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Artificial neural network based torque calculation of switched reluctance motor without locking the rotor

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Feedback of motor torque is required in most of switched reluctance (SR) motor applications in order to control torque and its ripple. An SR motor shows highly nonlinear property which does not allow calculating torque analytically. Torque can be directly measured by torque sensor, but it inevitably increases the cost and has to be properly mounted on the motor shaft. Instead of torque sensor, finite element analysis (FEA) may be employed for torque calculation. However, motor modeling and calculation takes relatively long time. The results of FEA may also differ from the actual results. The most convenient way seems to calculate torque from the measured values of rotor position, current, and flux linkage while locking the rotor at definite positions. However, this method needs an extra assembly to lock the rotor. In this study, a novel torque calculation based on artificial neural networks (ANNs) is presented. Magnetizing data are collected while a 6/4 SR motor is running. They need to be interpolated for torque calculation. ANN is very strong tool for data interpolation. ANN based torque estimation is verified on the 6/4 SR motor and is compared by FEA based torque estimation to show its validity. © *2009 American Institute of Physics*.
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I. INTRODUCTION

Switched reluctance (SR) motors have been attracting significant interest of industry due to their advantages such as simple structure, rugged behavior, and low cost in mass production. However, they have some drawbacks such as high torque ripple and noise. Most of SR motor applications need feedback of motor torque in order to control torque and reduce torque ripple. Nonlinear relationship between the electrical and mechanical terminals of the SR motor makes analytic calculation of torque almost impossible.

Torque can be directly measured by torque sensor, but it is expensive and has to be properly mounted on the motor shaft. Therefore, elimination of torque sensor and estimation of motor torque is an important issue to reduce cost and increase the reliability. Finite element analysis (FEA) softwares may be employed for torque calculation. However, they are also expensive. In addition, motor modeling and calculation takes relatively long time.

Few researches have been presented on torque estimation or calculation so far. Artificial neural network (ANN) is employed as a direct torque estimator in Ref. 1 but torque sensor has to be used first to collect data. Different kinds of torque estimation based on measuring static torque characteristic are given in Refs. 2–5. Torque sensor is also required for them. Moreover, measuring of static characteristics needs an extra assembly for rotor locking, which is not available on most of commercial motors. Torque estimation from measuring static flux linkage characteristic eliminates the torque sensor, but rotor locking is still required as in Ref. 6. The rest researches are based on curve fitting to measured data collected from running SR motor.[7–9] However, they are using some simplifications which are contrary to the SR motor nature. In this study, a novel method is presented for calculating the phase torque from measured data without locking the rotor.

II. SR MOTOR BASICS

Flux linkage of an SR motor can be calculated from Faraday's equation,

$$\psi_k(i_k,\theta) = \int (v_k - R_k i_k)dt, \tag{1}$$

where v_k, R_k, and i_k are the voltage, resistance, and current of kth phase, respectively. Integration of the flux linkage with respect to the current at a constant rotor position results coenergy,

$$W'_k(i_k,\theta) = \int \psi_k di_k\Big|_{\theta=\text{const}}. \tag{2}$$

Mutual inductance between the phases can be neglected for a 6/4 SR motor in most cases and phase torque can be written as a derivation of coenergy with respect to the rotor position at a constant current,

$$T_k = \left.\frac{\partial W'_k(i_k,\theta)}{\partial\theta}\right|_{i_k=\text{const}}. \tag{3}$$

There is no exact representation of the flux linkage with respect to the current and rotor position because of high nonlinearity. Therefore, Eqs. (2) and (3) cannot be evaluated analytically. However, torque can be calculated if the flux linkage with respect to the current and rotor position is dis-

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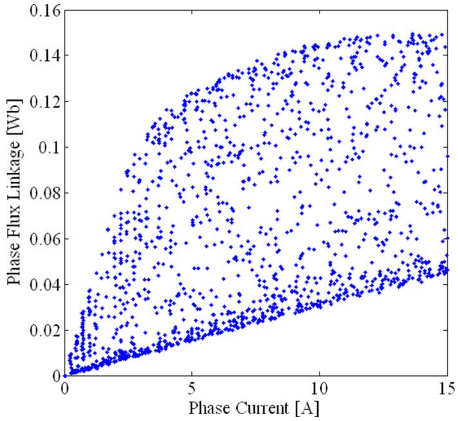


FIG. 1. (Color online) Flux linkage characteristic measured from running 6/4 SR motor.

