Reducing the output torque ripple of switching reluctance motors using a fuzzy logic system

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ABSTRACT

Torque control for the Switched Reluctance Motor (SRM) is always a complex problem because continuous switching between phases is required during operation. This inherent characteristic often causes the SRM's torque profile to fluctuate significantly [1]. In recent years, researchers have endeavored to investigate control methods aimed at improving the torque characteristics of the SRM. These methods have relied on experimental approaches to select appropriate switching times (or switching angles) [2-4]. In a previous paper, we proposed a data table for selecting the switching time based on the reference speed [14]. To enhance the effectiveness of the proposed solution, in this paper, a Fuzzy Logic System (FLS) is constructed to automate the process of selecting the switching time for the SRM. The FLS is built upon the Takagi-Sugeno (TS) fuzzy model. The fuzzy inference system is implemented using the SUMPROD principle, and defuzzification is performed using the Center of Gravity (CoG) method. The TS fuzzy system is trained using the Steepest Gradient method. The research results will be analyzed through digital simulation.

Keywords: Switching reluctance motors; Fuzzy logic system; Torque ripple reduction; Optimization, Takagi-Sugeno fuzzy model.

1. INTRODUCTION

The torque characteristic is always a critical factor that determines the overall performance of an electric motor. For Switched Reluctance Motors (SRMs), it becomes even more significant since the commutation process typically causes large torque oscillations. Therefore, improving the torque characteristic is a key factor in ensuring the operational capability of SRMs over a wide speed range, especially in the low-speed region, while also enhancing the overall performance of the electromechanical system. Excessive torque oscillations can lead to vibrations, disturbances, and instability during operation, which may result in serious consequences such as mechanical wear on bearings, shafts, and transmission components. This issue is particularly critical when the motor operates at low speeds [1].

Among the commonly used torque ripple mitigation techniques, researchers often focus on methods implemented within the control scheme itself, as seen in works such as [2-5], and [10]. In [5], the authors combined the Sliding Mode Control (SMC) technique with Direct Torque Control (DTC) to suppress output torque harmonics of the SRM, based on the assumption that the effects of load torque and disturbance torque are neglected. In this work, the torque ripple of the SRM depends linearly on the rotor acceleration. Thus, SMC was integrated to minimize rotor acceleration.

Another intervention approach for controlling torque ripple was presented in [2], where reference current trajectories were generated for each phase, and the phase currents were controlled to follow these trajectories. This method significantly reduces torque ripple; however, its effectiveness heavily depends on how the current trajectories are designed, which inadvertently reduces flexibility in practical applications and may cause localized heating due to continuous current variation. In general, such methods tend to be relatively complex and highly dependent on the characteristics of the proposed controller.

For SRMs, torque characteristic oscillations mainly arise from phase commutation. Adjusting the commutation so that the sum of the phase torques remains constant is extremely challenging and has not yet been achieved. Therefore, improving torque characteristics by optimizing commutation timing between phases using logic-based control for SRMs has attracted increasing attention from researchers. Some studies have explored non-simultaneous phase switching [11] or optimal commutation timing selection [12]. However, research works in this direction remain limited. Following this line of investigation, this paper proposes employing a fuzzy logic system to determine the optimal commutation instants, thereby reducing torque ripple. Unlike manual tuning approaches, the proposed method utilizes adaptive fuzzy logic to perform real-time adjustments, thus reducing dependency on motor parameters. This is the main contribution of this paper.

The paper is organized as follows: Section 2 presents the theoretical background and problem formulation. Section 3 details the design of the fuzzy logic system. Section 4 discusses the simulation results. Section 5 provides conclusions.

2. TAKAGI-SUGENO FUZZY SYSTEM DESIGN

The fuzzy logic system is designed with the motor's reference speed as the input and the desired switching time as the output $\hat{\tau}(ms)$ according to table 1. The proposed fuzzy logic system utilizes the Takagi-Sugeno fuzzy model, abbreviated as the TS fuzzy model, with the system structure presented in the figure 1.

