Neural Network Based Modeling and Parameter Identification of Switched Reluctance Motors

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Abstract — **Phase windings of switched reluctance machines are modeled by a nonlinear inductance and a resistance that can be estimated from standstill test data. During online operation, the model structures and parameters of SRM's may differ from the standstill ones because of saturation and losses, especially at high current. To model this effect, a damper winding is added into the model structure. This paper proposes an application of artificial neural network to identify the nonlinear model of SRM's from operating data. A 2-layer recurrent neural network has been adopted here to estimate the damper currents from phase voltage, phase current, rotor position and rotor speed. Then the damper parameters can be identified using maximum likelihood estimation techniques. Finally the new model and parameters are validated from operating data.**

Index Terms — **Neural Network, Modeling, Parameter Identification, Switched Reluctance Motor**

I. INTRODUCTION

SWITCHED reluctance motors (SRM) have undergone rapid development in hybrid electric vehicles, aircraft starter/generator systems, washing machines, and automotive applications over the last two decades. This is mainly due to the various advantages of SRM's over other electric motors such as simple and robust construction, and fault-tolerant performance.

In most of these applications, speed and torque control are necessary. To obtain high quality control, an accurate model of the SRM is often needed. At the same time, to increase reliability and reduce cost, sensorless controllers (without rotor position/speed sensor) are preferred. With the rapid progress in microprocessors (DSP), MIPS-intensive control techniques such as sliding mode observers and controllers [1] become more and more promising. An accurate nonlinear model of the SRM is essential to realize such control algorithms.

The nonlinear nature of SRM and high saturation of phase winding during operation makes the modeling of SRM a challenging work. The flux linkage and phase inductance of SRM change with both the rotor position and the phase current. Therefore the nonlinear model of SRM must be identified as a function of the phase current and rotor position. Two main models of SRM have been suggested in the literature – the flux model [2] and the inductance model [3]. In the latter one, "the position dependency of the phase inductance is represented by a limited number of Fourier series terms and the nonlinear variation of the inductance with current is expressed by means of polynomial functions" [3]. This model can describe the nonlinearity of SRM inductance quite well.

Once a model is selected, how to identify the parameters in the model becomes an important issue. Finite element analysis can provide a model that will be subjected to substantial variation after the machine is constructed with manufacturing tolerances. Therefore, the model and parameters need to be identified from test data. As a first step, the machine model can be estimated from standstill test using maximum likelihood estimation (MLE) techniques. This method has already been applied successfully to identify the model and parameters of induction and synchronous machines [4, 5].

Furthermore, during online operation, the model structures and parameters of SRM's may differ from the standstill ones because of saturation and losses, especially at high current. To model this effect, a damper winding may be added into the model structure, which is in parallel with the magnetizing winding. The magnetizing current and damper current are highly nonlinear functions of phase voltage, rotor position, and rotor speed. They are not measurable during operation, and are hard to be expressed with analytical functions. Neural network mapping are usually good choices for such tasks [7, 8, 9]. A 2-layer recurrent neural network has been adopted here to estimate these two currents, which takes the phase voltage, phase current, rotor position and rotor speed as inputs. When the damper current is estimated and damper voltage is computed, the damper parameters can be identified using output error or maximum likelihood estimation techniques.

In this paper, the procedures to identify an 8/6 SRM parameters from standstill test data are presented after a brief introduction to the inductance model of SRM. Then a 2-layer recurrent neural network is trained and applied to identify the damper parameters of SRM from operating data. Model validation through on-line test is also given, which proves the applicability of the proposed methods.

II. Inductance Model of SRM At Standstill

The inductance model of switched reluctance motor is shown in Fig. 1.

Fig. 1   Inductance model of SRM at standstill

Since the phase inductance changes periodically with the rotor position angle, it can be expressed as a Fourier series with respect to rotor position angle θ.

$$L(\theta,i) = \sum_{k=0}^{m} L_k(i) \cos kN_r\theta,$$

(1)

where N_r is the number of rotor poles.

