The Design of BP Neural Network Modeling for Switched Reluctance Motor

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Abstract. The model parameters of 8/6 poles switched reluctance motor (SRM) were determined through using the measured magnetization curve and the establish BP neural network model, selecting Sigmoid function as the hidden layer activation function and using gradient descent method to train the network. The simulated results show that the motor flux linkage model established has a good convergence rate, higher accuracy and generalization ability. It is significant to improve the reliable running and high precision speed control of SRM motor.

Introduction

The structural characteristics of SRM make it have the advantages of high reliability, low cost and high efficiency, and the speed regulating system composed of SRM has the advantages of both AC and DC speed regulating system, which has been widely used in the field of electrical transmission in recent years[1-2].So SRM has a promising future in this field. However, due to its double salient pole structure, the SRM drive system itself is a serious nonlinear system. The torque ripple, motor vibration, noise and other problems are particularly obvious. These defects, especially torque ripple, greatly limit its wide application in servo control and other fields. The traditional motor control method is not suitable for SRM drive system, so the suppression of motor torque ripple has become a research focus of SRM at present.

Although it is difficult to study SRM torque pulsation due to the complexity of magnetic circuit structure, however, but some progress has been made by scholars over these years. To solve the torque ripple of SRM motor, the most important thing is to establish correct and reliable SRM motor model.

There is a complex functional relationship between the stator flux and winding current and rotor position of SRM, and the relationship between them is nonlinear, and establishing accurate and practical magnetic chain model is a hot research today. Traditional table method[3], has high accuracy, but needs a lot of calculations, and is unable to meet the real-time control and motor rapid modeling requirements. Although the function analytical method[4-5] can improve the system performance, but it’s adaptability is poor in the change of load and parameters. With the continuous development of artificial intelligence technology, intelligent control theory in SRM modeling is used more widely. Literature [6-7], respectively, use sliding mode variable structure fuzzy neural network and RBF neural network to establish a magnetic chain model of the motor. Error Back Propagation Neural Network (BPNN) is connection type of feedback neural network, based on the kind of multilayer feedback networks, and compared with other neural network, it is the most widely used and versatile neural network model, which has better characteristics [8-10] in the aspect of classification, pattern recognition, function approximation, global convergence and generalization ability, and shows good development potential in the field of SRM modeling.

BP Neural Network Modeling

Based on the sample shown as magnetization curve by measuring[13], we can come up with a model which aims at SRM's BP neural network magnetic linkage model.

Network Structure

The BP learning algorithm belongs to a learning way with teacher's supervising. After the training pattern is provided to BP network, firstly, the input single is sent to implicit node forward via a excitation function and output single from implicit node is sent to output node, it gives output result, and then, in accordance with the direction of reducing the deviation between idea output and actual output, it recondition the network's weighting and threshold value layer-by-layer from output layer to implicit layer until back to output layer and archiving minimum error repeatedly. Recently, BP network is a neural network model which has the most extensive application and the best versatility.

BP neural network magnetic linkage model has three level structures. Input includes stator winding group's current and rotor's position angle. Output is corresponding flux linkage value. Input layer and output layer use linear function to implement full join between them. Implicit layer's neurons use S type functions and output neurons use excitation linear function. Network structure is shown in Fig.1.

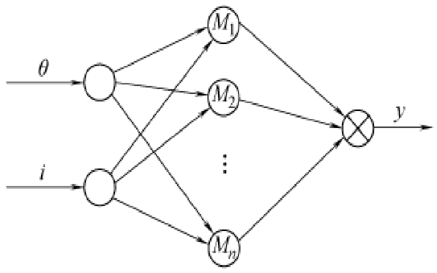

Figure 1. Flux linkage model based on BPNN

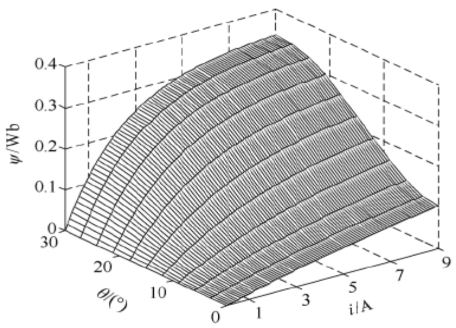

Figure 2. Flux linkage surface obtained by WNN

In Fig.1, input's mathematical expression and output's mathematical expression are as follow.

$$\psi(i,\theta) = L(i,\theta)i \tag{1}$$

$$M(j) = f(\sum_{i=1}^{m} w_{ij}x_i - \theta_j) \tag{2}$$

$$\psi = f(\sum_{j=1}^{n} w_j M_j - \theta) \tag{3}$$

$$f(t) = \frac{1}{1+e^{-at}} \tag{4}$$

The (1) ~ (4) formula:

j—the number of implicit nodes, j∈[1,n],n = 10;

m—the number of input layer's nodes, m = 2;

xi—***i***=1 means rotor's relative position angle, *i*=2 means winding group's current;

f (·)—implicit excitation function;

w_{ij}—implicit excitation function's connection weight;

θ_j—unit value;

Ψ—network output's flux linkage;

w_j—the connection value from implicit layer to output layer.

Here f (·) is selected as S type function.

Model Parameter Initialization and Training

(1) Initialization for network, whose value is the random number between -1 and +1, sets the connecting weights and threshold value, select wj =0.

