G.U. Journal of Science
22(2): 89-96 (2009)

www.gujs.org

Inductance Estimating of Linear Switched Reluctance Motors with the Use of Adaptive Neuro-Fuzzy Inference Systems

Ferhat DALDABAN [1♠], Nurettin USTKOYUNCU [1]

[1] *Erciyes University, Faculty of Engineering, Department of Electrical & Electronics Engineering , Kayseri, Turkey*

Received: 05.06.2006 Revised: 09.10.2007 Accepted:13.02.2009

ABSTRACT

In this paper, a new method based on adaptive neuro-fuzzy inference system (ANFIS) to estimate the phase inductance of linear switched reluctance motors (LSRMs) is presented. The ANFIS has the advantages of expert knowledge of fuzzy inference system and learning capability of neural networks. A hybrid learning algorithm, which combines the back-propagation (BP) algorithm and the least square method (LSM), is used to identify the parameters of ANFIS. The translator position and the phase current of the three-phase LSRM are used to estimate the phase inductance. The phase inductance results estimated by ANFIS are in very good agreement with the results of finite element analysis (FEA).

Key Words: *Linear Switched Reluctance Motor, ANFIS, Inductance*.

1. INTRODUCTION

There has been widespread interest in the switched reluctance motor (SRM) drives in recent years. Although many articles have been published on modeling and analysis of the rotary switched reluctance motor (RSRM), there is a paucity of the literature on linear switched reluctance motors (LSRMs) [1-9]. LSRMs are the attractive alternative due to lack of windings on either the fixed or moved parts of the motor. Furthermore, the windings are concentrated rather than distributed, making them ideal for low cost manufacturing and maintenance. This paper presents inductance estimation of a double-sided LSRM by using adaptive neuro-fuzzy inference system (ANFIS).

The LSRM is often operated with extreme saturation to achieve high force density. The inductance, flux-linkage, and force of the LSRMs are highly nonlinear functions of both translator position and phase current due to the extreme saturation effects and the variation of magnetic reluctance. The nonlinearities make the analysis and design of LSRMs difficult. In LSRM designs, it is important to obtain the inductance of the motor accurately because the inductance is a critical performance parameter of LSRMs. A number of methods [1-11] using different levels of approximation have been proposed and used to compute the inductance of SRMs and LSRMs. These methods can be broadly classified into two categories: simple analytical methods and rigorous numerical methods. The analytical methods, based on some fundamental simplifying physical assumptions, are the most useful for practical design as well as providing a good intuitive explanation of the operation of the LSRMs. However, these analytical methods are not very accurate to compute the magnetic characteristics of the LSRMs. Most of the limitations of analytical methods can be overcome by using the numerical methods. The numerical methods such as finite element analysis (FEA) [6, 7, 9, 12-15] provide accurate results but usually require tremendous computational effort and numerical procedures. They suffer from a lack of computational efficiency, which in practice can restrict their usefulness due to high computational time and costs. For these reasons, in this paper the phase inductance of LSRMs is computed by using ANFIS.

The ANFIS can simulate and analysis the mapping relation between the input and output data through a learning algorithm to optimize the parameters of a given fuzzy inference system (FIS) [16, 17]. It combines the benefits of artificial neural networks (ANNs) and FISs in a single model. Fast and accurate learning, excellent explanation facilities in the form of semantically meaningful fuzzy rules, the ability to accommodate both data and existing expert knowledge about the problem, and good generalization capability features have made neuro-fuzzy systems popular in the last few

♠Corresponding author, e-mail: daldaban@erciyes.edu.tr

years [16-21]. Because of these fascinating features, in this paper, a method based on ANFIS is presented for computing the phase inductance of LSRMs. First, the LSRM parameters related to the phase inductance are determined, and then the phase inductance depending on these parameters is calculated by using the ANFIS.

Even though ANFIS was used for the position estimation [22], the control [23, 24] and the inductance estimation [25] of SRMs, there is no work about LSRMs in the literature to the best of our knowledge. In the following sections, the basic principles of the LSRM are given briefly, and the application of ANFIS to the calculation of the inductance of an LSRM is then explained.

2. DESCRIPTION OF THE LSRM

Figure 1 shows a cross-sectional figure of the double sided LSRM with three phases. Excitation windings are located on two outer stator laminated structures. The active stator (translator) is shown at the position of minimum reluctance in Figure 1. If phase C were excited, then the translator movement would be towards the left direction. Otherwise, phase B should be energized.

