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

Nguyen Van Thanh
Faculty of Mechanical Engineering and Technology, Ho Chi Minh City University of Food Industry (HUFI), 140 Le Trong Tan street, Tay Thanh ward, Tan Phu district, Ho Chi Minh city, Vietnam, Telp 0084-0385213083
Email: thanhnv@hufi.edu.vn

Abstract

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.

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

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.

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)

$$\frac{de}{dt} = \frac{d\left(\omega_{ref} - \omega\right)}{dt}$$ (2)

where $\omega_{ref}$ and $\omega$ are reference 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 $A_i$, $i = 1, \ldots, 5$. In this paper, the node function is a triangular membership function:

$$O_i^1 = \mu_{A_i}(e) = \begin{cases} 
0, & e \leq a \\
n\frac{e - a_i}{b_i - a_i}, & a_i \leq e \leq b_i \\
n\frac{c_i - e}{c_i - b_i}, & b_i \leq e \leq c_i \\
n0, & c_i \leq e 
\end{cases} \quad (3)$$

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

$$O_i^2 = w_i = \min(\{\mu_{A_1}(e), \mu_{A_2}(de)\}), i = 1, \ldots, 5 \quad (4)$$

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.

$$O_i^3 = \bar{w}_i = \frac{w_i}{\sum_{j=1}^{n} w_j} \quad (5)$$

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:

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

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

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i z_i = \frac{\sum_{i=1}^{2} \bar{w}_i z_i}{\bar{w}_1 + \bar{w}_2} \quad (7)$$

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 ($5 \times 5 = 25$). 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 $4.7 \times 10^{-6}$ and $5.3 \times 10^{-6}$ 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.
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 $\theta_c = 30^\circ$, initial motor starting with empty loads ($T_{load} = 0$), after 0.5 seconds with load turn in 3 cases ($T_{load} = 1.0, 2.0, 3.0$). 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 $T_{load}$ torque = 3.0 (N.m), off angle $\theta_c = 30^\circ$. This study set the speed to two cases. Case 1: the setting speed $w_{ref} = 1000$ (rpm) is in the range $[0 - 0.5s}$ and $w_{ref} = 5000$ (rpm) in the range $[0.5 - 1.0s}$. Case 2: set speed $w_{ref} = 5000$ (rpm) in the range $[0 - 0.5s}$, $w_{ref} = 2000$ (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 $30^\circ$, $35^\circ$ and $40^\circ$ 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

| $W_{\text{ref}}$ (rpm) | $\theta_c = 30^\circ$ | $\theta_c = 35^\circ$ | $\theta_c = 40^\circ$ |
|------------------------|------------------------|------------------------|------------------------|
|                        | $T_{\text{max}}$  | $T_{\text{min}}$  | Tripple % | $I_{\text{pha}}$ (A) | $T_{\text{max}}$  | $T_{\text{min}}$  | Tripple % | $I_{\text{pha}}$ (A) | $T_{\text{max}}$  | $T_{\text{min}}$  | Tripple % | $I_{\text{pha}}$ (A) |
| 500                    | 4.008                 | 1.177                 | 94.23     | 8.968                 | 3.466                 | 2.076                 | 46.26     | 5.4                     |
| 1000                   | 4.029                 | 1.621                 | 80.05     | 7.239                 | 3.494                 | 2.193                 | 42.25     | 5.044                   |
| 2000                   | 3.843                 | 2.105                 | 57.64     | 5.806                 | 3.807                 | 2.417                 | 45.99     | 4.677                   |
| 3000                   | 3.678                 | 2.331                 | 45.56     | 5.383                 | 3.958                 | 2.528                 | 47.19     | 4.693                   |
| 4000                   | 3.656                 | 2.397                 | 41.55     | 5.115                 | 4.171                 | 2.53                  | 54.03     | 4.687                   |
| 5000                   | 3.581                 | 2.418                 | 38.29     | 5.044                 | 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 moment 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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