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NEFCLASS BASED MODELING OF INDUCTANCE VARIATION OF SRM

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Abstract: Switched reluctance motors (SRMs) are increasingly employed in industrial applications because of their simple construction, ease of maintenance, low cost and high efficiency. But, modeling of SRMs is difficult due to its non-linearities and parameter uncertainties. To tackle these problems, a NEFCLASS based estimator has been proposed for modeling of inductance variation of SRMs. Simulation results of the inductance variation demonstrated the applicability of the proposed estimator.

Keywords: Neuro-fuzzy systems, NEFCLASS, Switched reluctance motor

ARM'LERİN ENDÜKTANS DEĞİŞİMLERİNİN NEFCLASS TABANLI MODELLENMESİ

Özet: Anahtarlamalı relüktans motorların (ARM) yapılarının basit, kurulumlarının kolay, düşük fiyat ve yüksek verimli olmalarından dolayı endüstriyel uygulamalarda artarak kullanılmaktadırlar. Ancak, ARM'lerin modellenmesi parametrelerinin belirsizliği ve doğrusal olmayan karakteristiklerinden dolayı zordur. Bu çalışmada, bu problemlerin giderilmesi için NEFCLASS tabanlı endüktans modellemesi önerilmiştir. Endüktans değişimine ait benzetim sonuçları önerilen modelin uygulanabilirliğini göstermiştir.

Anahtar Kelimeler: Sinirsel-bulanık sistemler, NEFCLASS, Anahtarlamalı relüktans motor

1. Introduction

Switched reluctance motors (SRMs) have undergone rapid development in hybrid electric vehicles, aircraft starter/generator systems, washing machines, and automotive applications over the last two decades. SRMs have various advantages over other electric motors, such as simple and robust construction and fault-tolerant performance [1]. 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 digital signal processors, sensorless control techniques have been successfully applied to SRMs [2] become more and more promising. An accurate nonlinear model of the SRM is essential to realize such control algorithms. But, due to the fact that SRMs typically operate at high levels of saturation of the magnetic circuit to obtain high efficiency, the mapping among the SRM input variables, output variables and parameters is highly nonlinear [3]. The inductance of the magnetic circuit is a nonlinear function of both phase current and rotor position. In addition, the system handles energy most efficiently when the energy conversion cycles are made as square as possible, maximizing the ratio of energy converted to energy input [4,5]. This leads a particularly difficult problem because of their complicated magnetic circuit, which operates at varying levels of saturation under operating conditions. Many researchers have studied on modeling of inductance variation of SRMs. Stephenson and Corda proposed a quite successful method to model the flux linkage as a function of current and rotor position [6]. This method has been modified by Miller and McGilp [7,3]. Torrey and Lang have also proposed a method to provide analytical expression for the flux linkage and current for every rotor position within a single summary equation [8]. Bay and Elmas have first proposed different method based on fuzzy logic [9]. Akcayol has used neuro-fuzzy estimator having a simple structure for inductance variation [10].

NEuro Fuzzy CLASSification (NEFCLASS) algorithm is one of the tuning methods of the fuzzy systems based on adding and deleting fuzzy system rules [11,12]. This algorithm is based on a common multilayered neural network structure whose weights are determined by fuzzy sets. The activation, the output and the propagation functions are then adapted accordingly. This approach preserves the common neural network (NN) structure, but allows the interpretation of the resulting system by the associated fuzzy system. The shape and position of the triangular membership functions (MFs) are adapted iteratively during the learning procedure.

In this paper, NEFCLASS based modeling of inductance variation of the SRM has been described. Initial values of MFs and rule base have been obtained using experimental measurements of the SRM.

In the following, Section 2 introduces measurements of phase inductance in details. NEFCLASS based modeling and results are expressed in Section 3 within details. The work is finally concluded in Section 4.

2. Measurements of The Phase Inductance

Phase current of the SRM is directly proportional to the rate of change in rotor position and excitation current. The instantaneous value of the phase current depends on the instantaneous phase inductance. Because of this, accurately modeling of inductance variation is required to obtain satisfactory performance. So far, many researchers have proposed different methods [13,14,15]. Each method has its own advantages and disadvantages in terms of its accuracy and difficult to set up process. In this work, a simple measurement method based on measuring of the phase impedance was used. The measurements were performed on OULTON 4KW experimental motor. The phase impedance was measured at every third mechanical degree with respect to rotor position. A power supply was used to adjust current in the range of 1A and 8A. The experimental circuit is demonstrated in Figure 1.

