Abstract—A method is presented for position control of a permanent magnet synchronous motor (PMSM). First a linear descretized state-space model of a PMSM with unknown parameters is identified; the identified model is then controlled using state feedback with integrator techniques. The simulation results of a typical motor are obtained and the influence of pole placement, noise and load variations is studied. Finally, simulation results are confirmed with experimental results.

Key words: Adaptive control, identification, neural network, PMSM, vector control

1. Introduction

Ac servo drives using permanent magnet synchronous motors (PMSM) are widely used in robotics, computer numerically controlled (CNC) machine tools, elevators and many other applications in the area of mechatronics. The desirable features of the PMSM are its compact structure, high air gap flux density, high power density and high torque capability. The PMSM operates at a higher power factor and it has lower rotor losses compared to other machines. In addition, advances in magnetic materials, solid-state devices and control theory have made the PMSM drive play an important role in the low-to-medium power range of motion-control applications.

The basic principle of controlling a PMSM is based on vector control [1-3]. The control performance is influenced by the uncertainties of the plant, usually comprising plant parameter variations, external load disturbances, un-modeled and non-linear dynamics. Many control theories such as nonlinear control [4], optimal control [5], variable structure system control [6-8], adaptive control [9-10] and robust control [11] have been applied to the design of the PMSM drive to deal with these uncertainties. Nevertheless, system performance under parameter variations in controllers is also an important problem. Many techniques basically control the speed and then a PI controller is used for position control However, these controllers are not robust due to parameter and dynamic variations.

This paper considers the robust tracking problem by direct position control of the motor without a PI controller. In addition, the capability of neural networks in the identification of nonlinear dynamics and its ability to learn is used for identification of the PMSM drive. This technique identifies a model from a vector model of the motor. The controller is then designed using the identified model. The advantage of this technique is that the controller is independent of the identification. Thus, the range of controller designs can be varied based on the required accuracy and the speed of the processor. Other advantages of the technique are that the convergence rate of the response may be adjusted and the parameters of the motor are unnecessary.

Fig. 1: Two-pole three-phase PMSM

2. Mathematical model of the PMSM

A two-pole three-phase PMSM and its dq model are shown in Fig. 1. The state space model of PMSM is as follows:
Here there are four variables and nonlinear dynamics. In this model $i_d$ and $i_q$ are currents, $v_d$ and $v_q$ are voltages. Of course, this model is not used directly, but is estimated by an ANN.

3. Identification by Artificial Neural Network

The linear time-discretized state space model of the system is:

$$x(k+1) = Ax(k) + Bu(k)$$

(A and B are 4x4 and 4x1 matrices respectively. A single-layer network, shown in Fig. 2, can be used to identify A and B. This network has input neurons equal to the number of the state variables. Thus, this network has five input neurons and four output neurons. $v_q$ is considered as the single input of the system.)

Based on Eqn. 1, the state variables are considered as follows:

$$x = [\theta \ \omega \ \ i_q \ \ i_d]$$

(3)

In the neural network shown in Fig. 2, if $W_q$ is taken as the weights matrix of the trained ANN, then A and B will be as follow:

$$A = [W_q]_{ij} \quad 0 < i \leq 4, 0 \leq j < 4$$

$$B = [W_q]_{ij} \quad i = 0, 0 \leq j < 4$$

(4)

Therefore, the linear model of the state space system is identified using an ANN. A single-layer neural network is used here and the network function is as follows:

$$f(x) = x$$

(5)

A multi-layer network with one hidden layer is used here for identification (Fig. 3):

$$y = [W * V]*x_{in}$$

(6)

![Fig. 3: Multi-layer network for system identification](image)

4. Position control

Since the identified model of the motor is in state space form, a state feedback technique is used. In this technique the control signal is generated using all state variables. The technique is one of strong linear system control methods that generally leads to a good response. The robustness of this method is the use of all state variables, which sometimes are not available or not economical to obtain. In such a case an observer is necessary. However, all state variables are easily
available in the PMSM. Most control techniques of the motor, except sensorless methods, use position and current transducers.

Now, a controller system in the state space is designed using the state space model. The poles of the system moves to a proper position by feedback from state variables. Thus:

\[
\begin{align*}
    x_{i+1} &= Ax_i + Bu_i \\ 
    u_i &= -kx_i
\end{align*}
\]

(10)

substituting \( u_k \) in the first equation of (10) yields:

\[
\begin{align*}
    x_{i+1} &= Ax_i + Bu_i \\ 
    u_i &= -kx_i
\end{align*}
\]

(11)

Since the linear model is considered as a time-discretized, the desired poles must be taken inside of the unit circle. \( k \) can be determined using different methods such as Ackerman, Bass and Gura and Mayne-Murodoch. Since there is steady state error in the state feedback technique, an integrator for error reduction can be added. There is also one more desired pole to facilitate the convergence of the error. The error integrator is added to the state variables and matrices A and B are extended. Finally the gain factor is determined by one of the gain methods.

