Design of Extended Kalman Filter Speed Estimator and Single Neuron-Fuzzy Speed Controller for Sensorless Brushless DC Motor

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***Abstract*—Methods of estimation and control of BLDC presented in this paper. Because BLDCM is a motor without a brush then BLDC requires the sensor position to rotate the rotor and this is a weakness of the BLDC. A sensorless algorithm of Extended Kalman Filter (EKF) was proposed to cover this weakness. Additionally, BLDC is also a non-linear system. Thus, it is difficult to obtain accurate and good value PID parameter controller with a conventional PID method. In this paper, a single neural network - Fuzzy PID for BLDC developed. The experimental results show that the EKF is able to estimate the speed of the BLDC and single neural networks - Fuzzy PID controller makes BLDC system faster.**

***Index Terms*—BLDC; Extended Kalman Filter; Sensorless; Single Neuron-Fuzzy.**

I. INTRODUCTION

The brushless DC (BLDC) motors are increasingly used in various sectors such as automotive, industrial, and household because of its better speed versus torque characteristics, high efficiency, high dynamic response, long operating life, low maintenance, good reliability and durability. The BLDC is motor without brush and electronically controlled, then to turn the rotor, BLDC need rotor position information by sensor position. In addition, it also causes problems at high cost and reliability of the sensor. Many researchers have developed a sensorless technique to overcome this problem. Effective solutions will be driving the use of BLDC to all areas as a low-cost and high reliability.

In the last few decades, many sensorless drive solutions have been developed to replace sensor position, i.e. with trapezoidal back-EMFs [1-9]. The back-EMF voltage sensing [1-2], back-EMF integration [5-6], detection of the freewheeling diodes conduction [7], flux estimation [3]-[4], and motor modification technique [9]. However, almost entirely unable to work well at all speeds and still there is the problem of accuracy, complexity, and reliability.

On the other hand, the control of BLDC motor drive requires a complex process such as modeling, control the selection scheme, simulation and parameter tuning etc. Required knowledge and experience to get and tune the controller parameters in order to get optimal performance. More recently, a variety of modern control solution is proposed to design optimal control of BLDC motors [10-11]. However, this method is not good because it has not been able to obtain the optimal control parameters.

In this paper, Extended Kalman Filter Estimator and Single Neuron-Fuzzy Controller scheme is proposed for BLDCM speed estimator and control. The paper is organized in the following manner. Section 2 describes of BLDC motor, section 3 explains the design of Extended Kalman Filter Speed Estimator for Sensorless Brushless DC Motor, section 4 briefly illustrate the design of Single Neuron-Fuzzy Speed Controller for Sensorless Brushless DC Motor, section 5 presents the comparison between the results obtained by the Single Neuron-Fuzzy and Sensorless method and finally, section 6 concludes the paper.

II. THE BRUSHLESS DC MOTOR

The BLDCM has three-phase windings and they are Y connected. The motor is operated in two-phase conduction and six-step driven mode. Under the assumption: (1) The distribution of air gap magnetic field is square; (2) All phase resistance, phase inductance, and mutual inductance are identical; (3) The cogging torque and armature reaction are neglected. The switching between two phases is assumed to be completed instantaneous; (4) the saturation in magnetic circuit and core losses are neglected, the mathematical equation of BLDCM can be given as below:

$$\mathrm{v_a = Ri_a + L\frac{di_a}{dt} + e_a} \tag{1}$$

$$\mathrm{v_b = Ri_b + L\frac{di_b}{dt} + e_b} \tag{2}$$

$$\mathrm{v_c = Ri_c + L\frac{di_c}{dt} + e_c} \tag{3}$$

where $v_a; v_b; v_c$ are the phase voltages, R is the stator winding resistances, L is the total phase inductances, $i_a; i_b; i_c$ are the phase currents, and $e_a; e_b; e_c$ are the back EMFs with equation:

$$\mathrm{e_a = k_b\omega_n F(\theta_e)} \tag{4}$$

$$\mathrm{e_b = k_b\omega_n F(\theta_e + \frac{4\pi}{3})} \tag{5}$$

$$\mathrm{e_a = k_b\omega_n F(\theta_e + \frac{2\pi}{3})} \tag{6}$$

and

$$F(\theta_e) = \begin{cases} 1 & 0 \le \theta_e < \frac{2\pi}{3} \\ 1 - \frac{6}{\pi}\left(\theta_e - \frac{2\pi}{3}\right) & \frac{2\pi}{3} \le \theta_e < \pi \\ -1 & \pi \le \theta_e < \frac{5\pi}{3} \\ -1 - \frac{6}{\pi}\left(\theta_e - \frac{5\pi}{3}\right) & \frac{5\pi}{3} \le \theta_e < 2\pi \end{cases} \tag{7}$$

