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SWITCHED RELUCTANCE MOTOR CONTROL BASED ON ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

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Abstract

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This paper gives some studies on the model of Switched Resistor Motor (SRM). The adaptive neuro-fuzzy inference system (ANFIS) is used to model the inductance and moment of the SRM. Then, the PI Controller is applied to model the inductance and flux bond of the SRM. Comparing these two types of modeling method, it is clear that although the PI Controller method can do online research, it is not as accurate as ANFIS.

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Keyword: neuro-fuzzy; Switched Resistor Motor; PI controller; ANFIS

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Introduction

Controlling the Switched Reluctance Motor (SRM) is a very complicated problem, in particular, the aim of controlling is to reduce the moment/torque variation and optimize the energy consumption. The are many researchers have been doing this topics (Daldaban, Ustkoyuncu & Guney (2006); Dehkordi, Parsapoor, Moallem, & Lucas (2011); Ding & Liang (2008); Espinosa-Pérez, Maya-Ortiz, Velasco-Villa, & Sira-Ramírez (2004); Hasanien (2013); Karaboga & Kaya (2019); Şahin & Erol (2018); Tahour, Abid & Aissaoui (2007), they mainly focused on two: (1) design of motor to reduce the moment variation such as increasing the pole of rotor and stator and appropriate design of magnetic poles' dimensions. However, this solution can only partially satisfy because it depends on manufacturing technology and product cost; (2) Use appropriate control methods such as: using the nonlinear model, choosing the power converter structure and opening/closing angles accordingly, using the optimal control algorithm, using fuzzy logic, neural-fuzzy to current compensation, cut angle compensation, etc.

Therefore, the study of magnetic motor control methods is very necessary. This paper researches and builds the mathematical model of fuzzy logic controller and ANFIS (Adaptive Neuro-Fuzzy Inference System) controller used to control the cutting angle for SRM motors to reduce the variation of torque.

This paper is distributed as follows: the next section describes the research in detail. Section 3 will describe fuzzy inference algorithm to control motors. Digital experiments will be used to evaluate the effectiveness of the algorithm. The last Section will be the conclusion of the article.

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ANFIS Controller

The ANFIS controller makes a change to the reference current (I_{ref}) based on the speed error and the derivative for the defined speed error:

$e = \omega_{ref} - \omega$	(1)
$\mathrm{d}e = \dfrac{\mathrm{d}\left(\omega_{ref} - \omega\right)}{\mathrm{d}f}$	(2)

where ω_{ref} are ω are referecence and real speed, respectively. In this research, ANFIS model is used to build a controller with following rules: If e is A_i and de is B_i then z = f (e, de), where A and B are the given fuzzy sets and z = f (e, de) is a precise and explicit function of results.

Characteristics of ANFIS structure

Layer 1: Each of the adaptive nodes in this layer produces membership function points for the input vectors A_i, i = 1,…,5. In this paper, the node function is a triangular membership function:

$$O_i^1 = \mu_{Ai}(e) = \begin{cases} 0, & e \le a \\ \dfrac{e-a_i}{b_i-a_i}, & a_i \le e \le b_i \\ \dfrac{c_i-e}{c_i-b_i}, & b_i \le e \le c_i \\ 0, & c_i \le e \end{cases} \tag{3}$$

Layer 2: The number of total rules is 25 in this layer. Each node output represents the trigger level of the rule:

$$O_i^1 = w_i = \min\left(\left(\mu_{Ai}(e), \mu_{Bi}(de)\right)\right), i = 1,...,5 \tag{4}$$

Layer 3: The fixed node i in this layer calculates the ratio of the i-th rule activation level to the sum of all activation levels.

$$O_i^3 = \bar{w}_i = \frac{w}{\sum_{j=1}^{n} w_j} \tag{5}$$

Layer 4: Adaptive node i in this layer calculates the contribution of the i-th rule to the overall output, with the node function as follows:

$$O_i^4 = \bar{w}_i z_i = \bar{w}_i\left(p_i e + q_i \mathrm{de} + r_i\right) \tag{6}$$

Layer 5: The single fixed node in this layer calculates the overall output as the sum of the contributions from each rule:

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i z_i = \frac{w_1 z_1 + w_2 z_2}{w_1 + w_2} \tag{7}$$

