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Robust Speed Control of Permanent Magnet Synchronous Motors Using Adaptive Neuro Fuzzy Inference System Controllers

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Abstract: In this study, an Adaptive Neuro Fuzzy Inference System (ANFIS) controllers using error and derivative of error inputs is proposed for the speed control of a Permanent Magnet Synchronous Motors (PMSM). The PMSM is often used in electrical drives because of their simple structures, ease of maintenance and efficiency. However, the PMSM drive systems have a nonlinear characteristic arisen from motor dynamics and load characteristics. So they are required adaptive and robust speed control in industry applications. To overcome with this problem, an ANFIS is designed and adapted to the drive system. Neural Network (NN) is used to adjust input and output parameters of membership functions in the Fuzzy Logic Controller (FLC). The back propagation learning algorithm is used for training this network. Simulation and experimental results show that the ANFIS controller is reliable and high effectiveness in the speed control of the PMSM.

Key words: Permanent magnet synchronous motor, a daptive neuro fuzzy inference system, neural network

INTRODUCTION

Permanent Magnet Synchronous Motors (PMSM) are a popular method for motion actuation due to their long life, efficient use of power and low maintenance requirements. PMSM have been used widely in the control system of high performance depending development of the power electronic and control technology[1]. However, the performances of the PMSM are very sensitive to parameter and load variations. To overcome with these problems several control strategies such as Fuzzy Logic Control (FLC), Neural Network (NN) and Sliding Mode Control have been proposed for speed control of the PMSM [2]. FLC, NN algorithms have been used currently as effective methods in the control of system effected by destroyed entrance which is unknown quality and unstraight line[3,4]. Because of absence in structure of both methods has not been removed ANFIS algorithm has been created by connection of both methods superiority. In this study, the ANFIS controller is designed for speed control of the PMSM.

Adaptive Neuro Fuzzy Inference System (ANFIS) Controller for the PMSM

The ANFIS block diagram is shown in Fig. 1. The ANFIS controller is composed of a pattern set, an off-line learning algorithm with back propagation and a neuro-fuzzy network [5,6]. The network is trained using off-line learning algorithm in MATLAB package program. For the learning, a pattern set is realized using dynamic signal analysis of the motor.

The ANFIS controller has two inputs, speed error e_ω and the derivative of speed error ce_ω. The output is change of the control current Δi_q is computed. I is number of pattern.

Training of the ANFIS: To set the desired controller performance of the ANFIS, it is necessary to adaptation of parameters obtained. Thus, the ANFIS needs to train to neural network. Speed follow error for on-line training of the ANFIS and reduced function according to harmony parameters could write as Eq. 1[6,7].

$$e(k) = (\omega r(k)) \\ E = \frac{1}{2}e^2(k) \qquad (1)$$

Here $\_\omega_r$ shows reference speed, $\omega_$shows actual motor speed, e is the tracking error and E is the cost function to be minimized. If n learning ratio and è trained are parameters, harmony rule parameters according to learning algorithms back propagation, defines as Eq. 2.

$$\theta(k) = \theta(k-1)+\Delta\theta(k) = \theta(k-1)+\left(\frac{-\partial E(k)}{\partial\theta}\right) \qquad (2)$$

If parameter vector è are described *è=[a,b,c,p,q,r]^T* for a membership group and output function, gradient of

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$$\frac{\delta E}{\delta a} = \delta^1 \frac{\delta y^5}{\delta y^4}\frac{\delta y^4}{\delta y^3}\frac{\delta y^3}{\delta y^2}\frac{\delta y^2}{\delta y^1}\frac{\delta y^1}{\delta y^a} \quad (3)$$

function according to parameters defined as Eq. 3.

In the present study, delta adaptation rule which is more effective than others methods has been used and described as Eq. 4.

$$\delta^1 = Ae + \dot{e} \quad (4)$$

Here, A is positive number. As a conclusion delta parameters which is in Eq. 3 could calculated and parameters of trained rules could produced.

Hardware for Speed control of the PMSM Control: Fig. 2 is an overview of the hardware required to implement speed control of the PMSM. Six PWM outputs from the Digital Signal Processing (DSP) are used to drive a 3-phase power inverter. Two resistors on inverter legs are used to sense motor phase currents. The voltages across the resistors are amplified and fed in the Anolog Digital Converter (ADC) input channels of the DSP. The DSP samples these voltages right at the right time of a shaft of the motor for rotor angle measurement. The outputs from the encoder are interfaced directly to the QEP/CAP inputs of the DSP. The DSP obtains the rotor angle by reading the QEP counter. It then uses the sampled motor currents and obtained rotor angle to implement the ANFIS control algorithm to control the motor.

Simulation and Experimental Results: ANFIS controller given in Fig. 1. is simulated for the speed control of the PMSM using MATLAB.

Motor parameters are

R=11.05 Ù, L=21.5 H, J=0.0001kg.m2, P=6, Tn=0.9 Nm, Ez=39 v/1000 rpm., n=3000 d/dak., In=1.7 A.

To obtain a favorable current tracking performance, PI parameters are determined by trial and error as kp=10, ki=4 and sampling time is selected as Ts=100ìs considering the time constants of the motor.

The ANFIS is started with the randomly assigned parameters and then; off-line training of the ANFIS is continued with the sinusoidal speed reference. Training is stopped when the sum of the squared error during the one period of the speed reference (0.1 second or 1000 samples) is reduced a predetermined value, such as 0.0007. Then, optimum parameters found by training are recorded. To discuss the performance of the ANFIS, sum squared error for every epoch and, actual and reference speed during the training is also recorded.

The speed tracking performance of the PMSM with the ANFIS for the sinusoidal speed reference input used in the training is shown in Fig. 3. Nominal load torque is also applied to the motor at the times between 0.015 - 0.04 and 0.055 - 0.085 seconds. It is shown that the performance of the ANFIS is favorable.

In order to seen that performance of the ANFIS, sinusoidal reference speed was applied to PMSM. Fig. 4 illustrates sinusoidal reference speed and sinusoidal actual speed response of the PMSM. The motor is under load. High tracking accuracy is observed at Fig. 4.

CONCLUSIONS

This study proposes the ANFIS controller for the PMSM, which is widely used in automation systems. Simulation and experimental results show the effectiveness of the control system. Although the complex and nonlinear model of the PMSM, ANFIS is fairly favorable and design of the ANFIS does not need the exact mathematical model of the system. Main drawback of the neuro-fuzzy systems is that it has many parameters to be trained.

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