To determine the coefficients $L_k(i)$ in the Fourier series, we need to know the inductances at several specific positions. Use $L_\theta(i)$ to represent the inductance at position θ, which is a function of phase current i and can be approximated by a polynomial:

$$L_\theta(i) = \sum_{n=0}^{p} a_{\theta,n} i^n.$$

(2)

where p is the order of the polynomial and $a_{\theta,n}$ are the coefficients of polynomial. In our research, $p = 5$ is chosen after we compare the fitting results of different p values (we tried $p = 3$, 4, 5, and 6).

For an 8/6 machine, $N_r=6$. When $\theta=0^\circ$ is chosen at the aligned position of phase A, then $\theta=30^\circ$ is the unaligned position of phase A. Usually the inductance at unaligned can be treated as a constant [3]:

$$L_{30^0} = const.$$

(3)

In [3], The authors suggest using the first three terms of the Fourier series, but more terms can be added to meet accuracy requirements.

Three-term inductance model

If three terms are used in the Fourier series, then we can compute the three coefficients L_0, L_1, and L_2 from L_{0^0} (aligned position), L_{30^0} (unaligned position), and L_{15^0} (a midway between the above two positions). Since

$$\begin{bmatrix} L_{0^0} \\ L_{15^0} \\ L_{30^0} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & \cos(6*15^0) & \cos(12*15^0) \\ 1 & \cos(6*30^0) & \cos(12*30^0) \end{bmatrix} \begin{bmatrix} L_0 \\ L_1 \\ L_2 \end{bmatrix},$$

(4)

we have

$$\begin{bmatrix} L_0 \\ L_1 \\ L_2 \end{bmatrix} = \begin{bmatrix} 1/4 & 1/2 & 1/4 \\ 1/2 & 0 & -1/2 \\ 1/4 & -1/2 & 1/4 \end{bmatrix} \begin{bmatrix} L_{0^0} \\ L_{15^0} \\ L_{30^0} \end{bmatrix}.$$

(5)

Four-term inductance model

If Four terms are used in the Fourier series, then we can compute the four coefficients L_0, L_1, L_2, and L_3 from L_{0^0} (aligned position), L_{10^0}, L_{20^0}, and L_{30^0} (unaligned position). Since

$$\begin{bmatrix} L_{0^0} \\ L_{10^0} \\ L_{20^0} \\ L_{30^0} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & \cos(60^0) & \cos(120^0) & \cos(180^0) \\ 1 & \cos(120^0) & \cos(240^0) & \cos(360^0) \\ 1 & \cos(180^0) & \cos(360^0) & \cos(540^0) \end{bmatrix} \begin{bmatrix} L_0 \\ L_1 \\ L_2 \\ L_3 \end{bmatrix},$$

(6)

we have

$$\begin{bmatrix} L_0 \\ L_1 \\ L_2 \\ L_3 \end{bmatrix} = \begin{bmatrix} 1/6 & 1/3 & 1/3 & 1/6 \\ 1/3 & 1/3 & -1/3 & -1/3 \\ 1/3 & -1/3 & -1/3 & 1/3 \\ 1/6 & -1/3 & 1/3 & -1/6 \end{bmatrix} \begin{bmatrix} L_{0^0} \\ L_{10^0} \\ L_{20^0} \\ L_{30^0} \end{bmatrix}.$$

(7)

Voltage equation and torque computation

Based on the inductance model described above, the phase voltage equations can be formed and the electromagnetic torque can be computed from the partial derivative of magnetic co-energy with respect to rotor angle θ. They are listed here:

$$V = R \cdot i + \frac{d\psi}{dt} = R \cdot i + \frac{d(Li)}{dt},$$

$$= R \cdot i + L\frac{di}{dt} + i(\frac{\partial L}{\partial \theta}\omega + \frac{\partial L}{\partial i}\frac{di}{dt})$$

(8)

where

$$\omega = \frac{d\theta}{dt}$$

$$\frac{\partial L}{\partial i} = \sum_{k=0}^{m} \frac{\partial L_k(i)}{\partial i} \cos kN_r\theta,$$

(9)

$$\frac{\partial L}{\partial \theta} = -\sum_{k=1}^{m} L_k(i)kN_r \sin kN_r\theta.$$