The electromagnetic torque can be presented as:

$$T_e = J\frac{d\omega_m}{dt} + B\omega_m + T_L \tag{8}$$

$$T_e = k_t\left[F(\theta_e)i_a + F\left(\theta_e + \frac{4\pi}{3}\right)i_b + F\left(\theta_e + \frac{2\pi}{3}\right)i_c\right] \tag{9}$$

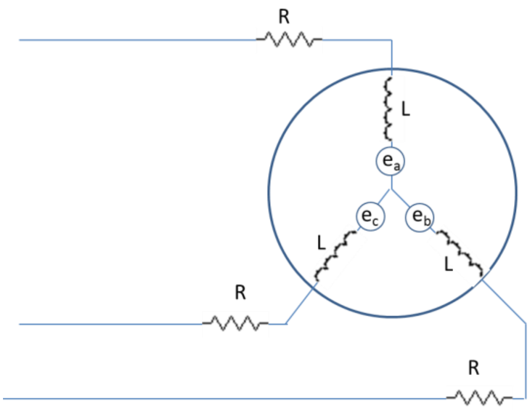

Figure 1: Equivalent Circuit of BLDC Motor

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III. EXTENDED KALMAN FILTER SPEED ESTIMATOR

The classical Kalman filter was invented for linear systems only. Many real systems, including BLDC motor, are however non-linear. If the nonlinearities are of minor importance, they can often be neglected. Non-linearity that cannot be neglected has to be compensated for in one way or the other, before a Kalman filter can be applied to the system. One effective method to linearize non-linear equations around a certain working point is by using Taylor series. Applying the Taylor series to nonlinearities in the system equations, results in a version of the Kalman filter called the Extended Kalman Filter (EKF). This observer is capable of handling almost any non-linear system at the cost of calculating Taylor series at each time sample. The Extended Kalman Filter cannot be proved to be optimal, but this does not mean that the solution is bad. On the contrary, the non-linear version of the Kalman filter usually performs very well.

The Extended Kalman Filter is necessary to estimate speed of BLDC motor continuously by using measured voltages and currents. At each time step, the motor current is estimated in two stages to correct the predicted speed and the estimated flux linkage. The accuracy of the speed estimation depends significantly on the motor parameter variation and accuracy of the measured voltage and current.

The main design steps for a speed sensorless BLDC motor drive implementation using a discretized Extended Kalman Filter algorithm are as follows:

- Selection of the time domain machine model
- Discretization of the machine model
- Determination of the noise and state covariance matrices Q, R, P
- Implementation of the discretized Extended Kalman Filter algorithm tuning.

It is possible to have EKF implementations using time domain machine models expressed in the stationary reference frame, or expressed in the rotor reference frames. Generally the model is expressed in stator reference frame with the following assumptions.

The effects of saturation of the magnetic paths of the machine have been neglected, Stator inductance is assumed to be constant, Rotor speed deviation is negligible, In EKF, the rotor speed is considered as a state variable. This makes the system matrix A nonlinear i.e. A = A(X).

The state space representation of the system is as follows. The equations (10) and (11) describe the time domain model of the BLDC motor and can be visualized by the block diagram shown in Figure. 2.

