Brushless DC Motor Speed Control System Based on Fuzzy Neural Network Control

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Abstract—As brushless DC motor (BLDCM) is a multivariable and non-linear system, using conventional PID control can not obtain satisfied control effect. Based on the mathematical model of BLDCM, a fuzzy neural network controller is designed, and the membership function is composed by Guass function. The system illustrates that excellent flexibility and adaptability as well as high precision and good robustness is obtained by the proposed strategy.

Index terms—Guass function; BLDCM; fuzzy neural network; learning arithmetic

I. INTRODUCTION

The More Electric Aircraft (MEA) [1,2,3] is the important feature of the next generation of advanced fighter aircraft. It is possibility that the MEA can be implemented because of today’s technological standards. The MEA initiative emphasizes the utilization of electrical power in place of hydraulic, pneumatic, and mechanical power to optimize the performance and life cycle cost of the aircraft [4]. One of the most important features of the MEA is substantially using of the electric actuator. Because the electric actuator is a key-board equipment of the MEA, which directly affects the safety of the flight, thus, the reliability, response speed, weight, power of actuation system have put forward a very high performance requirements. There are three basic approaches to electric actuation being developed today for air vehicle flight control surfaces. They are electromechanical actuators (EMA), electro hydrostatic actuators (EHA), and integrated actuator packages (IAP). Because the electric actuators are mostly used rare-earth permanent magnet motor as a power source, it is urgently to study the control system of the aviation brushless DC motor.

It is very promising to use neural networks and fuzzy control at BLDCM for it’s highly nonlinear, it has the ability to improve the performance such as system speed, stability and robustness [5]. Neuro-fuzzy control is a kind of intelligent control theory which combine fuzzy logic and neural network to the together. Neural networks are of highly parallel processing and distributed storage of the information, which has a strong self-learning and self-organization ability [6]. In this connection, the learning ability of neural networks and the memory capacity of fuzzy control are combined to design a neuro-fuzzy controller. The controller will be used to the speed control system of aviation high-voltage brushless DC motor [7].

In this paper, a fuzzy neural network is introduced in the speed control system of aviation high-voltage brushless DC motor to improve the performance of the speed system. The simulation results show that effect of the control method is superior to the conventional PID control.

II. MATHEMATICAL MODEL OF BLDCM

It is used one 3-phase 6-state BLDCM with Y-connected windings and 2 magnetic poles as the example [8]. Hence the three-phase stator voltage balance equation can be expressed by the following state equation.

\[
\begin{bmatrix}
U_a \\
U_b \\
U_c
\end{bmatrix} =
\begin{bmatrix}
r & 0 & 0 \\
0 & r & 0 \\
0 & 0 & r
\end{bmatrix}
\begin{bmatrix}
a_i \\
b_i \\
c_i
\end{bmatrix} +
\begin{bmatrix}
L-M & 0 & 0 \\
0 & L-M & 0 \\
0 & 0 & L-M
\end{bmatrix}
\begin{bmatrix}
e_a \\
e_b \\
e_c
\end{bmatrix}
\]

(1)

Where, \( U_a, U_b, U_c \) are the phase voltage, \( a_i, b_i, c_i \) are the phase current; \( e_a, e_b, e_c \) are back electromotive force(EMF), \( P = d/dt \) is differential operator.

The electromagnetic torque of BLDCM is generated by the interaction of the current in stator windings and the magnetic field in rotor magnet. The electromagnetic torque equation is

\[
T_{em} = P_{em} \frac{e_a a_i + e_b b_i + e_c c_i}{\omega}
\]

(2)

The motor mechanical equation of motion is

\[
T_{em} - T_L = J \frac{d\omega}{dt} + B\omega
\]

(3)

Where, \( T_{em} \) is the electromagnetic torque, \( T_L \) is the load torque, \( B \) is the viscous damping coefficient, \( \omega \) is motor speed, \( J \) is the rotational inertia of rotor and load.

According to the proposed mathematical model above, the simulation model of the BLDCM has been established.

III. NEURAL-FUZZY NETWORK CONTROLLER DESIGN
A. System structure

System architecture is shown in Figure 1. From among, \( \omega^* \) is the expectations speed of BLDCM, \( \omega \) is the actual speed, \( x_1 \), \( x_2 \) and \( u \) are the input and output of Gaussian function of the neural-fuzzy network, it is in the domain \([0, 1]\). The error \( e \) and error change rate \( e_n \) are converted to the input, \( 1x \), \( 2x \) of the neural-fuzzy network through \( \chi \) mapping. \( \Upsilon \) mapping is the role of translating the network output \( u \) to the control current \( i(t) \) of the BLDCM. \( J_n \) is objective function for the error \( \frac{1}{2}(\omega^* - \omega)^2 \), because the online learning algorithm can be regulating online, the system has a self-learning function.

\[
I^{(4)} = \sum_{i,j=1}^{7} O_{ij} \ast W_{ij} \quad (9)
\]

Output node

\[
O^{(4)} = \frac{I^{(4)}}{\sum_{i,j=1}^{7} O_{ij}} \quad (10)
\]

Where, \( x_i \) is network input, \( W_{ij} \) is the connection weights of the network, \( a_{ik} \), \( b_{ik} \) are namely the mean and the width of Gaussian function; \( u \) is the output of the network.