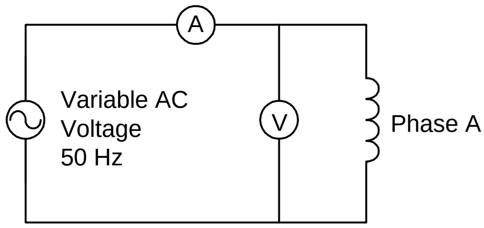

Figure 1. The circuit for measurement of inductance.

The measured impedance values are shown in Table 1.

Table 1. The measured impedance values.

Current

Position	1A	2A	3A	4A	5A	6A	7A	8A
0°	38,20	75,78	112,47	148,60	168,00	179,40	187,70	195,00
3°	35,90	71,17	106,05	139,20	162,00	174,70	184,10	191,30
6°	32,37	64,60	96,00	125,70	148,50	162,70	173,10	181,50
9°	27,85	55,10	82,12	108,50	129,00	144,40	156,00	166,00
12°	22,45	44,88	67,20	89,50	107,70	121,80	132,50	142,80
15°	18,01	35,92	53,67	71,20	84,60	97,50	107,80	116,90
18°	12,94	25,79	35,58	51,40	62,80	72,10	80,50	89,10
21°	7,88	15,73	23,60	31,30	39,10	46,40	53,70	60,70
24°	5,45	10,89	16,30	21,72	27,15	32,55	37,90	43,32
27°	4,85	9,69	14,54	19,38	24,20	29,00	33,80	38,40
30°	4,64	9,28	13,92	18,55	23,16	27,78	32,40	37,00

By using measured phase impedance values, phase inductance values were calculated by means of $X_L = 2\pi f L$, where X_L is the impedance, f is the frequency of the supply (50Hz used in this study), L is the inductance of a phase. The calculated impedance values are shown in Table 2.

Table 2. The calculated inductance values (mH).

Current

Position	1A	2A	3A	4A	5A	6A	7A	8A
0°	121,87	120,57	119,29	118,21	106,90	95,12	85,29	77,52
3°	114,23	113,22	112,48	110,73	103,08	92,62	83,65	76,04
6°	103,01	102,76	101,80	99,98	94,48	86,25	78,65	72,14
9°	88,61	87,63	87,07	86,28	82,06	76,57	70,87	65,97
12°	71,41	71,37	71,23	71,15	68,49	64,53	60,16	56,72
15°	57,27	57,09	56,06	56,57	54,91	51,62	48,91	46,40
18°	41,08	40,93	40,81	40,78	39,85	38,11	36,47	35,30
21°	24,91	24,84	24,83	24,70	24,68	24,40	24,21	23,94
24°	17,08	17,05	17,00	16,99	16,98	16,97	16,95	16,94
27°	15,10	15,10	15,09	15,09	15,08	15,05	15,04	14,94
30°	14,43	14,43	14,43	14,42	14,40	14,39	14,38	14,37

In the following section, designing the NEFCLASS based estimator for inductance variation of SRM is introduced.

3. Nefclass Based Modeling of Inductance Variation and Results

The block diagram of the estimator based on NEFCLASS is shown in Figure 2. Input variables are i (current), θ (position) and output variable is L (inductance). The system consists of fuzzy logic estimator (FLE), and NEFCLASS used to optimize FLE's rule base and MFs.

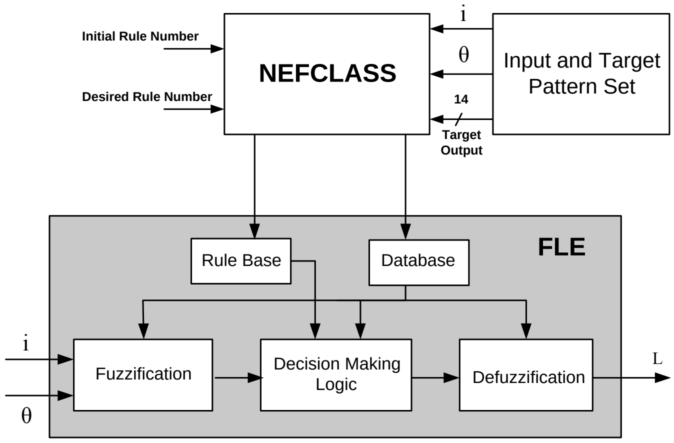

Figure 2. Block diagram of the NEFCLASS based estimator.