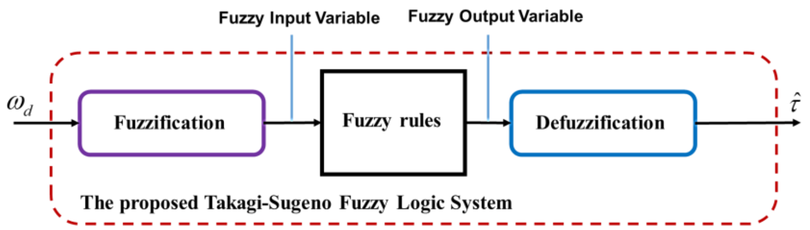


Figure 1. *Proposed fuzzy system structure.*

Input linguistic variable: During the simulation process, when different numbers of membership functions were selected for the input linguistic variable, the case with five membership functions provided the best performance. The membership function $\mathbf{T_i}$ for the input linguistic variable i = 1, 2, 3, 4, 5 has the form:

$$\mu T_i(\omega_d) = \exp\left(-\frac{(\omega_d - c_i)^2}{2\sigma_i^2}\right) \tag{1}$$

in which $c_i, \sigma_i > 0$ are pre-selected and correspond to the parameters of the input membership function. The membership functions T_i at the input fuzzification stage are illustrated in figure 2.

Construction of composition rules: The composition rules consist of five "If ... Then ..." rules, which are interpreted as follows.

R1:	If ω_d is T_1 then $y_1 = a_1\omega_d + b_1$	OR
R2:	If ω_d is T_2 then $y_2 = a_2\omega_d + b_2$	OR
R3	If ω_d is T_3 then $y_3 = a_3\omega_d + b_3$	OR
R4:	If ω_d is T_4 then $y_4 = a_4\omega_d + b_4$	OR

R5: If ω_d is T_5 then $y_5 = a_5\omega_d + b_5$ (2)

The output y_i of the fuzzy rule R_i is a crisp value that depends linearly on the crisp input signal ω_d. The parameters a_i and b_i ($i = 1,2,3,4,5$) are the trainable parameters of the fuzzy system. Let α_i denote the degree of fulfilment of the antecedent of the fuzzy rule R_i. Using the SUMPROD inference rule and the centroid defuzzification method, we obtain:

$$\hat{\tau} = \hat{\tau}(a_i, b_i) = \frac{\sum_{i=1}^{5} \mu_{Ti}(\omega_d)\, y_i}{\sum_{i=1}^{5} \mu_{Ti}(\omega_d)} = \frac{\sum_{i=1}^{5} \alpha_i y_i}{\sum_{i=1}^{5} \alpha_i} \quad (3)$$

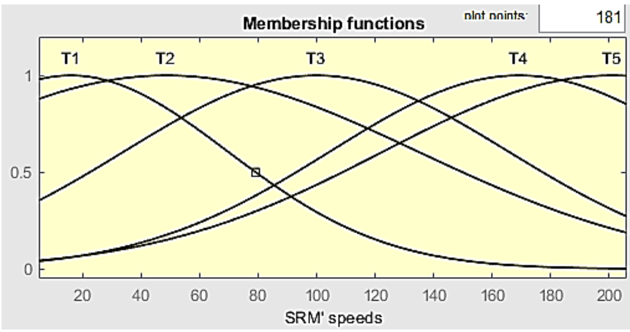


Figure 2. *Membership functions of the input fuzzification stage.*

3. EXPERIMENTAL DATA FOR FUZZY SYSTEM DESIGN

3.1. Data for switching time according to speed

The data serves as the foundation to design and train the fuzzy system, which is collected after roughly 3000 times running a simulation.

Table 1. *Switching time data corresponding to each speed value.*
Units: ω - [rad/s]; τ - [ms]; Δt_{off} - [ms].