(10)

And

$$T = \frac{\partial W_c(\theta,i)}{\partial \theta} = \frac{\partial\{\int [L(\theta,i)i]di\}}{\partial \theta}$$

$$= \frac{\partial\{\int \sum_{k=0}^{m}[L_k(i)\cos(kN_r\theta)i]di\}}{\partial \theta}.$$

(11)

$$= -\sum_{k=1}^{m}\{kN_r \sin(kN_r\theta)\int[L_k(i)i]di\}$$

III. Maximum Likelihood Estimation

To minimize the effects of noise caused by the converter harmonics and the measurement, maximum likelihood estimation (MLE) technique can be applied to estimate the parameters. Suppose the dynamic response of the system is represented by

$$\begin{cases} x(k+1) = A(\theta_p)x(k) + B(\theta_p)u(k) + w(k) \\ y(k) = C(\theta_p)x(k) + v(k) \end{cases}, \qquad (12)$$

where θ_p represents the system parameters, $x(k)$ represents system states, y(k) represents the system output, $u(k)$ is the system input, $w(k)$ is the process noise, and $v(k)$ is the measurement noise.

The maximum likelihood estimation is performed based on the mechanism shown in Fig. 2. A model of the phase winging is excited with the same voltage as the real winding. The error between the estimated output and the measured output is used to adjust the model parameters (according to output error estimation algorithm) to minimize the cost function $V(\theta)$. This process is repeated till the cost function is minimized.

The model structure in Fig. 1 is a first-order system. The dynamic equation for it can be expressed as

$$V = R \cdot i + L \frac{di}{dt} \qquad (13)$$

When transformed to discrete-time state space form, the states, input, output, and parameters vector are

$$\begin{aligned} x &= [i], \quad u = [V], \quad y = [i] \\ \theta_p &= [R,L]^T \end{aligned} \qquad (14)$$
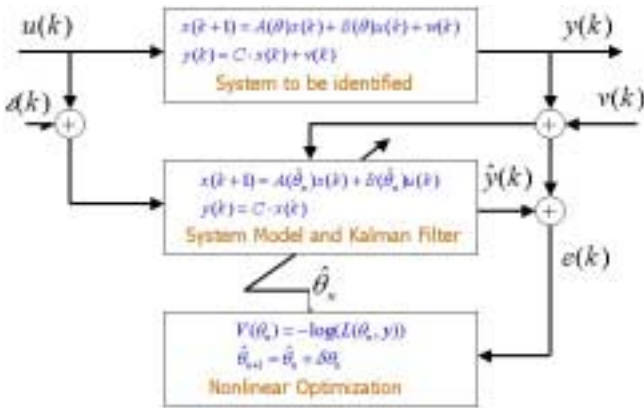

Fig. 2   Block diagram of Maximum Likelihood Estimation

IV. PARAMETER IDENTIFICATION FROM STANDSTILL TEST DATA

The basic idea of standstill test is to apply a short voltage pulse to the phase winding with the rotor blocked, record the current generated in the winding, and then use maximum likelihood estimation to estimate the resistances and inductances of the winding. By performing this test at different current level, the relationship between inductance and current can be curve-fitted with polynomials.

The experimental setup is shown in Fig. 3. An 8/6 SRM is used in this test. Before testing, the motor is rotated to a specific position (with one of the phase windings aligned, unaligned, or at other positions) and blocked. A DSP system (dSPACE DS1103 controller board) is used to generate the

gating signal to a power converter to apply appropriate voltage pulses to that winding. The voltage and current at the winding is sampled and recorded. Later on, the test data is used to identify the winding parameters.
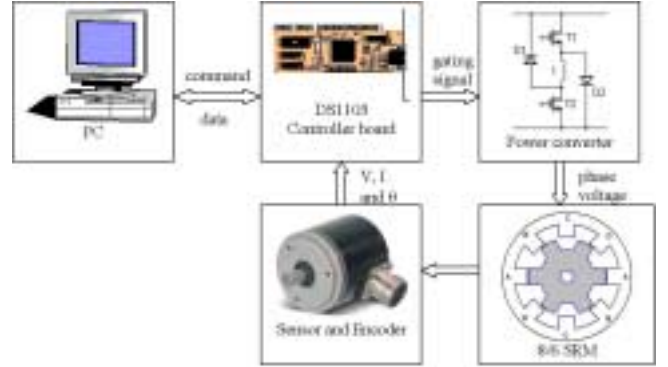