The FLE combines fuzzification, rule base, database, decision-making logic, and defuzzification units. Fuzzification, fuzzy inference and defuzzification are the FLE features. Multiple measured crisp inputs firstly have to be mapped into fuzzy MFs. This process is called fuzzification [16]. Fuzzy inference uses the knowledge base consisting of the rule base and the database, and the decision-making logic reside. The database contains descriptions of the input and output variables. The decision-making logic evaluates the control rules. The rule base includes the relations between the outputs and the inputs of the estimator. The output of the inference mechanism is fuzzy output variables. The FLE must convert its internal fuzzy output variables into crisp values so that the actual system can use these variables. This conversion is called defuzzification. One may perform this operation in several ways. In this study, the weighted average method has been used for defuzzification. In the weighted average method [16], the centroid of each MF for each rule is first evaluated. The final output L is then calculated as the average of the individual centroid weighted by their heights as follows,

$$L = \frac{\sum_{i=1}^{n} u_i \mu(u_i)}{\sum_{i=1}^{n} \mu(u_i)} \tag{1}$$

where $\mu(u_i)$ is minimum value of membership degree of input values. The initial membership functions of the current and the position are defined in the range of $1 \leq i \leq 8$ and $0 \leq \theta \leq 30$ and the inductance is defined in the range of $14 \leq L \leq 122$.

Figure 3 demonstrates the initial membership functions. 10 levels were chosen for i, 13 for θ and 13 for L. According to our experience and simulation results, the better response of the system was obtained in these levels membership functions compared to others.

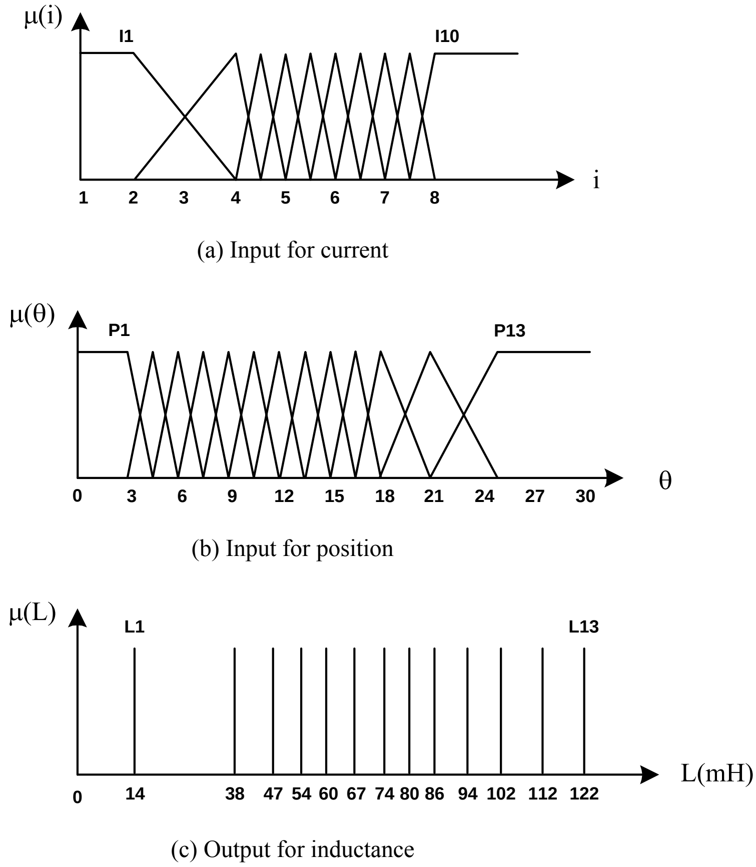

Figure 3. The initial membership functions.

NEFCLASS is used to optimize the membership functions and the rule base. The NEFCLASS system has a 3-layer feed-forward structure [11]. The NEFCLASS structure used in this work is shown in Figure 4. The first layer contains the inputs i and θ. The hidden layer holds rules, and the third layer consists of outputs. In this study, the hidden layer contains 88 fuzzy rules initially and the third layer contains 13 output units.