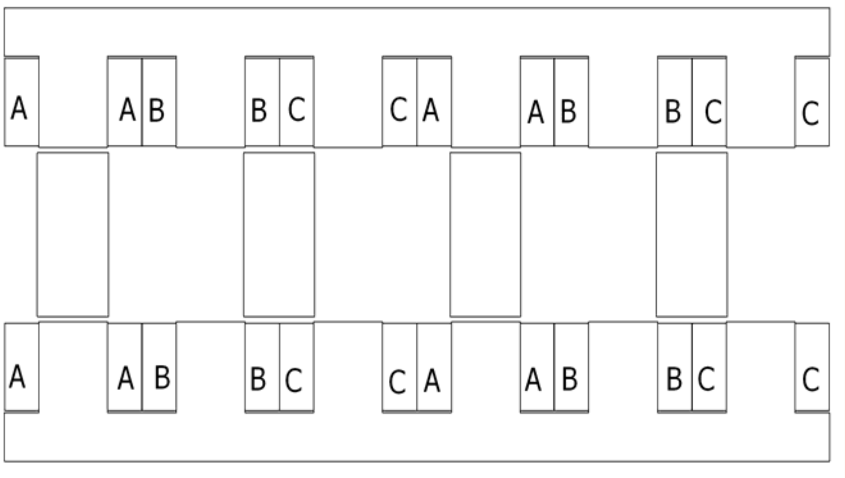

Figure 1. Cross-sectional figure of the double sided LSRM.

The translator and rotor platforms of the LSRM are modeled with the use of M19 laminated steel sheet properties for FEA. The mechanical and electrical parameters of the LSRM designed by authors are summarized in Table 1. These parameters are obtained after the optimizing processes realized by using analytical calculations. According to the specifications listed in Table 1, the geometrical dimensions and three-dimensional model of the LSRM is shown in Figure 2.

Table 1. Mechanical and electrical parameters of the LSRM.

Phase numbers	3
Stator (Translator) pole width	17 mm
Stator slot width	17 mm
Stator pole height	25 mm
Stator depth	50 mm
Rotor pole width	17.6 mm
Rotor depth	50 mm
Overall length	204 mm
Overall width	112 mm
Air gap width	1 mm
Steel type	M19
Wire diameter	1 mm
Total numbers of phase turns	320

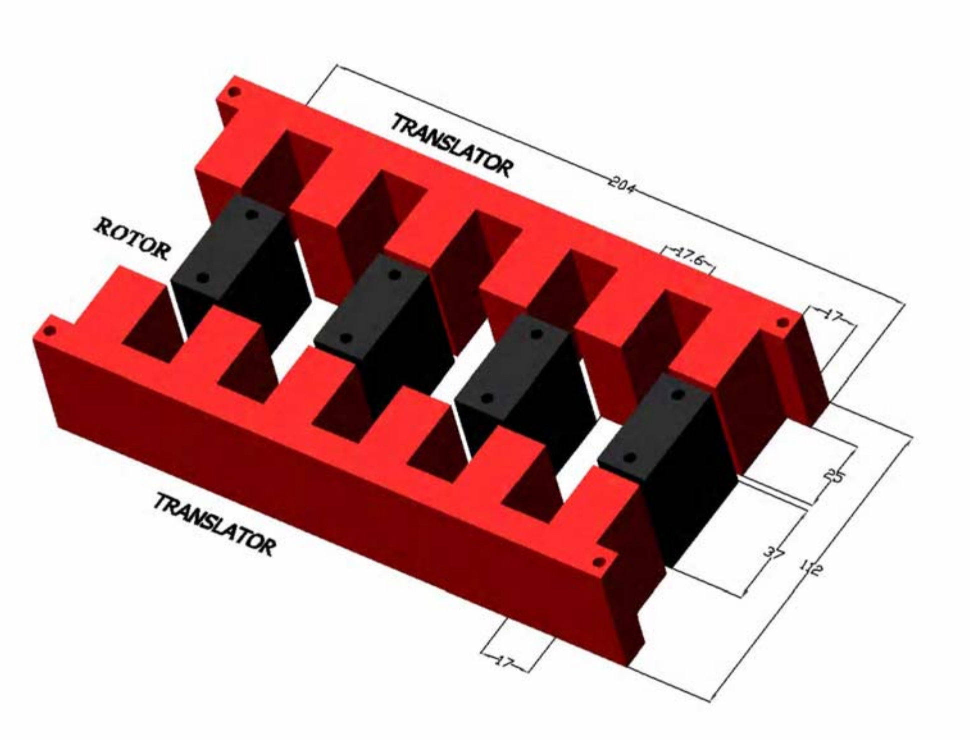

Figure 2. Three-dimensional model of the LSRM.