(2) Offering training sample, then select a pair of training sample (XP, YP). (XP is input, YP is

expected output)

(3) The calculation of input pattern forward processing. According to expressions (1) ~ (3), calculating network's initial output flux linkage (Ψ).

(4) Error's Inverse Propagation Procession

After finishing once input pattern's forward processing, from assuming it is numbered p sample we can get the deviation for network's expected value and actual output:

$$e_k^p = (Y_k^p - y_k^p) \tag{5}$$

When we take the neurons' output mean square deviation as the training sample which is numbered p, network's objective function is followed.

$$E^p = \sum_{k=1}^{n} \frac{1}{2}[e_k^p]^2 = \sum_{k=1}^{n} \frac{1}{2}(Y_k^p - y_k^p)^2 \tag{6}$$

Supposing network's objective function as global error for all training samples which is followed.

$$E = \sum_{p=1}^{P} E^p = \sum_{p=1}^{P}\sum_{k=1}^{n} \frac{1}{2}[e_k^p]^2 = \sum_{p=1}^{P}\sum_{k=1}^{n} \frac{1}{2}(Y_k^p - y_k^p)^2 \tag{7}$$

(5) The calculation of various layers' network weight and threshold value.

Negatively adjusting various layers' network weight and threshold value by gradient descent algorithm, we can solve objective function's weight when needing the minimum along with E's negative gradient direction. BP network's various layers whose correction value is followed.

$$\Delta w_j = -\eta \frac{\partial E}{\partial w_j} = -\eta \sum_{p=1}^{P} \frac{\partial E^p}{\partial w_j} \tag{8}$$

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = -\eta \sum_{p=1}^{P} \frac{\partial E^p}{\partial w_{ij}} \tag{9}$$

$$\Delta \theta_j = -\eta \sum_{p=1}^{P} \delta_k^p \tag{10}$$

Here, η is learning rate, 0＜η≤1, and the greater theηthe faster convergence.

(6) Return to step (2), according to modified connection weights and threshold value, we have to calculate again for each learning samples, until the result achieves expected global error for the objective function of network (E<ε, ε=a pre-set allowable error for parameters), then learning is ending.

Simulation Verification

After finish the training, we can put certain parameters in equation (1~3) to get an integrated mathematical model for flux linkage. Then, regarding actual measurements which are groups of motor's input current and angle as input model, we can calculate fluxes' output of the model developed. The graphics are shown in Fig.2.

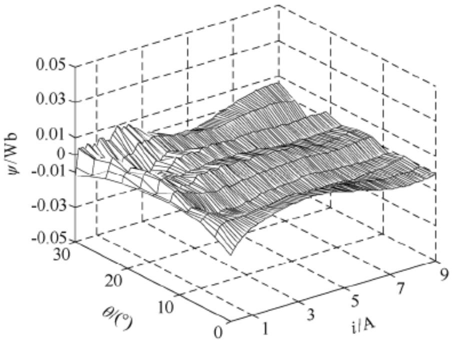

Figure 3. Error surface of the flux linkage model

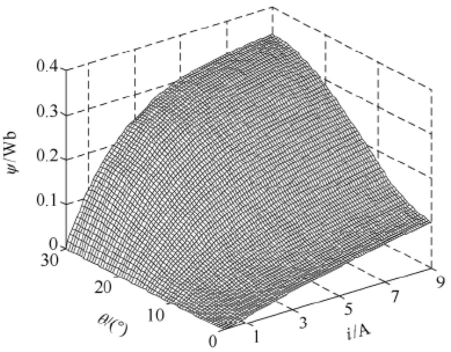

Figure 4. Generalized surface of the flux linkage model based on BPNN

From the Fig.2 we can know, for different rotor's position angle and input current, we can get smoother flux linkage curved surface through model calculation. The Fig.2 also proves model which is continues and undistorted in a output range, and reflects change rules which are belong to both current and rotor's position angle with change of linkage. Comparing the model's output to actual measurement data for linkage, we get the error curved surface as shown in Figure 3.

Model's calculation value is less different from actual value (the biggest error less than 0.02Wb) shown in Fig.3, it illustrates that the SRM flux linkage model was founded by BP network has higher accuracy and reference value. In order to certify the generalization ability of the model, with current every 0.1 A, angle every 0.5° as model input, we achieve flux linkage characteristics of curved surface for BP neural network output as shown in Fig.4.

When taking the input as non-measured data, the linkage has very smooth output curved surface which is founded by BP network shown in Fig.4. Comparing to measured linkage curved surface, we can find that they are very close and put up the model has very strong generalization ability.

Conclusion

This research controller uses TMS320LF2407 DSP to set up a SRM flux detection system with high reliability and adaptability. Therefore, accurate SRM flux characteristics and nonlinear models are obtained. These studies are of great value for improving motor design and high precision speed regulation. The experiment shows that the system has low cost, high accuracy of flux characteristics obtained by the system and very good effect. Based on measured flux linkage characteristic, it uses BP network to found SRM's flux linkage mathematical model. By comparison calculated flux linkage model and measured flux linkage model, it indicates model has very high accuracy and very strong generalization ability. It has actual significance for SRM's high-performance speed control and online prediction and also provide basis of nonlinear modeling and optimal control for the motor.

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