Rule base has been first created, and it has been then refined by modifying the initially given membership functions. The rule base is created by finding a rule for each pattern in the training set. If a rule is not already in the rule base, it is added. While learning process, each rule is evaluated, and deleted some of them to keep only the best rules. The learning algorithm of the MFs uses the output error. This error is used to change input fuzzy sets by shifting the membership functions, and making their supports larger or smaller [12].

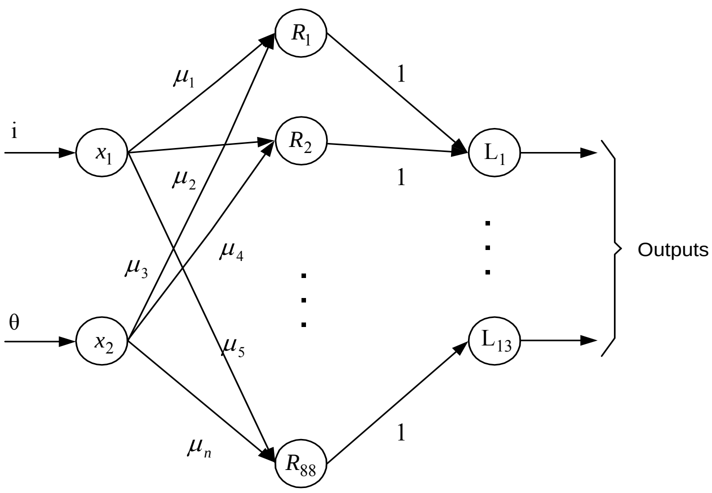

Figure 4. The NEFCLASS structure with 2 inputs, 88 rules and 13 outputs.

NEFCLASS training algorithm requires an input and target pattern set defined between inputs and output. Although, the input and target pattern set has 88 rows, only some of them are shown in Table 3.

Table 3. NEFCLASS training set

Row No	i	θ	L_1	L_2	L_3	L_4	L_5	L_6	L_7	L_8	L_9	L_{10}	L_{11}	L_{12}	L_{13}
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	1	3	0	0	0	0	0	0	0	0	0	0	0	1	0
3	1	6	0	0	0	0	0	0	0	0	0	0	1	0	0
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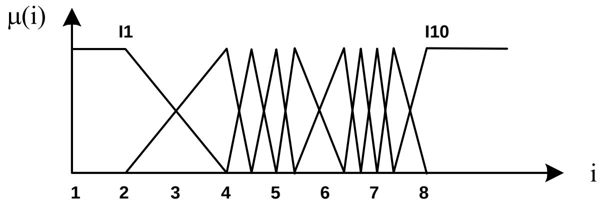
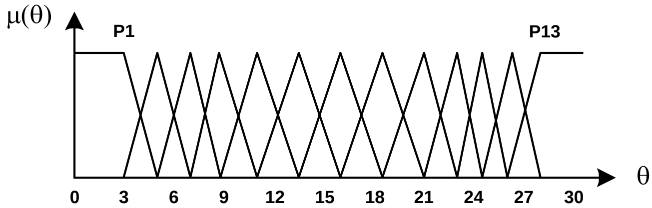
86	8	24	1	0	0	0	0	0	0	0	0	0	0	0	0
87	8	27	1	0	0	0	0	0	0	0	0	0	0	0	0
88	8	30	1	0	0	0	0	0	0	0	0	0	0	0	0

First and second columns in Table 3 are the inputs i and θ, respectively. The other columns are the outputs values of NEFCLASS. Output values, which are 1, show the highest value of outputs. The fuzzy sets are adjusted by a back propagation-like algorithm. The error is propagated from the outputs towards the inputs and used to change the membership function parameters. More information about NEFCLASS can be found in [11].

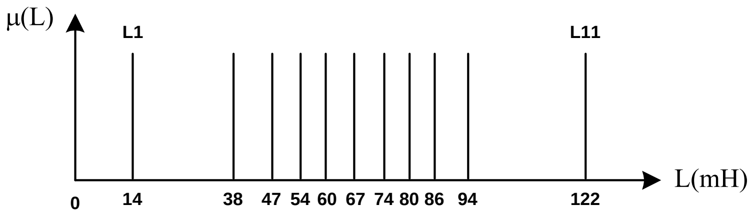
The learning phase yields optimized membership functions for both current and position. Figure 5 shows optimized membership functions for current, position and inductance.