Fig. 3   Experimental setup

The motor used in this test is an 8/6 SRM. Tests are performed at several specific positions for current between 0~50 ampere. The inductance estimation and curve-fitting results at aligned, midway, and unaligned position are shown in Fig. 4-6 (Results are obtained using Matlab/Simulink®).
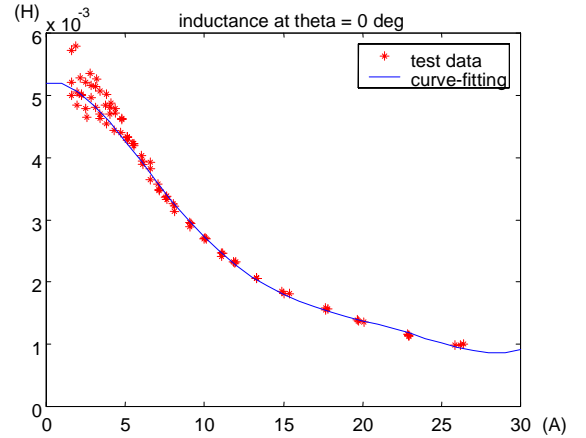

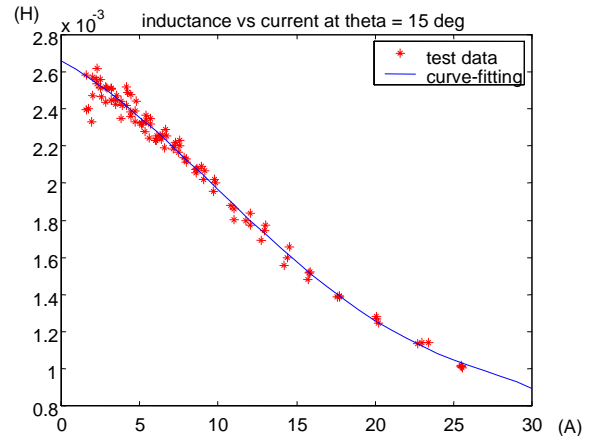Fig. 4   Standstill test results for inductance at 0°

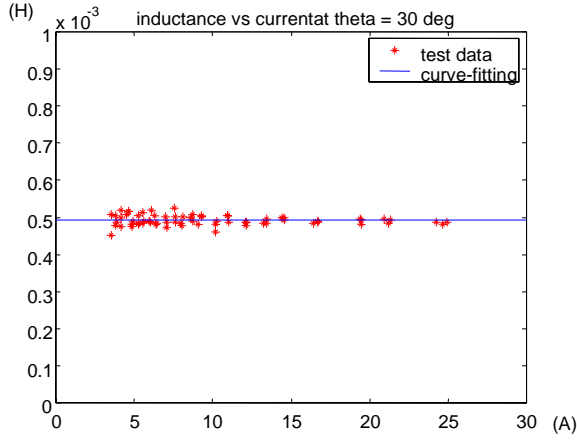Fig. 5   Standstill test results for inductance at 15°

Fig. 6 Standstill test results for inductance at 30°

The results show that the inductance at unaligned position doesn't change much with the phase current and can be treated as a constant. The inductances at midway and aligned position decrease when current increases due to saturation. A 3-D plot of inductance shown in Fig. 7 depicts the profile of inductance versus rotor position and phase current.
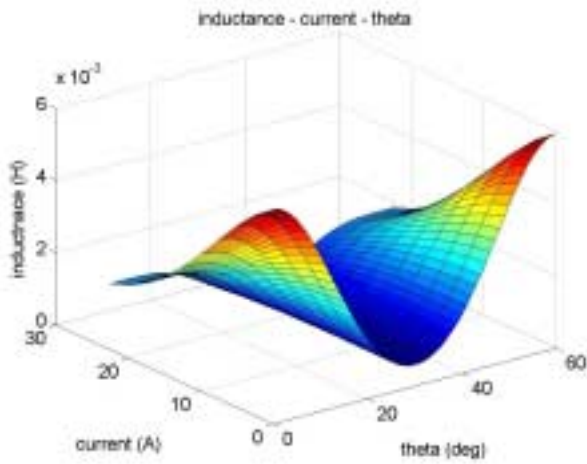