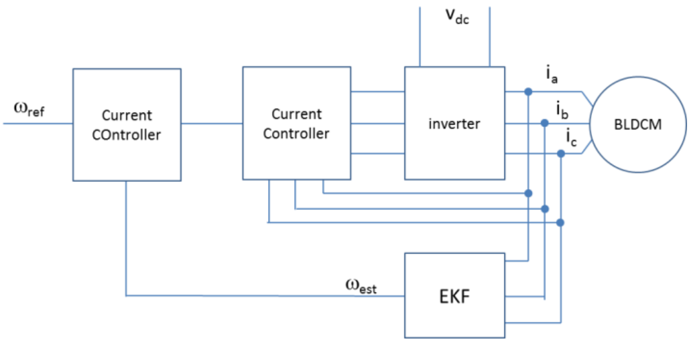

Figure 2: System Configuration

$$\dot{x} = Ax + Bu \tag{10}$$

$$y = Cx \tag{11}$$

with:

$$x = [i_a \quad i_b \quad i_c \quad \omega_n \quad \theta_e]^T \tag{12}$$

$$u = [v_a \quad v_b \quad v_c \quad T_L]^T \tag{13}$$

$$A = \begin{bmatrix} -\frac{R}{L} & 0 & 0 & -\frac{k_b}{L}F(\theta_e) & 0 \\ 0 & -\frac{R}{L} & 0 & -\frac{k_b}{L}F\left(\theta_e + \frac{4\pi}{3}\right) & 0 \\ 0 & 0 & -\frac{R}{L} & -\frac{k_b}{L}F\left(\theta_e + \frac{2\pi}{3}\right) & 0 \\ \frac{k_b}{J}F(\theta_e) & \frac{k_b}{J}F\left(\theta_e + \frac{4\pi}{3}\right) & \frac{k_b}{J}F\left(\theta_e + \frac{2\pi}{3}\right) & -\frac{B}{J} & 0 \\ 0 & 0 & 0 & pole & 0 \end{bmatrix} \tag{14}$$

$$B = \begin{bmatrix} \frac{1}{L} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{L} & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{L} & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{J} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{15}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad (16)$$

IV. SINGLE NEURON-FUZZY SPEED CONTROLLER

Figure 3 shows the single neuron-Fuzzy controller which realized the self-adapting and self-organization by making on-line alteration on the weight coefficient of single-neuron and the weight coefficient is adjusted by Supervised Hebbian Learning Rule

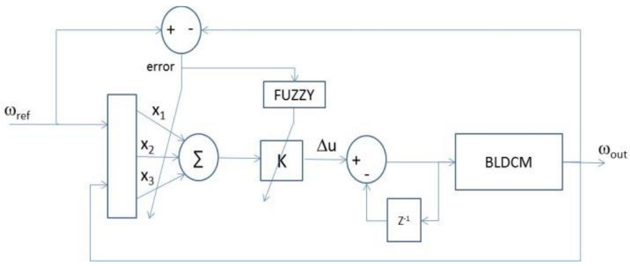

Figure 3: The structure of the single neuron-Fuzzy controller for BLDCM

Then the learning arithmetic and advanced control arithmetic are given as follow:

$$u(k) = u(k-1) + K\sum_{i=1}^{3} w_i(k)x_i(k) \quad (17)$$

$$w_i(k) = w_j(k)\sum_{j=1}^{3}|w_j(k)| \quad (18)$$

$$w_1(k) = w_1(k-1) + \eta z(k)u(k)x_1(k) \quad (19)$$

$$w_2(k) = w_2(k-1) + \eta z(k)u(k)x_2(k) \quad (20)$$

$$w_3(k) = w_3(k-1) + \eta z(k)u(k)x_3(k) \quad (21)$$

and:

$$x_1 = \Delta e(k) \quad (22)$$

$$x_2 = e(k) \quad (23)$$

$$x_3 = \Delta e(k) - \Delta e(k-1) \quad (24)$$

In formulas given above, w_i (i=1,2,3) is the weight coefficient of single-neuron. K_P, K_I and K_D are the learning velocities of Proportion, Integral and Differential coefficient, respectively. Utilizing the modified arithmetic, the performances of the single-neuron will be concerned by choosing the proportion factor K. When the value of K is large, the response of system is fast. But it may also cause a large overshoot even unstable. If the value of K is small, the system may response slowly. For getting a faster response and avoiding overshoot, the value of K should be adjusted on-line according to the different response stage. When the error is large, the value of K should be large to get a fast response. When the error is small, the value of K should be small to avoid overshoot and keep the system stable.