ω	τ	Δt_{off}	ω	τ	Δt_{off}	ω	τ	Δt_{off}	ω	τ	Δt_{off}
5	4	0.45	53	5	0.25	111	9	0.45	159	8	0.3
6	2	0.3	54	4	0.4	112	5	0.45	160	8	0.45
7	4	0.45	55	4	0.05	113	4	0.4	161	2	0.15
8	4	0.45	56	9	0.4	114	4	0.1	162	10	0.3
9	5	0.3	57	5	0.25	115	9	0.05	163	1	0.15
10	10	0.3	58	8	0.25	116	5	0.15	164	5	0.35
11	5	0.1	59	8	0.2	117	4	0.2	165	10	0.45
12	1	0.05	60	2	0.35	118	8	0.4	166	1	0.35
13	6	0.05	61	10	0.3	119	1	0.3	167	7	0.25
14	7	0.25	62	1	0.25	120	8	0.05	168	6	0.05
15	2	0.3	63	2	0.1	121	5	0.05	169	6	0.15
16	8	0.45	64	4	0.45	122	2	0.45	170	3	0.05
17	9	0.3	65	3	0.1	123	8	0.05	171	4	0.25
18	3	0.3	66	1	0.4	124	8	0.15	172	9	0.4
19	4	0.15	67	10	0.05	125	2	0.25	173	8	0.25
20	2	0.4	68	1	0.15	126	7	0.2	174	8	0.4
21	2	0.25	69	2	0.45	127	7	0.15	175	8	0.05
22	10	0.45	70	2	0.45	128	1	0.4	176	5	0.2
23	10	0.35	71	1	0.35	129	2	0.1	177	9	0.4

ω	τ	Δt_{off}	ω	τ	Δt_{off}	ω	τ	Δt_{off}	ω	τ	Δt_{off}
24	2	0.15	72	1	0.3	130	4	0.2	178	3	0.25
25	5	0.4	73	2	0.35	131	7	0.2	179	7	0.1
26	1	0.4	74	7	0.3	132	8	0.15	180	4	0.2
27	7	0.25	75	5	0.2	133	5	0.1	181	3	0.4
28	9	0.1	76	5	0.1	134	4	0.15	182	6	0.1
29	6	0.25	77	7	0.3	135	7	0.1	183	8	0.25
30	2	0.35	78	2	0.15	136	3	0.4	184	7	0.05
31	5	0.45	79	4	0.1	137	1	0.4	185	10	0.2
32	2	0.45	80	5	0.2	138	3	0.05	186	3	0.45
33	6	0.4	81	8	0.1	139	6	0.3	187	2	0.2
34	9	0.3	82	3	0.4	140	7	0.25	188	6	0.2
35	1	0.05	83	4	0.35	141	4	0.05	189	2	0.25
36	2	0.15	84	10	0.35	142	4	0.1	190	6	0.4
37	5	0.1	85	9	0.35	143	3	0.4	191	3	0.2
38	3	0.15	86	4	0.35	144	6	0.45	192	6	0.3
39	2	0.45	87	5	0.35	145	5	0.35	193	5	0.05
40	4	0.1	88	5	0.4	146	7	0.15	194	3	0.4
41	1	0.05	89	8	0.4	147	6	0.4	195	8	0.15
42	8	0.4	90	9	0.4	148	7	0.05	196	2	0.1
43	10	0.3	91	5	0.25	149	8	0.45	197	1	0.05
44	1	0.15	92	9	0.1	150	1	0.3	198	1	0.3
45	5	0.4	93	9	0.35	151	6	0.1	199	7	0.15
46	5	0.15	94	6	0.15	152	3	0.3	200	6	0.25
47	6	0.35	95	7	0.4	153	8	0.25	201	2	0.4

3.2. Fuzzy system training process

The parameters of the fuzzy system, including a_i and b_i ($i = 1,2,\ldots,5$), are trained to minimise the error between the output switching time value $\hat{\tau}(\eta_i) = \hat{\tau}$ and the reference switching time values given in table 1. The objective function used for training the parameters is defined as follows:

$$J(a_i, b_i) = \frac{1}{2}\sum_{n=1}^{201}\left[\tau(n) - \hat{\tau}(a_i, b_i)\right]^2 \to \min \tag{4}$$