The trained parameters a_i, b_i, and c_i are the edge parameters and p_i, q_i and r_i are parameters of results. The training algorithm requires the training set to be defined between input and output. Though, the input and output sample set has 150 rows. The number of epochs is 100 for training. The number of membership functions for the input variables *e* and *de* are 5 and 5 respectively. The number of rules is 25 (5.5 = 25). Triangular function is used for two input variables. This membership function is defined by two parameters. Therefore, the ANFIS used here contains a total of 95 parameters, of which 20 are the circumference parameters and 75 resultant parameters. The RMS error for testing and training obtained from ANFIS is 4.7×10^{-6} and 5.3×10^{-6} respectively.

Simulation

ANFIS controller modelling

In this section, an ANFIS control model is proposed. Figure 1 shows the fuzzy logic diagram for e and de, Figure 2 shows the SRM motor control model using ANFIS. And Figure 3 shows the SRM simulation model with a PI speed control unit.

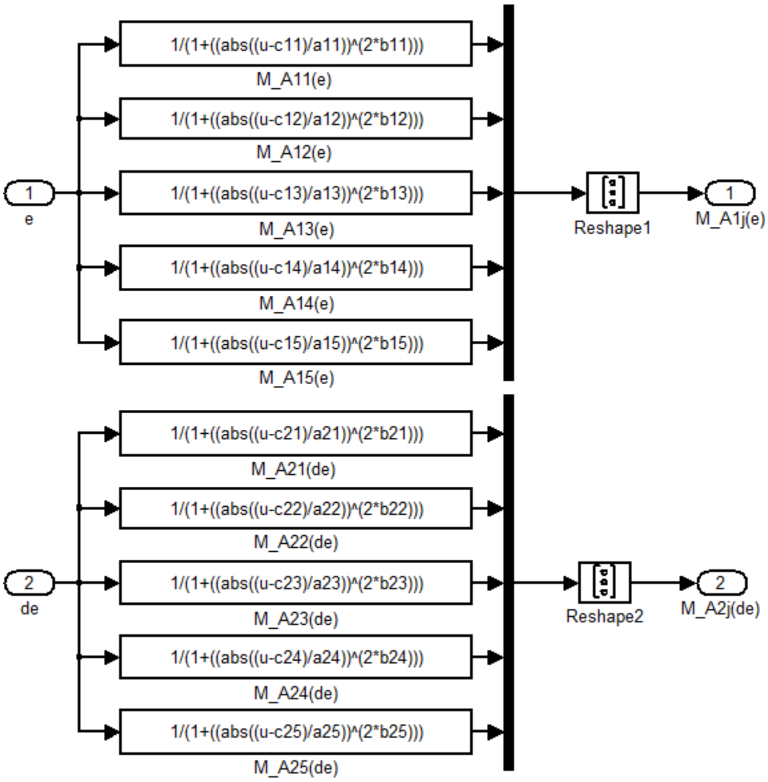

Figure 1. Schematic diagram of Fuzzy logic model.