Fuzzy logic is a flexible, general purpose method of implementing non-linear functions. So it is useful in control applications. One of its advantages is that a combination of expert knowledge, expressed either linguistically or numerically, machine learning, or other techniques may be used in its design. So, in this paper, it is employed to tune the parameter K online.

Normally, the Fuzzy Logic has three main stages, given in Figure 4, which are as follows (1) Fuzzification, a process of converting a crisp input to a fuzzy input. (2) Inference engine and rule-base, in this stage, fuzzy inputs are transformed into a fuzzy output by dealing with fuzzy rules and as a result the response corresponding to the inputs is produced. Usually, the expert's knowledge about how to control a plant could be expressed by a set of linguistic control rules. So the rule-base can be setup according to expert's knowledge. (3) Defuzzification, a process of producing a crisp output on the base of a fuzzy one.

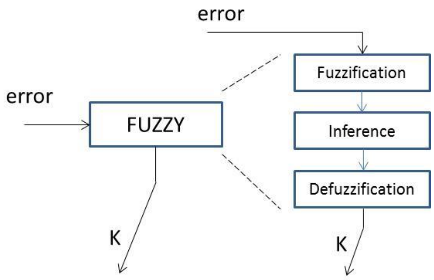

Figure 4: The Structure of Fuzzy Logic Controller

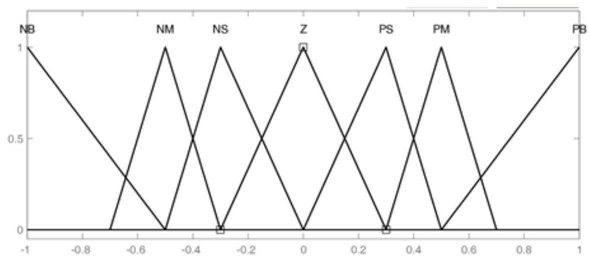

Figure 5: Error MF

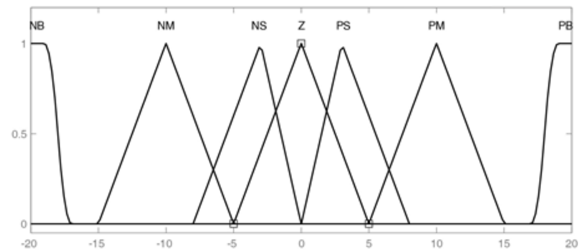

Figure 6: Gain MF

The fuzzy partition of input space and output space will be partitioned into seven-term set, show in Figure 5 and Figure 6. The linguistic values of linguistic variables of E and K are the same as NB (negative big), NM (negative medium), NS (negative small), Z (zero), PS (positive small), PM (positive medium), PB (positive big). The inference rules, show in Table 1, are got from the analysis of the dynamic response period which is then tuned through the experiment. At the beginning, the value of K should be large in order to get a fast response. When the rotor speed reaches near the command speed, the value K should be small in order to avoid overshoot and unstable. By using Fuzzy to adjust the parameter K of the single neuron, response speed of the system can be improved and overshoot of the system can be reduced.

Table 1
Inference Mechanism

Error						
NB	NM	NS	Z	PS	PM	PB
PB	PM	PM	PS	PM	PM	PB

V. SIMULATION RESULTS

The BLDC model drive with speed and current controllers is simulated in Matlab. The speed response for a step change in input is shown in Figure 7.

A Figure 8 is the actual and estimated rotor positions by EKF algorithm. The motor speed command is initially set at 104.7 rad/sec (1000 rpm) and at t = 0.05 sec; the reference speed is change to 157.1 rad/sec (1500 rpm). The estimated speed response clearly follows the actual speed after the transient period.

In Figure 9, the curve stands for the speed response of the system under the control of the conventional PI controller. The parameters of the conventional PI controller are tuned as K_P = 1.78, K_I=0.0178.