Structure of the motor reduces the mass production cost because windings are located on the translator. In addition, the rotor parts do not need to be continuous because of the flux distribution of the motor as shown in Figure 3. However, the rotor parts have to be continuous for the flux flow and force production of the LSRM when the single sided structure is used.

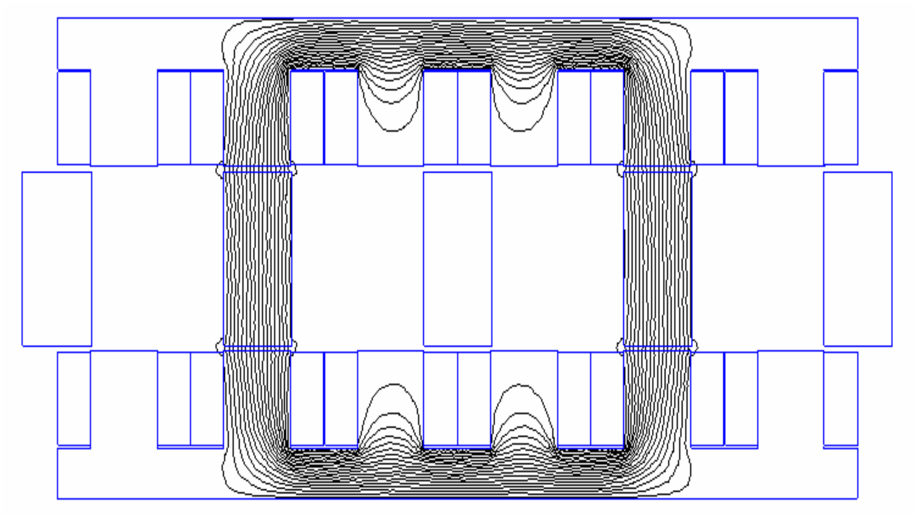

Figure 3. Flux distribution of the LSRM in aligned position.

Operation principle of the motor is based on forward force generation. Because of the double-sided structure, the lateral forces produced by two stator sides of the motor are eliminated by each other.

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The FIS forms a useful computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The ANFIS [16, 17] is a FIS implemented in the framework of an adaptive fuzzy neural network. It combines the explicit knowledge representation of FIS with the learning power of ANNs. Usually, the transformation of human knowledge into a fuzzy system (in the form of rules and membership functions) does not give exactly the target response. So, the parameters of the FIS should be determined optimally. The main aim of the ANFIS is to optimize the parameters of the equivalent FIS by applying a learning algorithm using input-output data sets. The parameter optimization is realized in a way such that the error measure between the actual output and the target is minimized [25].

The ANFIS used in the paper implements a first-order Sugeno fuzzy model. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules can be expressed as:

Rule 1: If x is A_1 and y is B_1, then

$$z_1 = p_1 x + q_1 y + r_1 \tag{3.1.a}$$

Rule 2: If x is A_2 and y is B_2, then

$$z_2 = p_2 x + q_2 y + r_2 \tag{3.1.b}$$

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i, and r_i are the design parameters that are determined during the training process. The ANFIS consists of five layers:

Layer 1: Every node i in the first layer employ a node function given by

$$O_i^1 = \mu_{A_i}(x), \ \ i = 1,2 \tag{3.2}$$

$$O_i^1 = \mu_{B_{i-2}}(y), \ \ i = 3,4 \tag{3.3}$$

where $\mu_{A_i}(x)$ and $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function (MF). In the paper, the following Gaussian MF is used.

$$gaussian(x;c,\sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{3.4}$$

where $\{c_i, \sigma_i\}$ is the parameter set that changes the shapes of the MF. Parameters in this layer are referred to as the "premise parameters".

Layer 2: Every node in this layer calculates the firing strength of a rule via multiplication:

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \ \ i = 1,2$$

. (3.5)

Layer 3: The i th node in this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' (1-a) firing strengths:

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}, \ \ i = 1,2$$

..(3.6) (1-b)

where $\overline{\omega_i}$ is referred to as the “normalized firing strengths”.