The training process is performed using the steepest gradient descent method, in which the learning rate δ is also adaptively updated at each iteration to accelerate the convergence of the objective function [11]. The initial learning rate is selected as $\delta_0 = 0.1$, and the update formulas for a_i^k and b_i^k at the k-th iteration are expressed as follows:

$$a_i^{k+1} = a_i^k + \delta_k \left(\nabla_{a_i}\hat{\tau}(a_i, b_i)\right)\Big|_{\substack{a_i = a_i^k \\ b_i = b_i^k}} = a_i^k - \delta_k \sum_{n=1}^{201}\left[\tau(n) - \hat{\tau}(a_i^k, b_i^k)\right]\left(\nabla_{a_i}\hat{\tau}(a_i, b_i)\right)\Big|_{\substack{a_i = a_i^k \\ b_i = b_i^k}} \tag{5}$$

$$b_i^{k+1} = b_i^k + \delta_k \left(\nabla_{b_i}\hat{\tau}(a_i, b_i)\right)\Big|_{\substack{a_i = a_i^k \\ b_i = b_i^k}} = b_i^k - \delta_k \sum_{n=1}^{201}\left[\tau(n) - \hat{\tau}(a_i^k, b_i^k)\right]\left(\nabla_{b_i}\hat{\tau}(a_i, b_i)\right)\Big|_{\substack{a_i = a_i^k \\ b_i = b_i^k}} \tag{6}$$

Where $\nabla_{a_i}\hat{\tau}(a_i, b_i)$ is the gradient vector of the fuzzy system's output with respect to the direction of a_i, and $\nabla_{b_i}\hat{\tau}(a_i, b_i)$ 1 is the gradient vector of the fuzzy system's output with respect to the direction of b_i. δ_k is the k-th learning rate, which is determined by [13]:

$$\delta_{k+1} = \arg\min_{\delta>0} \frac{1}{2}\sum_{n=1}^{201}\left[\tau(n) - \hat{\tau}\left(a_i^{k+1}, b_i^{k+1}\right)\right]^2 \tag{7}$$

From (5) – (7), we obtain the updating rules for a_i^{k+1}, b_i^{k+1} in $k+1$ from their previous values a_i^k, b_i^k and the output of the designed fuzzy system (3) with $i = 1,2,...,5$:

$$a_i^{k+1} = a_i^k - \omega_d \delta_k \sum_{n=1}^{201}\left[\tau(n) - \left(\sum_{i=1}^{5}\mu_i(\omega_d)\right)^{-1}\sum_{i=1}^{5}\mu_i(\omega_d)\left(a_i^k\omega_d + b_i^k\right)\right] \tag{8}$$

$$b_i^{k+1} = b_i^k - \delta_k \sum_{n=1}^{201}\left[\tau(n) - \left(\sum_{i=1}^{5}\mu_i(\omega_d)\right)^{-1}\sum_{i=1}^{5}\mu_i(\omega_d)\left(a_i^k\omega_d + b_i^k\right)\right] \tag{9}$$

$$\delta_{k+1} = \left[201\left(1+\omega_d^2\right)\sum_{i=1}^{5}\mu_i(\omega_d)\right]^{-1} \tag{10}$$

The algorithm terminates when both stopping conditions, $\left|a_i^{k+1} - a_i^k\right| < \varepsilon$ and $\left|b_i^{k+1} - b_i^k\right| < \varepsilon$, are simultaneously satisfied. If the stopping conditions are not met, set $k \leftarrow k+1$, and then continue performing the update formulas (8)–(9). Here, ε is a small user-defined constant.