With no load, the speed response of the BLDCM under the control of the proposed controller is shown in Figure 10. When under the control of the proposed controller, the system responds quickly with little overshoot. The steady state error is zero. From Figure 10, it can be seen that after using the Fuzzy to adjust the parameter K, the dynamic response of the system is much quick

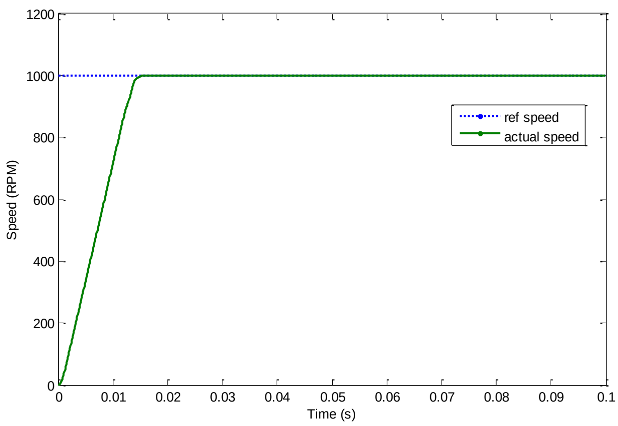

Figure 7: Speed Response with ref 1000 RPM

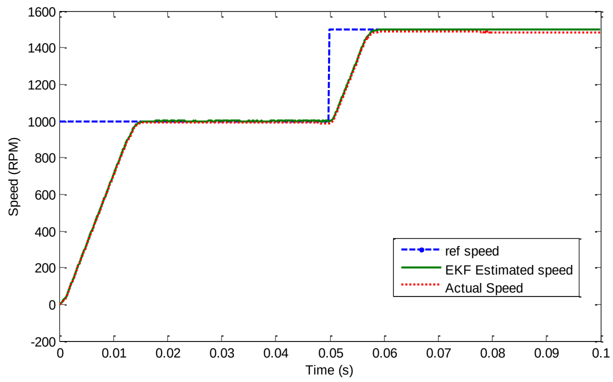

Figure 8: Actual and Estimated speed (EKF) responses

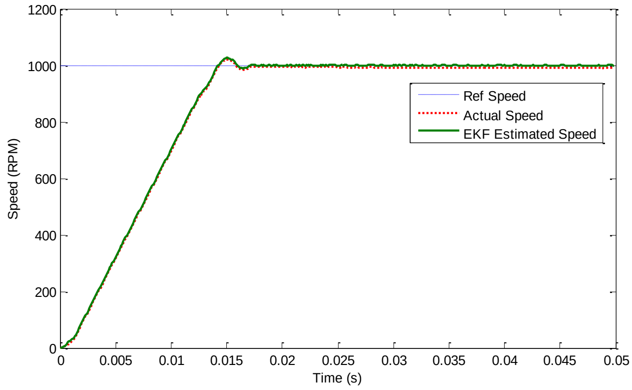

Figure 9: Actual and Estimated speed (EKF) responses with PI Controller

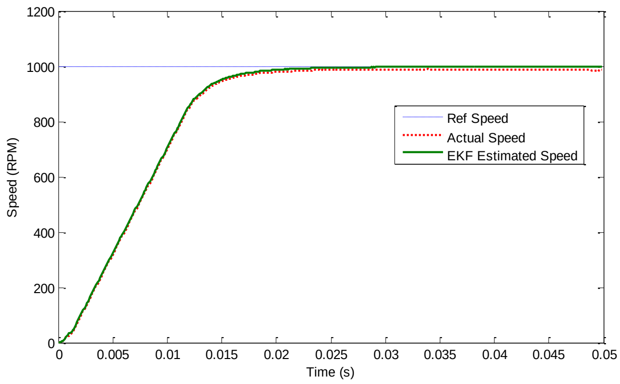

Figure 10: Actual and Estimated speed (EKF) responses with Single Neuron-Fuzzy Controller

VI. CONCLUSION

The speed of the BLDC motor is estimated using Extended Kalman Filter method. The speed is determined from the measured line voltages and currents of the motor. The simulation results prove that sensorless operation of the indirect position controlled drive system is possible. For the controller, while training the single neuron, the value of parameter K is very important. By using the universe approximation ability of fuzzy logic system, a single neuron-fuzzy controller is developed to tuning the value of parameter K online. Experimental results prove that a high performance is achieved under the control of the proposed controller. The using of single neuron fuzzy makes the BLDC with faster dynamic response.

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