B. Neural network structure based on fuzzy Gaussian function

The structure of neural network based on fuzzy Gaussian function is shown in Figure 2[9]. As shown in Fig.2, \( x_1 \), \( x_2 \) are introduced in the networks on the first layer, \( x_1 \), \( x_2 \) are fuzzed on the second layer, in which membership function is used for the Gaussian function \( \exp(-\frac{(x - a)^2}{b}) \) (where \( a \), \( b \) are the mean center of Gaussian function and standard deviation of the variable \( x \)). The third layer corresponds to fuzzy reasoning, replacing fuzzy AND operation with product operation, the forth layer corresponds to defuzzification operation. The input and output relationship of network is shown as follows:

The first layer, output node

\[
O^{(1)} = x_i \quad (4)
\]

The second layer, input node

\[
I_{ik}^{(2)} = -(x_i - a_{ik})^2/b_{ik}^2 \quad (5)
\]

Output node

\[
O_{ik}^{(2)} = \exp(I_{ik}^{(2)}) \quad (6)
\]

The third layer, input node

\[
I_{ij}^{(3)} = O_{ik}^{(2)} \ast O_{kj}^{(2)} \quad (7)
\]

Output node

\[
O_{ij}^{(3)} = I_{ij}^{(3)} \quad (8)
\]

The forth layer, input node

\[
U^{(4)} = \frac{1}{\sum_{i,j=1}^{7} O_{ij}^{(3)}} \quad (9)
\]

\[
O^{(4)} = \frac{1}{\sum_{i,j=1}^{7} O_{ij}^{(3)}} U(t) - u(t-1) + \epsilon = \delta_u \quad (13)
\]

Among them, \( \epsilon \) is a very small constant. So,
\[ w_q(t+1) = w_q(t) - \eta \frac{\partial J}{\partial w_q} = w_q(t) + \]

\[ \eta (\omega^* - \omega) \cdot \delta_i \frac{O^{(3)}_{ij}}{\sum_{j=1}^{7} O^{(3)}_{ij}} (i, j = 1, 2, \cdots, 7) \tag{14} \]

Through the same principle, it can infer the revise formula of \( a_{ik}, b_{ik} \) as follows:

\[ a_{ik}(t+1) = a_{ik}(t) + 2\eta (\omega^* - \omega) \cdot \delta_i \sum_{j=1}^{7} w_{ij}(t)O^{(2)}_{ij}O^{(2)}_{kj} \cdot \]

\[ \frac{x_i - a_{ik}(t)}{b_{ik}(t)} \quad (k = 1, 2, \cdots, 7) \tag{15} \]

\[ a_{ik}(t+1) = a_{ik}(t) + 2\eta (\omega^* - \omega) \cdot \delta_i \sum_{j=1}^{7} w_{ij}(t)O^{(2)}_{ij}O^{(2)}_{kj} \cdot \]

\[ \frac{x_i - a_{ik}(t)}{b_{ik}(t)} \quad (k = 1, 2, \cdots, 7) \tag{16} \]

\[ b_{ik}(t+1) = b_{ik}(t) + 2\eta (\omega^* - \omega) \cdot \delta_i \sum_{j=1}^{7} w_{ij}(t)O^{(2)}_{ij}O^{(2)}_{kj} \cdot \]

\[ \frac{(x_i - a_{ik}(t))^2}{b_{ik}(t)} \quad (k = 1, 2, \cdots, 7) \tag{17} \]

\[ b_{ik}(t+1) = b_{ik}(t) + 2\eta (\omega^* - \omega) \cdot \delta_i \sum_{j=1}^{7} w_{ij}(t)O^{(2)}_{ij}O^{(2)}_{kj} \cdot \]

\[ \frac{(x_i - a_{ik}(t))^2}{b_{ik}(t)} \quad (k = 1, 2, \cdots, 7) \tag{18} \]

Thus, the error back-propagation and adjustment of connection weights are implemented in the neural-fuzzy network. As a result of the modified BP learning algorithm, the fuzzy neural network has a high learning speed.

IV. SIMULATION AND ANALYSIS

According to the model of neural-fuzzy network control system for BLDCM mentioned above, some vital simulation works have been conducted. Motor model parameters used for simulation is, phase resistance of stator : \( r = 0.012\Omega \), phase reactance of stator : \( L = 0.00104H \), rotor moment of inertia : \( J = 0.002kg \cdot m^2 \), rated torque \( T_e = 5N \cdot m \), counter emf \( K_e = 0.198V/l(rad/s) \), rated speed \( n = 5000r/min \), DC voltage : \( U_d = 270V \). The Matlab simulation model for above system is as shown in Fig.3.

The speed control applies fuzzy-neural network regulator, current loop applies hysteresis current controller. The load torque is: \( T_L = 5N \cdot m \) simulation is seconds later.

A. When the given speed \( N \) equals 500 r/min

- Fig.4 speed response based on PID and neural-fuzzy network controller
- Fig.5 partial Enlargement chart of speed response when load disturbance is added

B. When the given speed \( N \) equals 5000 r/min

- Fig.6 speed response based on PID and fuzzy-neural network controller

It can be seen from Fig. 4 and Fig.6 that regardless of motor running at high speed or low speed, compared with PID control, neural-fuzzy network controller has not only a fast responding, but also small overshoot. From Fig.5 and Fig.7, we can see that when the system is greatly disturbed, motor can regulate itself quickly under the control of the proposed method, and the entire system has good adaptability and strong robustness.
V. CONCLUSION

This paper proposed fuzzy-neural network controller, which is based on Gaussian function, was successfully implemented herein in this study to achieve the control of the speed of the BLDCM. Through fuzzy inference based on the neural network and the ameliorated BP algorithm, the error back-propagation and adjustment of connection weights is implemented in the fuzzy-neural network, which makes the fuzzy-neural network have a high learning speed, so that the controller parameter is optimized. The simulation results show that the controller of the proposed method has a good adaptability and strong robustness when the system is disturbed, which is better than traditional PID control.

REFERENCES