3.3. Results

This section verifies the training results of the fuzzy system to determine the appropriate switching time $\hat{\tau}$, which serves as the basis for subsequent simulations. Using the fuzzy system designed in figure 1, the parameter training formulas given in (8)–(10), and the sample data values provided in table 1, the obtained training error is $\varepsilon = 4\times10^{-6}$. The training results are shown in figure 4 and figure 5. The proposed fuzzy system is integrated into the DSC control scheme designed in [6], and the control scheme is as figure 3.

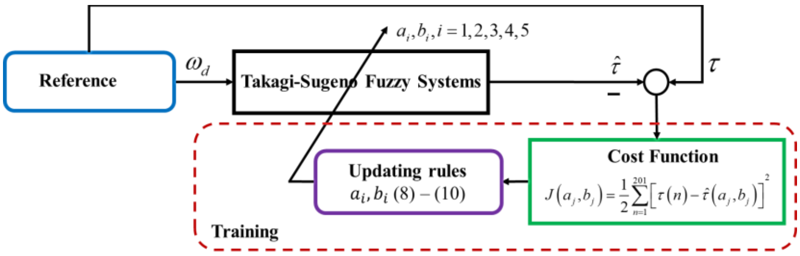


Figure 3. *The structure of the fuzzy training process.*

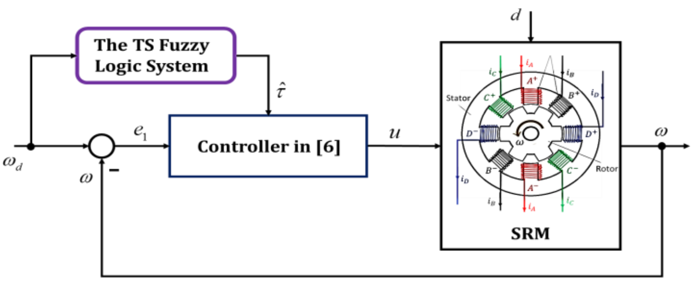


Figure 3. *The control scheme with the proposed TS fuzzy system.*

In figure 5, the output of the fuzzy system, illustrated by star markers, can be seen to closely follow the sample data in table 1, with a training error of $\varepsilon = 4\times10^{-6}$, after approximately 330 epochs (figure 6), obtaining the results: $a_1 = 0{,}0742$; $b_1 = 1{,}174$; $a_2 = 0{,}0504$; $b_2 = 1{,}096$; $a_3 = 0{,}0841$; $b_3 = 0{,}425$; $a_4 = 0{,}0719$; $b_4 = 0{,}0311$; $a_5 = 0{,}0157$; $b_5 = 0{,}0495$.

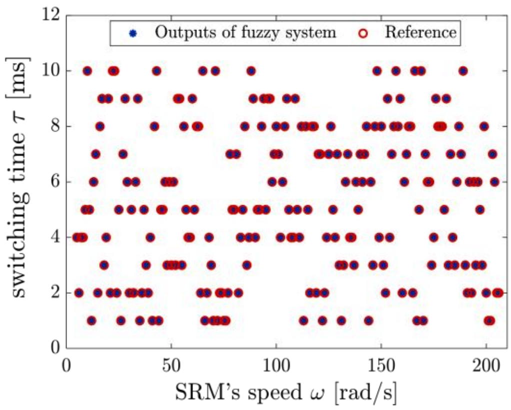


Figure 4. Result of training the proposed TS fuzzy system.

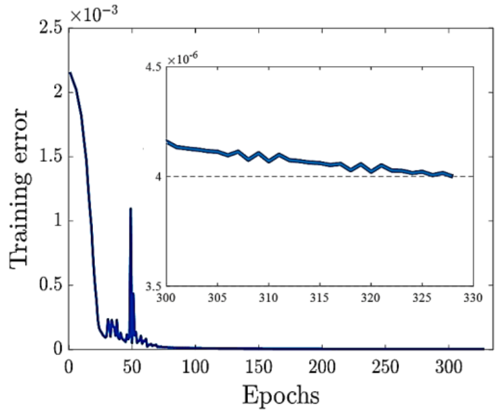


Figure 5. The training error.