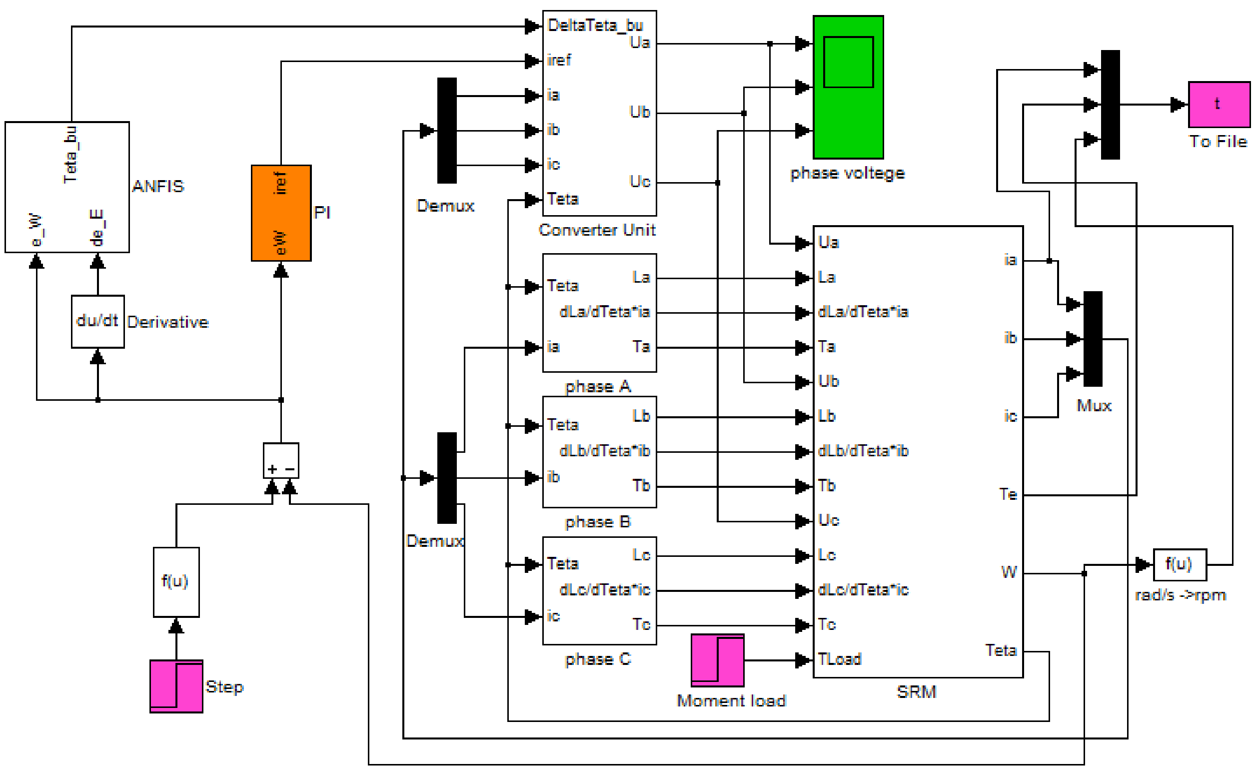

Figure 2. ANFIS model controlling the SRM motor.