cretely known as a table. Coenergy is the numerical integration of the flux linkage at a constant position,

$$W'_{kmn} \cong \Delta i \left(\frac{\psi_n}{2} + \sum_{t=1}^{n-1} \psi_t \right) \Bigg|_{m=\mathrm{const}}, \tag{4}$$

where n is the index of data along the constant position, and m is the index of data along the constant current. Torque is the numerical derivation of the coenergy with respect to the rotor position at a constant current,

$$T_{kmn} \cong \frac{\Delta W'_{kmn}}{\Delta \theta} \Bigg|_{n=\mathrm{const}}. \tag{5}$$

When current flows through the phase winding of a stator pole, the nearest rotor pole tends to come align with the stator pole. The rotor cannot stand any position between aligned and unaligned position itself. An assembly for rotor locking is needed. Most of SR motors do not have an assembly for locking the rotor. Therefore, it is important to calculate the torque from the data measured from running motor. ANN can take important role for this purpose as explained in Sec. III.

III. ANN BASED TORQUE CALCULATION

Figure 1 shows the flux linkage characteristic measured from running 6/4 SR motor. As seen in the figure, data points locate randomly. Coenergy and thereby torque cannot be calculated. For this reason, measured data must be interpolated. Because of the high nonlinearity, conventional interpolation methods do not give good results. However, ANN has the ability to adapt such a kind of data. ANN can establish a relation between rotor position-current and flux linkage if it is trained by enough data.

Block diagram of proposed method is illustrated in Fig. 2. ANN is trained by taking current and rotor position as inputs and flux linkage as output. Using the same weights and ANN structure, flux linkage data are interpolated according to reference current and rotor position. On the input side of the ANN, rotor position is kept constant while the current change from zero to maximum value. After position is changed to another value, the same current data are input again to ANN (Fig. 3). Flux linkage table with respect to the

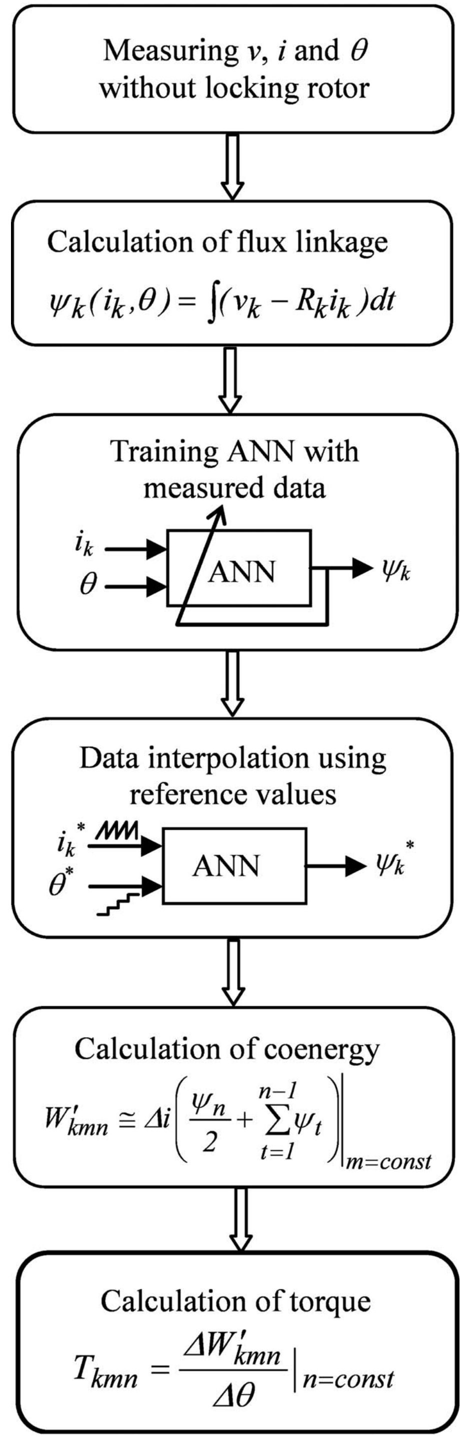


FIG. 2. Block diagram of the proposed method.

