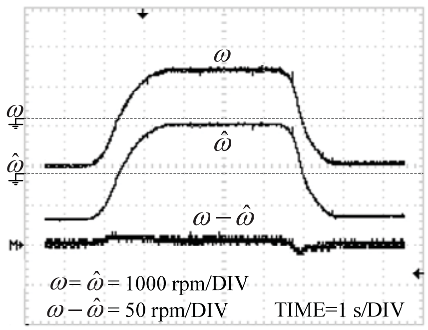

Fig. 6. Experimental results when speed reversal.

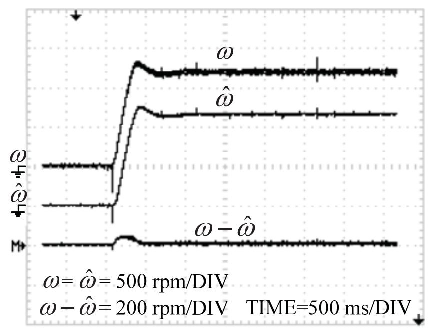

Fig. 7. Experimental results when step speed with full load.

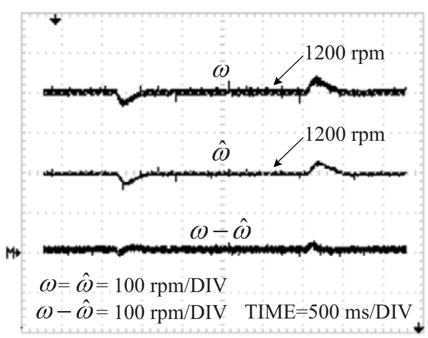

Fig. 8. Experimental results when step load in high speed range.

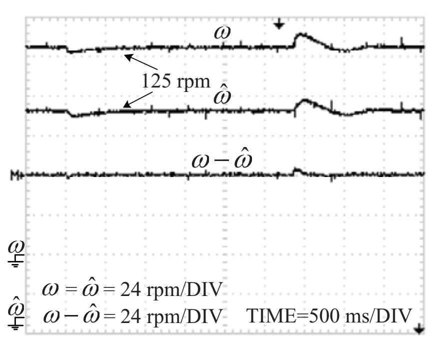

Fig. 9. Experimental results when step load in low speed range.

The experimental results can verify that the proposed speed estimation method can estimate speed precisely with very small speed difference in transient and steady-state operations. The PI speed controller incorporated with feedforward control can control speed and torque accurately both in low and high speed regions.

VI. Conclusions

This paper introduces an online speed estimator using ANN for sensorless speed control of separately excited DC motor. The proposed speed estimator can estimate speed correctly both in transient and steady-state conditions as seen from the simulation and experimental results. The sensorless speed control system is stable, has good transient and steady-state responses in low and high speed ranges. Furthermore, the proposed speed estimator can estimate the speed in real time implementation with simple structure and no requirement of offline training. However, it lacks the ability to compensate the variation of motor parameters.

Appendix

The parameters and rating of motor are shown as follows:

0.75 kW, 2000 rpm, $R_a = 7.55\ \Omega$, $L_a = 0.1114$ H, $K = 0.8704$ Nm/A, and $J = 0.01287$ kgm^2.

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