Layer 4: In this layer, every node *i* has the following function:

$$O_i^4 = \overline{\omega_i} z_i = \overline{\omega_i}(p_i x + q_i y + r_i), \ \ i = 1,2 \qquad (3.7)$$

where $\overline{\omega_i}$ is the output of layer 3, and {p_i, q_i, r_i} is the parameter set. Parameters in this layer are referred to as the “consequent parameters”.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, which is expressed as:

$$O_1^5 = \sum_{i=1}^{2} \overline{\omega_i} z_i = \frac{\omega_1 z_1 + \omega_2 z_2}{\omega_1 + \omega_2} \qquad (3.8)$$

In the paper, the hybrid learning algorithm [16, 17], which combines the least square method (LSM) and the back-propagation (BP) algorithm, is used to rapidly train and adapt the FIS. The algorithm converges faster since it reduces the dimension of the search space of the BP algorithm.

From the architecture of ANFIS, it is observed that if the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters:

$$z = (\overline{\omega_1} x) p_1 + (\overline{\omega_1} y) q_1 + (\overline{\omega_1}) r_1 + (\overline{\omega_2} x) p_2 + (\overline{\omega_2} y) q_2 + (\overline{\omega_2}) r_2 \qquad (3.9)$$

The LSM can be used to obtain the optimal values of the consequent parameters. When the premise parameters are not fixed, the search space becomes larger and the convergence of training becomes slower. The hybrid learning algorithm is adopted to solve this problem. The algorithm has a two-step process. First, the consequent parameters are identified using LSM when the values of premise parameters are fixed. After that, the consequent parameters are held fixed while the error is propagated from the output end to the input end, and the premise parameters are updated by the standard BP algorithm.

4. CALCULATION OF THE PHASE INDUCTANCE

ANFIS has been adapted to calculate the phase inductance of the LSRMs. For the ANFIS, the inputs are the phase current I and the translator position x, and the output is the phase inductance L.

Training the ANFIS by using the hybrid learning algorithm to calculate the phase inductance involves presenting it sequentially with different sets (I, x) and corresponding desired *L* values. Differences between the desired output *L* and the output of the ANFIS are evaluated by the hybrid learning algorithm. The adaptation is carried out after the presentation of each set (I, x) until the calculation accuracy of the network is deemed satisfactory according to some criterion (for example, when the error between the desired *L* and the actual output for all the training set falls below a given threshold) or when the maximum allowable number of epochs is reached.

There are two types of data generators, namely measurement and simulation for LSRMs. The selection of a data generator depends on the application and the availability of the data generator. In the paper, FEA was used to generate the data set for training the ANFIS because FEA is a useful method for obtaining accurate magnetic characteristics of SRMs and LSRMs [7-15]. 2D FEA was used to analyze the motor structure, because of the increasing computing time and efforts of 3D FEA. The name of the used software is FEMM and 15566 nodes are used in the analysis. The active translator of the LSRM is moved from the unaligned position with respect to the rotor to the aligned position for different excitation currents. Therefore, static inductance profile is obtained as a function of position and current. The excitation currents are chosen to be in steps of 5 A from 0 to 45 A.

The parameter values of the LSRM used in the paper are given in Table 1. Out of 2100 data sets generated, 1575 data sets were used for training and the rest were used for test the ANFIS. The ranges of training data sets are among $0 \le I \le 45A$ and $0 \le x \le 25mm$.

The number of epochs was 100 for training. The number of MFs for the input variables I and x is 9 and 9, respectively. The number of rules is then 81 (9x9=81). The phase inductance rule surface versus the translator position and the phase current is shown in Figure 4.