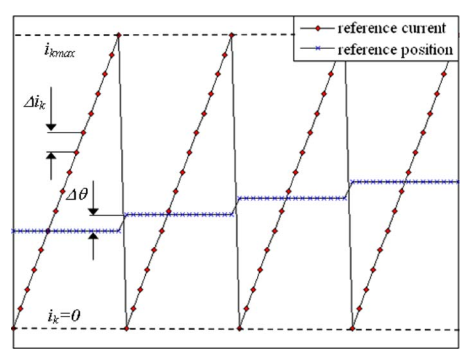
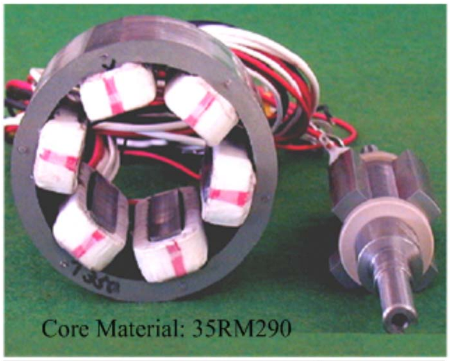


FIG. 3. (Color online) Reference current and rotor position for interpolation.



Parameter	Value
Stator pole arc	30 deg.
Rotor pole arc	32 deg.
Stack length	51 mm
Rotor outer diameter	40 mm
Stator inner diameter	82.1 mm
Number of winding/pole	72 turns
Winding resistance/phase	0.87 Ω

FIG. 4. (Color online) The 6/4 SR motor used in this research.

rotor position and current can be obtained for all operating region if the rotor position is changed between aligned and unaligned position. Finally, coenergy and then torque is calculated discretely as explained in Eqs. (3) and (4).

IV. EXPERIMENTAL RESULTS

Basic properties of the 6/4 SR motor used in this study is given in Fig. 4. The 6/4 SR motor was run by three-phase hysteresis controlled asymmetric bridge converter. Only one phase of the SR motor was energized to measure phase data. In order to generate gate signal and to control the SR motor, a DSP board named dSPACE DS1103 and MATLAB/SIMULINK real-time workshop were used together. Current was limited to maximum value of 15 A while data were collected. The converter was supplied with 70 V DC. ANN was constructed and trained with measured data in MATLAB/NEURAL NETWORK TOOLBOX. Optimum structure and learning algorithm was determined by trial and error. A feedforward network with Levenberg–Marquart learning algorithm was found to be good for flux linkage estimation. ANN has two hidden layers and each layer has five neurons. Activation function of the hidden layers was chosen as tangent hyperbolas while that of output layer as linear. After training with about 1250 measured data, ANN reached to enough accuracy for achieving interpolation. Figure 5 shows static torque characteristic calculated by using ANN. The 6/4 SR motor was run by energizing one phase at 1000 rpm to verify presented method experimentally. Load was adjusted to 0.5 Nm. Phase torque was estimated by both ANN based and FEA based torque estimation. The experimental results are given in Fig. 6.

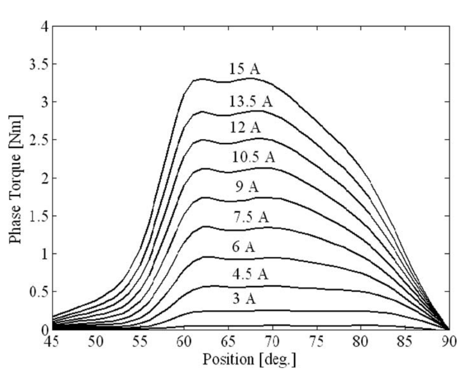


FIG. 5. Static torque characteristic calculated by using ANN.

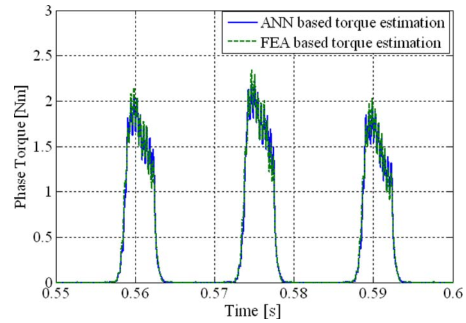


FIG. 6. (Color online) Experimental results of 6/4 SR motor running at 1000 rpm (load=0.5 N m).

V. CONCLUSION

ANN based torque calculation of an SR motor is introduced and then experimented in this research. ANN based torque estimation is compared by FEA based torque estimation to show its validity. The method is very simple and needs much less time for calculation, comparing the others. It is not only for the SR motor, but can be also applied to the other motors which have highly nonlinear characteristics. Phase torque in aligned and unaligned positions, which are shown as 45° and 90°, respectively, in Fig. 5, has to be zero theoretically. Phase torque has found nonzero in unaligned position. However, this error is not seen in the phase torque estimation. ANN based torque estimation has good accordance with the FEA based torque estimation.

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