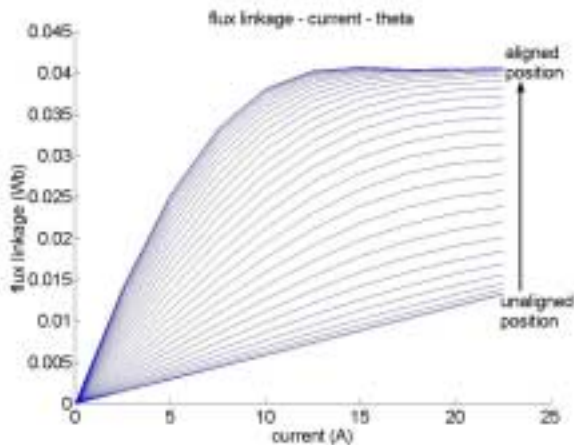Fig. 7 Standstill test result: nonlinear phase inductance

Fig. 8 Flux linkage at different currents and different rotor positions

At theta = 0 and 60 degrees, phase A is at its aligned positions and has the highest value of inductance. It decreases when the phase current increases. At theta = 30 degrees, phase A is at its unaligned position and has lowest value of inductance. The inductance here keeps nearly constant when the phase current changes.

In Fig. 8, the flux linkage versus rotor position and phase current based on the estimated inductance model is shown. The saturation of phase winding at high currents is clearly represented. At aligned position, the winding is highly saturated at rated current.

V. SRM Model for Online Operation

For online operation case, especially under high load, the losses become significant. There are no windings on the rotor of SRM's. But similar as synchronous machines, there will be circulating currents flowing in the rotor body and makes it works as a damper winding. Considering this, the model structure may be modified as shown in Fig. 9, with R_d and L_d added to represent the losses on the rotor.
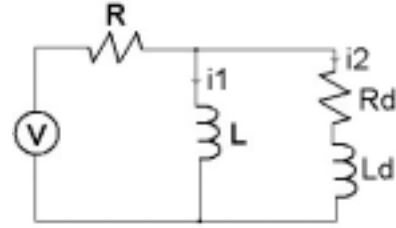

Fig. 9 Model structure of SRM under saturation

The phase voltage equations can be written as:

$$\begin{bmatrix} L & -L_d \\ 0 & L_d \end{bmatrix} \cdot \begin{bmatrix} \dot{i}_1 \\ \dot{i}_2 \end{bmatrix} = \begin{bmatrix} 0 & R_d \\ -R & -R-R_d \end{bmatrix} \cdot \begin{bmatrix} i_1 \\ i_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} V , \qquad (15)$$

where i_1 and i_2 are the magnetizing current and damper current.

It can be re-written in state space form as:

$$\dot{X} = AX + BU$$
$$Y = CX + DU \qquad (16)$$

where

$$X = [i_1 \quad i_2], \ Y = i_1 + i_2, \ U = [V],$$

$$A = \begin{bmatrix} L & -L_d \\ 0 & L_d \end{bmatrix}^{-1} \cdot \begin{bmatrix} 0 & R_d \\ -R & -R-R_d \end{bmatrix},$$

$$B = \begin{bmatrix} L & -L_d \\ 0 & L_d \end{bmatrix}^{-1} \cdot \begin{bmatrix} 0 \\ 1 \end{bmatrix},$$