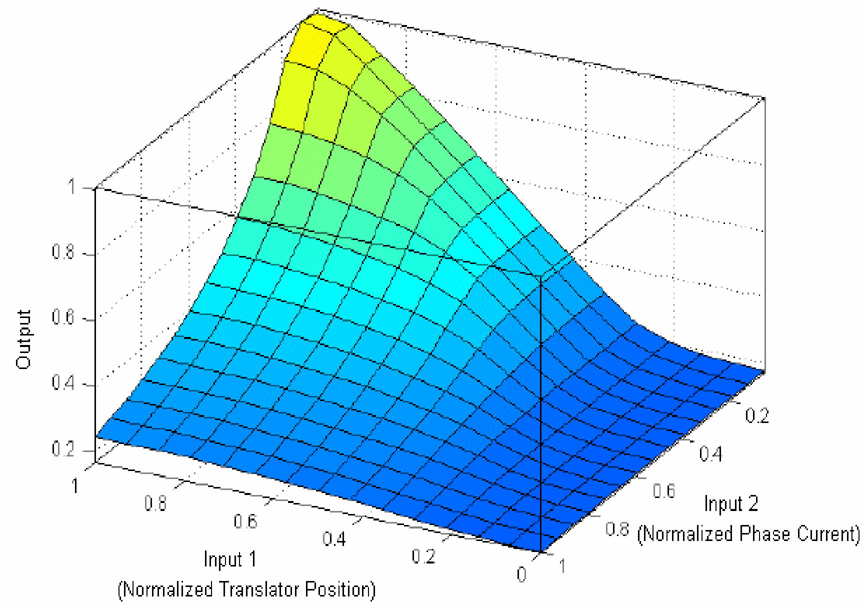

Figure 4. The phase inductance rule surface versus the translator position and current.

5. RESULTS

The phase inductance test results of the ANFIS for the different phase currents were compared with the results of FEA in Figure 5. It can be seen from the Figure 5 that the ANFIS test results are in very good agreement with the results of FEA. This very good agreement supports the validity of ANFIS proposed in this work. The test root mean square (RMS) error obtained from the ANFIS is $3.910x10^{-5}$.

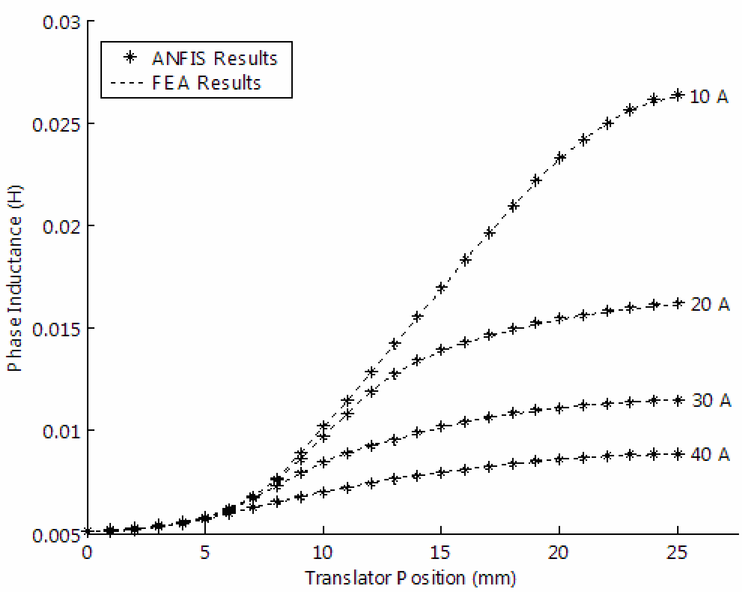

Figure 5. Comparison of the FEA results and the ANFIS test results.

The phase inductance can be calculated by using FEA. This method is very complex and requires high performance large-scale computer resources and a very large number of computations. A distinct advantage of ANFIS computation is that, after proper training, the ANFIS completely bypasses the repeated use of complex iterative processes for new cases presented to it.

6. CONCLUSIONS

The ANFIS is presented to accurately compute the phase inductance of the LSRM. The optimal values of premise parameters and consequent parameters are obtained by the hybrid learning algorithm. It was shown that the results of ANFIS are in excellent agreement with the results of FEA. Other methods such as look-up table with interpolation also can be used for this aim but results of these methods are not accurate enough because of the saturation effects and nonlinear nature of the motor. In addition, using of the ANNs can be an alternative to ANFIS.

The ANFIS is a very powerful approach for building complex and nonlinear relationship between a set of input and output data. It combines the benefits of ANNs and FISs in a single model. Accurate, fast, and reliable ANFIS models can be developed from measured/simulated LSRM data. Once developed, these ANFIS models can be used in place of computationally intensive numerical models to speed up LSRM design. The ANFIS offers an accurate and efficient alternative to previous methods for to calculate the phase inductance.

REFERENCES

[1] Miller, T.J.E., "Switched reluctance motor drives a reference book of collected papers", ***Intertec Communications Inc***., California, (1988).

[2] Miller, T.J.E., "Switched reluctance motors and their control", ***Oxford University Press***, Oxford, (1993).

[3] Krishnan, R., "Switched reluctance motor drives modeling, simulation, analysis, design and applications", ***CRC Press***, London, (2001).

[4] Corda, J., Stephenson, J.M., "Analytical estimation of the minimum and maximum inductances of a double-salient motor", ***Proc. Int. Conf. on Stepping Motors and Systems***, 50-59 (1979).