Fig. 4 shows a general identification and control diagram. As seen, following the identification, A and B and then the required gain factor characteristics are obtained and applied to the controller. In Fig. 4, \( L \) is the output gain defined as follows:

\[ L = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \]

(12)

Fig. 4: General diagram of identification and control

5. Simulation Results

The PMSM with specifications given in Table 1 is simulated. For training a two-layer network N5,6,4 with learning factor of 0.001 is used.

<table>
<thead>
<tr>
<th>Tab. 1: Parameters of PMSM</th>
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<tr>
<td>Rated speed</td>
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In order to obtain a desired response it is better to train offline the network, such that the initial weights in the online system also tends to the main values. The identified matrices A and B are as follows:

\[
A = \begin{bmatrix} 1.0000 & .0010 & .0000 & .0000 \\ .0000 & .9638 & 1.6012 & .0273 \\ .0000 & -.0046 & .7775 & .0249 \\ .0000 & .0000 & -.0055 & .9181 \end{bmatrix}
\]

(13)

\[
B = \begin{bmatrix} .0000 \\ 1.4429 \\ .1827 \\ .0010 \end{bmatrix}
\]

(14)

Fig. 5 presents the position response of system to the input pulse using state feedback techniques with an integrator. The desired poles in this design are as follows:

\[
P_1 = \begin{bmatrix} 0.90 & 0.95 & 0.88 & 0.92 & 0.86 \end{bmatrix}
\]

(15)

The criterion for pole selection are convergence rate, overshoot, rise time, settling time and other training parameters. In order to have a stable system, the poles are selected inside the unit circle. By approaching the unit circle, the convergence rate is lower, the amplitude of the control signal is smaller and noise effects are also lower. If the poles tend to the origin, a quiker response, larger control signals and higher noise effects are observed. Fig. 6 shows the system position response to the input pulse for the given poles. The system poles in this design is as follows:
7. Effect of Disturbance

The system response to load disturbances is studied in this section. As shown in Fig. 8, a gradual change of the load has not affected the system response. The effect of this load disturbance can be observed on \( i_q \) that is proportional to the developed torque of the motor.

8. Experimental Results

The technique was implemented on a DSP TMS320LF2407. The experimental model consists of: a DSP board that takes the program via the serial port of the computer and builds PWM signals. The inverter board takes the PWM signals and generates the input voltages of the motor, it also returns the encoder signals and motor currents to the DSP board, a low power 15 W motor with specifications given in Table 1. A 2000 p/r encoder is fixed on the motor. Fig. 9 presents the experimental setup of the system. The open-loop response of the system, used in the identification, is shown in Fig. 10. A and B are identified using these data. Matrices A and B are determined using pu values as follows:

\[
P_2 = \begin{bmatrix} 0.90 & 0.98 & 0.88 & 0.92 & 0.88 \end{bmatrix} \quad (16)
\]

\[
P_3 = \begin{bmatrix} 0.85 & 0.90 & 0.83 & 0.87 & 0.81 \end{bmatrix} \quad (17)
\]
For design of the state feedback with integrator, poles are taken to be $P_1$. Fig. 11 shows the system response in this case, which can be compared to the simulation results.

As the poles tend to the unit circle ($P_2$) this leads to a slower response, smaller control signals and lower measured noise on the response. The results for such a case are shown in Fig. 12.

When the poles approach the origin ($P_3$), this results in quicker response, larger control signal amplitudes and larger effect of the measured noise on the response. Fig. 13 presents the results for this case.

Fig. 14 shows that the load disturbance has no effect upon the position response. This effect can be observed on $i_q$.

9. Conclusions

In this paper an adaptive technique using neural networks for vector control of a PMSM system has been proposed and used for control design. The effects of pole changing and load disturbance upon the PMSM have been shown by simulation. The simulation results show that the technique does have better performance and robustness than other available techniques. It has shown that the pole changing effects are identical to the results of poles changing in state feedback for linear systems. The experimental results confirm the simulation results.

\[
A = \begin{bmatrix}
  1.0000 & 0.010 & 0.000 & 0.000 \\
  0.000 & 0.9795 & 0.0140 & 0.0035 \\
  0.000 & -0.4419 & 0.8819 & -0.0044 \\
  0.000 & 0.1937 & -0.0234 & 0.8385 \\
\end{bmatrix}
\]  

(18)

\[
B = \begin{bmatrix}
  0.000 \\
  -0.0001 \\
  0.0410 \\
  -0.1052 \\
\end{bmatrix}
\]  

(19)

Fig. 9: Photograph of experimental setup

Fig. 10: Open-loop position response of motor used for identification

Fig. 11: System position response for poles P1

Fig. 12: System position response for poles P2
Fig. 13: System position response for poles P3

Fig. 14: Effect of load disturbance on the position response

References