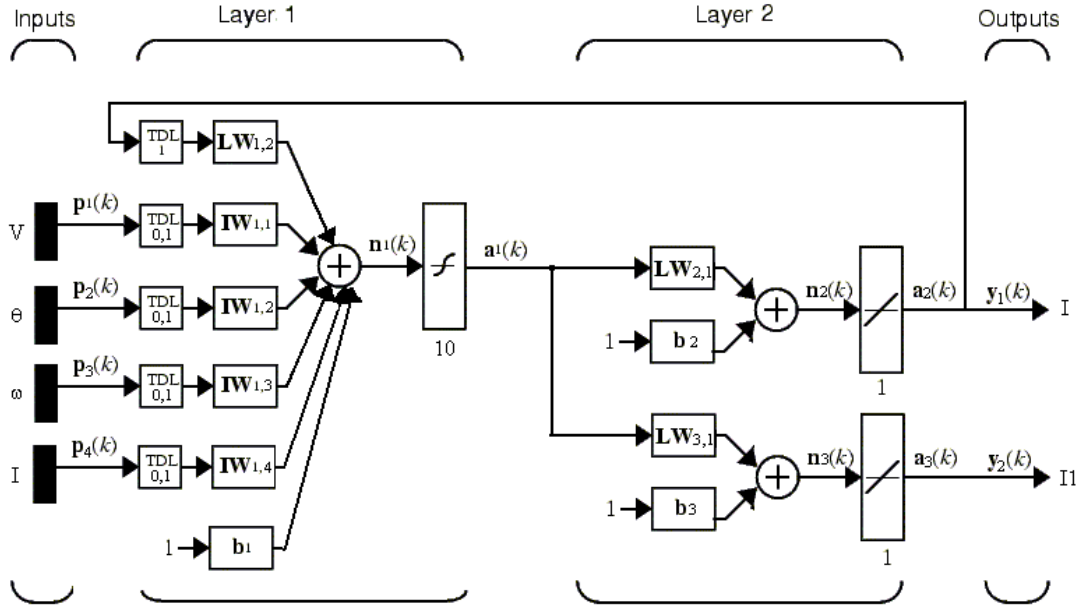$$C = [1 \quad 1], \text{ and}$$

$$D = 0.$$

Fig. 10 Recurrent neural network structure for estimation of exciting current

The torque can be computed as follows (notice that L is the magnetizing winding):

$$T = \frac{\partial W_c(\theta, i_1)}{\partial \theta} = \frac{\partial \{\int [L(\theta, i_1)i_1]di_1\}}{\partial \theta}$$

$$= \frac{\partial \{\int \sum_{k=0}^{m} [L_k(i_1)\cos(kN_r\theta)i_1]di_1\}}{\partial \theta} \quad (17)$$

$$= -\sum_{k=1}^{m} \{kN_r \sin(kN_r\theta)\int [L_k(i_1)i_1]di_1\}$$

During operation, we can easily measure phase voltage V and phase current $i = i_1 + i_2$. But we cannot measure the magnetizing current (i_1) and the damper winding current (i_2). Let's assume that the phase parameters R and L obtained from standstill test data are accurate enough for low current case. And we want to attribute all the errors at high current case to damper parameters. If we can estimate the exciting i_1 during online operation, then it will be very easy to estimate the damper parameters. This is described in later sections.

VI. 2-LAYER RECURRENT NEURAL NETWORK

During online operation, there will be motional back EMF in the phase winding. So the exciting current i_1 will be affected by:

- Phase voltage V,
- Phase current i,
- Rotor position θ, and
- Rotor speed ω.

To map the relation ship between i_1 and V, i, θ, ω, different neural network structures (feed forward or recurrent), with different number of layers, different number of neurons in each layer, and different transfer functions for each neuron, are tried. Finally the one shown in Fig. 10 is used. It is a two-layer recurrent neural network. The feeding-back of the output i to input makes it better in fitting and faster in convergence.

The first layer is the input layer. The inputs of the network are V, i, θ, ω (with possible delays). One of the outputs, the current i, is also fed back to the input layer to form a recurrent neural network.

The second layer is the output layer. The outputs are i (used as training objective) and i_1.