(a) Input for current



(b) Input for position



(c) Output for inductance

Figure 5. Optimized membership functions.

The consequent part of the rules is the output, which is the inductance. After learning phase, the optimized rule base of FLE is shown in Table 4.

Table 4. Optimized rule base

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
P1	L11	L10	L10	L9	L8					
P2	L11	L10	L9	L8	L8					
P3	L10	L10	L9	L8	L7					
P4		L9	L9	L7						
P5		L9	L8	L7						
P6		L8	L8	L7						
P7	L10	L8	L7	L6	L5					
P8	L9	L8	L7	L6	L5	L4				
P9	L9	L7	L6	L6	L5	L3	L3			
P10						L3	L3	L3		
P11						L3	L2	L2	L2	
P12						L3	L3	L2	L2	L2
P13					L3	L3	L3	L1	L1	L1

In Table 4, it can be seen that total 60 best rules were obtained. Since measured inductance values are very close to the estimated inductance values, these cannot be graphically shown together. For this reason, the following values (Eqn.2) have been calculated as deviation in inductance values, and these have been shown in Figure 6.

$$dL = \frac{L_{estimated} - L_{measured}}{L_{measured}} \tag{2}$$

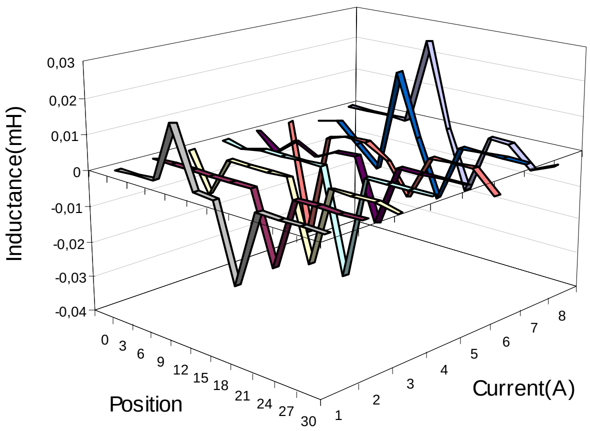


Figure 6. Deviation of inductance values.

It can be clearly seen from Figure 6 that the proposed estimator results are reasonable accurate. According to the results, maximum deviation between measured and estimated inductance values is 0,044%. Figure 7 shows a parity plot between measured and estimated inductance values by the proposed estimater. The predictions have R^2-value equal to 0,9998.

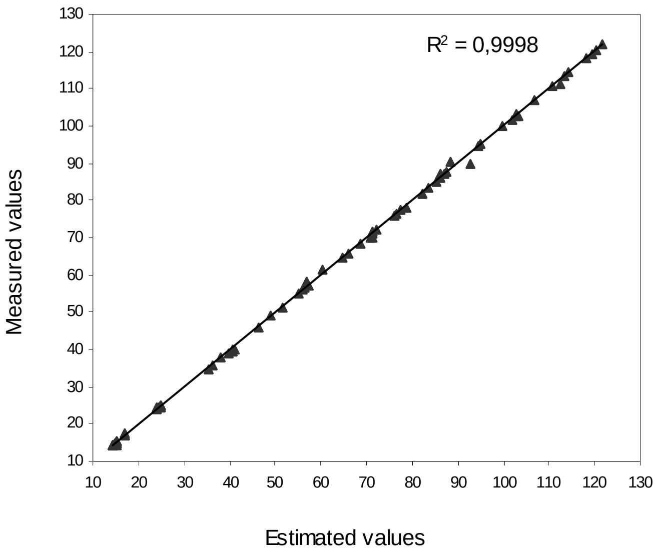


Figure 7. Comparison of the measured and estimated inductance values.

As can be clearly seen from Figures 6-7, proposed model has successfully predicted inductance values.

4. Conclusions

A NEFCLASS based estimator has been successfully presented in this study. The parameters of MFs and rule base were established and tuned using artificial neural network approach. The measured and the estimator inductance values were compared via graphics. The simulation results demonstrate the effectiveness of the proposed estimator. The main advantages of the proposed estimator are that it does not require complex mathematical model and it has faster operation.

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