[5] Ray, W.F., Davis, R.M., "Inverter drive for doubly-salient reluctance motor: its fundamental behavior, linear analysis and cost implications", ***IEE Electric Power App***. 2 (6): 185-193 (1979).

[6] Deshpande, U.S., Cathey, J.J. , Richter, E. "High-force density linear switched reluctance motors", ***IEEE Trans. on Industry Applications***, 31(2): 345-352 (1995).

[7] Deshpande, U., "Two-dimensional finite-element analysis of a high-force-density linear switched reluctance machine including three-dimensional effects", ***IEEE Trans. on Industry Applications***, 36 (4): 1047-1052 (1995).

[8] Bae, H.K., Lee, B.S., Vijayraghavan, P., Krishnan, R., "A linear switched reluctance motor: converter and control", ***IEEE Trans. on Industry Applications***, 36 (5): 1351-1359 (2000).

[9] Lee, B.S., Bae, H.K., Vijayraghavan, P., Krishnan, R., "Design of a linear switched reluctance machine", ***IEEE Trans. on Industry Applications***, 36 (6): 1571-1580 (2000).

[10] Gan, W.C., Cheung, N.C., Qiu, L., "Position control of linear switched reluctance motors for high-precision applications", ***IEEE Trans. on Industry Applications***, 39 (5): 1350-1362 (2003).

[11] Stumberger, G., Stumberger, B., Dolinar, D., "Identification of linear synchronous reluctance motor parameters", ***IEEE Trans. on Industry Applications***, 40(5): 1317-1324 (2004).

[12] Lindsay, J.F., Arumugam, R., Krishnan, R., "Finite-element analysis characterization of a switched reluctance motor with multi-tooth per stator pole", ***Proc. IEE***., 133: 347-353 (1986).

[13] Fulton, N.N., The application of CAD to switched reluctance drives, ***Int. Conf. on Electric Machines and Drives***, 275-279 (1987).

[14] Radun, A.V., "Design considerations for the switched reluctance motor", ***IEEE Trans. on Industry Applications***, 31 (5): 1079-1087 (1995).

[15] Omekanda, A.M., Broche, C., Renglet, M., "Calculation of the electromagnetic parameters of a switched reluctance motor using an improved FEM-BIEM application to different models for the torque calculation", ***IEEE Trans. on Industry Applications***, 33 (4): 914-918 (1997).

[16] Jang, J.S.R., "ANFIS: adaptive-network-based fuzzy inference system", ***IEEE Trans on Systems Man and Cybernetics***, 23 (3): 665-685 (1993).

[17] Jang, J.S.R., Sun, C.T., Mizutani, E., "Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence", ***Prentice-Hall***, Upper Saddle River, (1997).

[18] Brown, M., Haris, C., "Neurofuzzy adaptive modeling and control", ***Prentice-Hall***, Englewood Cliffs, (1994).

[19] Constantin, V.A., "Fuzzy logic and neuro-fuzzy applications explained", ***Prentice-Hall***, Englewood Cliffs, (1995).

[20] Lin, C.T., Lee, C.S.G., "Neural fuzzy systems: a neuro-fuzzy synergism to intelligent systems", ***Prentice-Hall***, Upper Saddle River, (1996).

[21] Kim, J., Kasabov, N., "HyFIS: Adaptive neuro-fuzzy inference systems and their application to nonlinear dynamical systems", ***Neural Networks***, 12 (9): 1301-1319 (1999).

[22] Paramasivam, S., Arumugam, R., Umamaheswari, B., Vijayan, S., Balamurugan, S., Vasudevan, M., "Indirect rotor position estimation of switched reluctance motor using ANFIS", ***The Fifth Int. Conf. on Power Electronics and Drive Systems PEDS***, 921-926 (2003).

[23] Akcayol, M.A., "Application of adaptive neuro-fuzzy controller for SRM", ***Advances in Engineering Software***, 35 (3-4): 129-137 (2004).

[24] Akcayol, M.A., Elmas, C., "NEFCLASS-based neuro-fuzzy controller for SRM drive", ***Engineering Applications of Artificial Intelligence***, 18: 595-602 (2005).

[25] Daldaban, F., Ustkoyuncu, N., Guney, K., "Phase inductance estimation for switched reluctance motor using adaptive neuro-fuzzy inference system", ***Energy Conversion and Management***, 47: 485-493 (2006).