A hyperbolic tangent sigmoid transfer function – "*tansig()*" is chosen to be the activation function of the input layer, which gives the following relationship between its inputs and outputs:

$$n_1 = \sum_{i=1}^{4} IW_{1,i} \cdot p_i + LW_{1,2} \cdot y_1 + b_1$$

$$a_1 = tansig(n_1) = \frac{2}{1 + e^{-2n_1}} - 1 . \quad (18)$$

A pure linear function is chosen to be the activation of the output layers, which gives:

$$n_2 = LW_{2,1} \cdot a_1 + b_2$$
$$y_1 = a_2 = purelin(n_2) = n_2 ; \quad (19)$$

$$n_3 = LW_{3,1} \cdot a_1 + b_3$$
$$y_2 = a_3 = purelin(n_3) = n_3 . \quad (20)$$

After the neural network is trained with simulation data (using parameters obtained from standstill test). It can be used to estimate exciting current during on-line operation. When i_1 is estimated, the damper current can be computed as

$$i_2 = i - i_1, \tag{21}$$

and the damper voltage can be computed as

$$V_2 = V - i \cdot R, \tag{22}$$

then the damper resistance R_d and inductance L_d can be identified using output error or maximum likelihood estimation.

VII. TRAINING OF NEURAL NETWORK

The data used for training is generated from simulation of SRM model obtained from standstill test. The model is simulated at different DC voltages, different reference currents, and different speed. The total size of the sample data is 13,351,800 data points. The training procedure is detailed as follows:

First, from standstill test result, we can estimate the winding parameters (R and L) and damper parameters (R_d and L_d). The R_d and L_d got from standstill test data may not be accurate enough for online model, but it can be used as initial values that will be improved later.

Second, build an SRM model with above parameters and simulate the motor with hysteresis current control and speed control. The operating data under different reference currents and different rotor speeds are collected and sent to neural network for training.

Third, when training is done, use the trained ANN model to estimate the magnetizing current (i_1) from online operating data. Compute damper voltage and current according to equations (21) and (22). Then estimate R_d and L_d from the computed V_2 and i_2 using output error estimation. This R_d and L_d can be treated as improved values of standstill test results.

Repeat above procedures until R_d and L_d are accurate enough to represent online operation (it means that the simulation data matches the measurements well).

In our research, the neural network can map the exciting current from and V, i, θ, ω very well after training of 200 epochs.

VIII. ESTIMATION RESULTS

The parameters for damper winding are successfully estimated from operating data by using the neural network mapping described above.

To test the validity of the parameters obtained from above test, a simple on-line test has been performed. In this test, the motor is accelerated with a fixed reference current of 20 ampere. All the operating data such as phase voltages, currents, rotor position, and rotor speed are measured. Then the phase voltages are fed to an SRM model running in Simulink, which has the same rotor position and speed as the real motor. All the phase currents are estimated from the

Simulink mode and compared with the measured currents. In Fig. 11, the phase current responses are shown. The dashed curve is the voltage applied to phase winding; the solid curve is the measured current; and the dotted curve is the estimated current. An enlarged view of the curves for phase A is shown in Fig. 12. It is clear that the estimation approximates to the measurement quite well.

To compare online model with standstill one, we compute the covariance of the errors between the estimated phase currents and the measured currents. The average covariance for standstill model is 0.9127, while that for online model is 0.6885. It means that the online model gives much better estimation of operating phase currents.
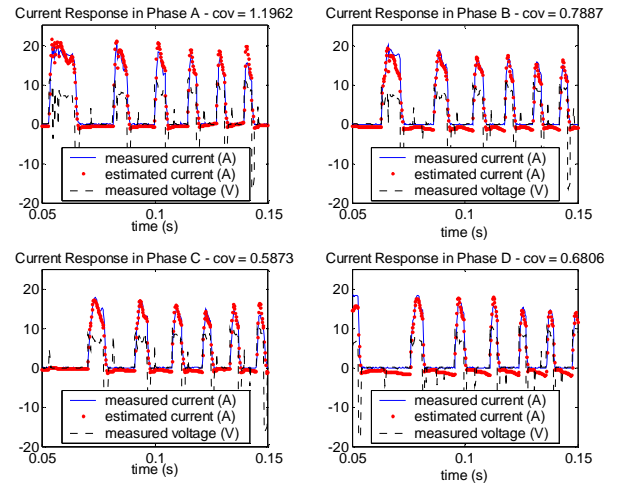