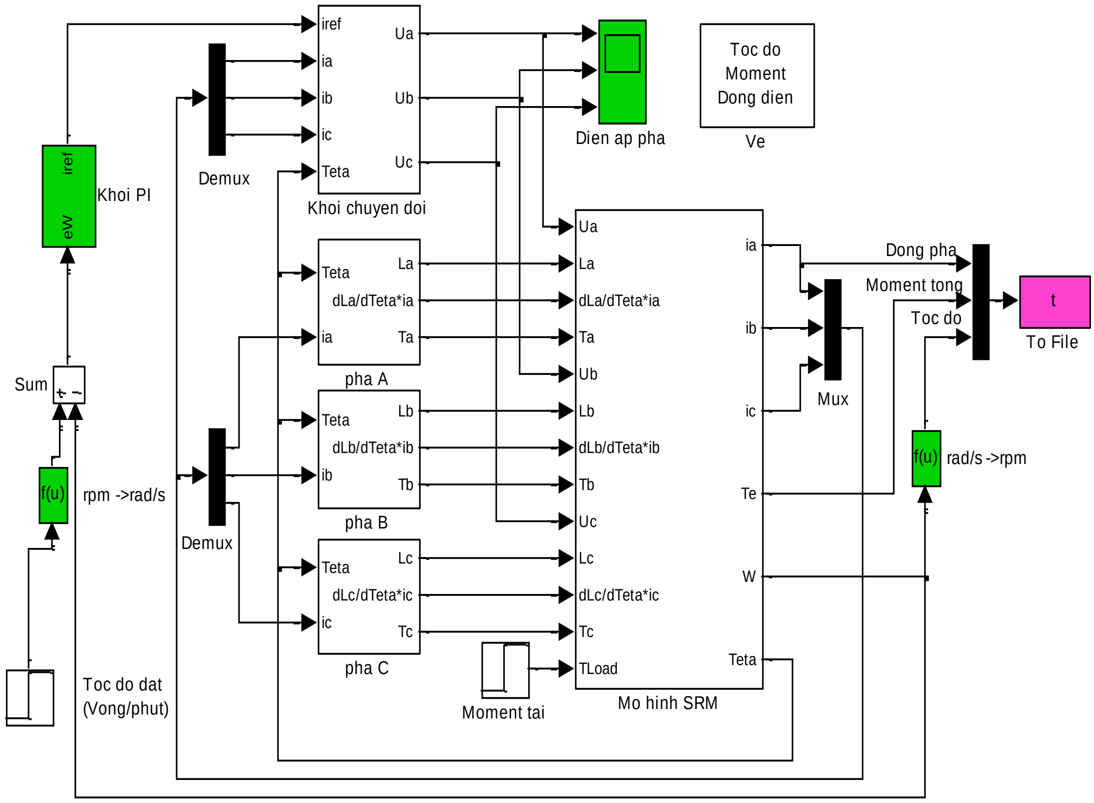

Figure 3. Simulation diagram of SRM with PI speed control unit.

Results of simulation

This paper examines three changing cases when simulating the problem: variable load moment, variable speed and changing cutting angle.

Moment of load changes: Investigation in the case of set speed W_{ref} = 5000 (rpm), angle off $\theta_c = 30^0$, initial motor starting with empty loads (Tload = 0), after 0.5 seconds with load turn in 3 cases (Tload = 1.0, 2.0, 3.0). After simulating, the results show that when the torque of load changes, the motor speed does not change and is equal to the preset speed. In addition, the greater the variation in current, the higher the load moment.

Variable speed: Investigated in the case of Tload torque = 3.0 (N.m), off angle $\theta_c = 30^0$. This study set the speed to two cases. Case 1: the setting speed wref = 1000 (rpm) is in the range [0 - 0.5s} and wref = 5000 (rpm) in the range [0.5 - 1.0s}. Case 2: set speed wref = 5000 (rpm) in the range [0 - 0.5s}, wref = 2000 (rpm) in the range [0.5 - 1.0s}. Through these two simulation cases: when The speed response is equal to the set speed and in the lower speed domain the higher the torque is.

Variable off angle: With this simulation, the set speed is 500, 1000, 2000, 3000, 4000 and 5000 rpm respectively. The off angle speed will be set to 30^0, 35^0 and 40^0 for each shutdown speed. Same shutdown angle and same load moment, but different speed, the torque is different and the current value is also different. The same speed is set and the same load moment, but the off angle is different, the ripple torque is different and the current value is also different. From there, we see that corresponding to a fixed speed and torque, there will be a corresponding off angle at which the undulating moment is the smallest. Table 1 shows all simulation results when the off angle changes.

Table 1. Simulation of off angle change

W_{ref} (rpm)	$\theta_c = 30^0$			
	T_{max}	T_{min}	Tripple %	I_{pha} (A)
500	4.008	1.177	94.23	8.968
1000	4.029	1.621	80.05	7.239
2000	3.843	2.105	57.64	5.806
3000	3.678	2.331	45.56	5.238
4000	3.656	2.397	41.55	5.115
5000	3.581	2.418	38.29	5.044
W_{ref} (rpm)	$\theta_c = 35^0$			
	T_{max}	T_{min}	Tripple %	I_{pha} (A)
500	3.466	2.076	46.26	5.4
1000	3.494	2.193	42.25	5.044
2000	3.713	2.337	45.63	4.828
3000	3.807	2.417	45.99	4.677
4000	3.958	2.528	47.19	4.693
5000	4.171	2.53	54.03	4.687
W_{ref} (rpm)	$\theta_c = 40^0$			
	T_{max}	T_{min}	Tripple %	I_{pha} (A)
500	3.383	2.418	32.12	4.945
1000	3.458	2.431	34.14	4.882
2000	3.684	2.425	41.75	4.905
3000	3.866	2.399	48.53	4.717
4000	4.022	2.417	52.97	4.781
5000	4.15	2.342	59.53	4.742

IV. Conclusion

This paper uses the adaptive network fuzzy inference algorithm (ANFIS) that has solved the problem of determining the optimal torque control angle in a variable resistor motor. During the optimization process, the quality parameters of the momnet oscillation and the stator coil loss are enhanced to meet the control needs. Through the simulation results, it can be confirmed that the algorithms and control structures presented in this study are appropriate and correct. This study is the premise for SRM engines that are commonly used in the industries in Vietnam.

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