Automatic Tuning Method for PMSM using Big Data based Artificial Neural Network

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Methods based on linear analysis have been studied for stable control of permanent magnet synchronous motors; however, they are difficult to apply in the operating regions and under control conditions that cannot be linearized. In such instances, trial and error tuning is required to obtain the desired characteristics. In this study, we investigate a method of learning for an artificial neural network using a large amount of tuned PMSM parameter data and derive the control parameters to stably drive the PMSM.

Keywords: PMSM, Automatic tuning, ANN, Big data, Sensorless control, Synchronous control

1. Introduction

A method based on linear analysis with equilibrium point approximation has been studied as a general gain design method for stable control of permanent magnet synchronous motors (PMSMs), however it is difficult to apply to operating regions and control conditions that cannot be linearly approximated. For example, it is necessary to sufficiently reduce torque and speed ripple during controller switching, which is performed in many products. In such a case, it is difficult to make a clear linear analysis of the design results of multiple controllers such as current control, speed control, sensorless control, etc., and the response associated with controller switching, and additional adjustment is necessary to achieve the desired operation.

Automatic tuning using optimization algorithms or neural networks has been studied as a countermeasure for such cases. However, these optimization methods require a large amount of time and may cause problems such as uncontrollable rotation of the motor due to inappropriate parameter settings.

On the other hand, a company’s development site may have a large amount of tuned control parameter data from past PMSM-applied products. In this paper, we consider the possibility of utilizing these design data. As mentioned earlier, the research examples of using neural networks for automatic tuning of motor control are generally learning rules using series time data of the driving control target, however the authors have conducted research on automatic tuning of control systems using big data of existing control designs. In this paper, we investigate a method for automatic tuning of control parameters that can be applied to control adjustments that are difficult to analyze linearly and can be achieved without iterative driving in optimization approaches. For this purpose, we develop a method to train an artificial neural network (ANN) using a large amount of tuned parameter data for PMSM, and report the effect of applying this method to improve the stability of controller switching.

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2. Problems in tuning PMSM control systems

Fig. 1(a) shows the control configuration for speed control and current control of the PMSM by flux estimation type sensorless controller. Where, \( \omega^*, \omega \) : reference speed, estimated speed, \( I_s^*, I_s \), \( I_s, I_q \) : d,q-axis reference currents, currents, \( V_s, V_q \) : d,q-axis voltages, \( \theta^*, \Delta \theta \) : estimated position, estimated position error. Since it is difficult for the estimator to calculate the pole positions at low speed, an open-loop controller called forced synchronous drive or pulling-in drive is used, as shown in Fig. 1(b) and Fig. 2(a), and the controller is switched to speed control in the medium speed range. These methods are used in fan and compressor motor applications. However, if the control gain is not sufficiently adjusted, torque and speed ripple occurs when switching from synchronous drive to speed control, as shown in Fig. 2(b). In order to sufficiently suppress this problem, not only basic settings such as initial values of controllers but also control gain adjustments that take into account the relationship between each controller are necessary. And these are difficult to obtain exactly in a linear analysis.

(a)Sensorless speed control (b)Synchronous operation

Fig. 1. Configuration of PMSM controller.

(a)Start up sequence (b)Operation waveform

Fig. 2. Problem of conventional stability analysis.
3. Automatic tuning method with ANN

In this paper, we construct an ANN that can output stable control parameters given unknown PMSM data by learning from the electrical and mechanical parameters of various PMSMs and the stable control parameters of each controller as teacher data. Fig. 3(a) shows the structure of the ANN and (b) shows the training data. The input layer contains a set of parameters such as winding resistance, magnetic flux and other motor parameters that define PMSM, and the control parameters of multiple controllers. The output layer, which is computed through the intermediate layer, outputs the result of judging whether those control parameters are stable or unstable. In other words, the ANN is a stable discriminator of the control parameters for an arbitrary PMSM specification. The teaching data is the result signal of judging whether the parameters of the input are stable or not. These training data are the control gains and other data of the PMSM that have been adjusted in the past. During training, the weighting of each neuron is performed by back-propagation to minimize the error evaluation function E shown in equation (1). \( y(N_{\text{in}}, N_{\text{p}1}, N_{\text{p}2}) \) is the output of the ANN for NM PMSMs with \( N_{\text{p}1} \) and \( N_{\text{p}2} \) parameters set, and \( t(N_{\text{in}}, N_{\text{p}1}, N_{\text{p}2}) \) is the stable discrimination result, which is the teacher signal and takes the value of 0 or 1. Equation (1) shows an example where the number of sample motors \( N_{\text{m}} \) is set to 628[rad/s], and the other two controllers are configured to adjust to the response of the current controller. In order to adjust all three controllers simultaneously, \( \omega_{\text{cr}} \) should be added as \( N_{\text{p}1} \) in equation (1). Such a configuration enables even more optimal adjustment.

\[
E = \sum_{N_{\text{in}}=1}^{N_{\text{max}}} \sum_{N_{\text{p}1}=1}^{N_{\text{p}1\text{max}}} \sum_{N_{\text{p}2}=1}^{N_{\text{p}2\text{max}}} \left[ y(N_{\text{in}}, N_{\text{p}1}, N_{\text{p}2}) - t(N_{\text{in}}, N_{\text{p}1}, N_{\text{p}2}) \right]^2 \quad \text{(1)}
\]

4. Experimental verification

The effect of automatic parameter tuning by ANN is verified using the sensorless control switching controller from synchronous operation as a motif. In this study, ANN is trained using motor specification parameters and stability discrimination data according to the cross-angle frequency between speed control and sensorless control of a PMSM with \( N_{\text{m}} = 20 \) sample motors as teaching data. Fig. 4 shows the distribution of rated torque and inverter DC voltage for 20 sample PMSMs. We prepare data for a wide variety of PMSMs, from small to large capacity. Furthermore, the number of frequencies \( N_{\text{p}1}, N_{\text{p}2} \) for \( \omega_{\text{cr}} \) and \( \omega_{\text{p}1} \) is 7 respectively. Fig. 5(a) shows the results of the ANN stability judgment after learning when unknown PMSM specification parameters are given. Fig. 5(b) shows the stable parameter range by actual operation tests, and they are in good agreement. Fig. 6 shows the operation waveform of the actual machine using the parameters at point A in Fig. 5(a), and the proposed adjustment method can suppress the speed and current ripple even during the controller switching. On the other hand, point B shows the parameters for the unstable case shown in Fig. 2.

5. Conclusion

We show that ANN can be trained with past control design data from the development site to make effective use of unknown PMSM control adjustments as well as adjustments for applications where linear analysis is difficult, such as reducing speed ripple during control switching.

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