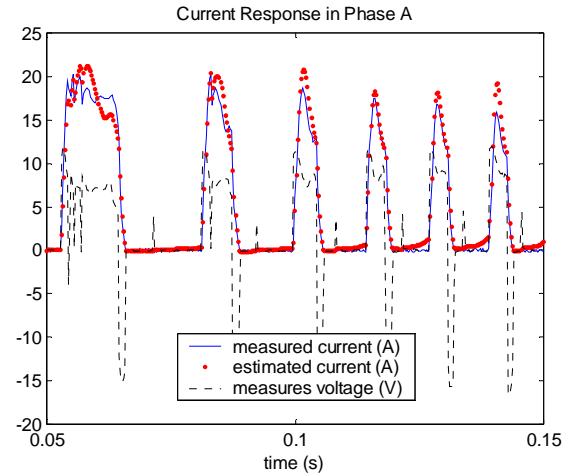Fig. 11 Validation of model with on-line operating data

Fig. 12 Validation of model with on-line operating data (Phase A)

IX. ADVANTAGES OF USING NEURAL NETWORK MAPPING

During online operation, the exciting current i_1 changes with phase voltage V, rotor position θ, and rotor speed ω. The relationship between them is highly nonlinear and cannot be easily expressed by any analytical equation. The neural

network can provide very good mapping if trained correctly. This makes it a good choice for such a task.

Once the NN is trained, it can estimate the exciting current from inputs very quickly, without solving any differential equations that is necessary in conventional methods. So it can be used for online parameter identification with no computational difficulties. This method has been successfully applied to synchronous machines and induction machines [6,8,9]; it can be applied to SRMs as well.

X. Conclusions

This paper presents the idea and procedure to use artificial neural network to help identify the resistance and nonlinear inductance of SRM winding from operating data. First the resistance and inductance of the magnetizing winding are identified from standstill test data. Then a 2-layer recurrent neural network is setup and trained with simulation data based on standstill model. By applying this neural network to online operating data, the magnetizing current can be estimated and the damper current can be computed. Then the parameters of the damper winding can be identified using maximum likelihood estimation. Tests performed on a 50-ampere 8/6 SRM show satisfactory results of this method.

XI. Acknowledgement

XII. References

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XIII. Biographies

Wenzhe Lu (S'00) received his BS from Xi'an Jiaotong University, Xi'an, China in 1993, and MS from Tsinghua University, Beijing, China in 1996, respectively. Now he is a PhD student in Electrical Engineering Department of The Ohio State University, Columbus, Ohio. Mr. Lu's research interests include modeling and control of switched reluctance motors for electric vehicle applications.

Ali Keyhani (S'72-M'76-SM'89-F'98) received his Ph.D degree from Purdue University, West Lafayette, Indiana in 1975. From 1967 to 1969, he worked for Hewlett-Packard Co., Palo Alto, CA, on the computer-aided design of electronic transformers. From 1970 to 1973, he worked for Columbus and Southern Ohio Electric Co. on computer applications for power system engineering problems. In 1974, he joined TRW Controls and worked on the development of computer programs for energy control centers. From 1976 to 1980, he was a professor of Electrical Engineering at Tehran Polytechnic, Tehran, Iran. Currently, Dr. Keyhani is a Professor of Electrical Engineering at the Ohio State University, Columbus, Ohio. His research interests are in control and modeling, parameter estimation, failure detection of electric machines, transformers and drive systems.

Abbas Fardoun (M'90) was born in Tyre, Lebanon. He received his BS degree from the University of Houston, in 1988, & MS and Ph.D. from the University of Colorado, Boulder in 1990 and 1994, respectively. He was with Advanced Energy Inc. from 1994-1996 where he was involved with high frequency power supply design. From 1996 until 1998, he was with Delphi where he worked on Electrical Power Steering. Since 1998, Dr. Fardoun has been with TRW Automotive. Dr. Fardoun received the Hariri Foundation distinguished graduate award in 1994. He has several patents related to automotive applications. His main interests are ac drives, power electronics and switched reluctance drives.