4. NUMERICAL SIMULATION

In this section, the results are compared with the case of fixed switching times at two specified values: $\tau = 8[ms]$ and $\tau = 13[ms]$, the desired speed: $\omega_{d1} = 55[rad/s]$ during the first 200 s, $\omega_{d2} = 20[rad/s]$ from 200 s to 400 s and $\omega_{d3} = 45[rad/s]$ lasting from 400 s to 800 s. The simulations were carried out using MATLAB–Simulink and are presented in figures 4 to 8. The simulation parameters for the switched reluctance motor are provided in [6]: $J = 9.68\times10^3\left[kg/m^2\right]$, $m = 150[kg]$, $a = 1.5\times10^{-3}[H]$, $b = 1.364\times10^{-3}[H]$, $N_r = 6$, $\psi_s = 0.2886[Wb]$, $l = 2[m]$, $g = 9.81\left[m/s^2\right]$, power: 1.2 kW, and number of poles: 4.

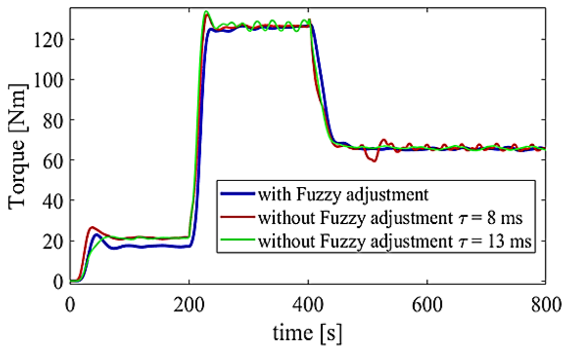
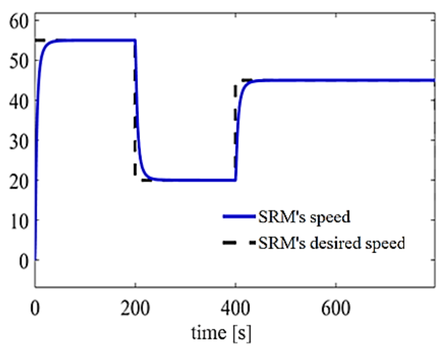


Figure 6. Torque regulation results using a fuzzy adaptive switching time.



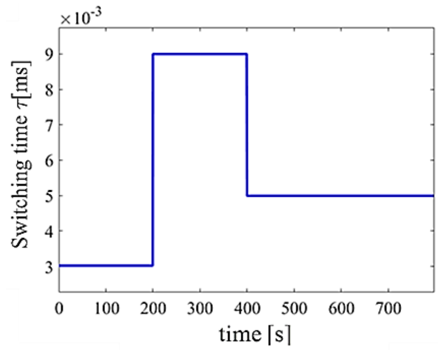


Figure 7. Output response of the fuzzy system. *Figure 8. Speed response of the motor.*

Observing figures 7 and 8 shows that the proposed fuzzy control system achieves very high tracking accuracy with respect to the reference signal. Specifically, from the graph on the left, the reference signal varies at three different levels: remaining at approximately $5\times10^{-3}s$ during 0 - 200 s, climbing to $8\times10^{-3}s$ during the period of 200 - 400 s, and afterwards dropping to $6\times10^{-3}s$ from 400 s onwards. Corresponding to these changes, the graph on the right shows the reference speed varying around the values of 50 rad/s, 20 rad/s, and 45 rad/s.

Moreover, the motor speed in figure 8 closely follows the reference signal throughout all time intervals. The steady-state error at each reference level is approximately. 0 rad/s (estimated error $|e_{ss}|<0.5$, meaning less than 1% in total), whereas the transient error only exists over a short time period (3 - 5 s) with an overshoot value smaller than 2%. These results confirm that the output of the fuzzy system not only fits well with the sample data from the input signal but also ensures accurate tracking of the reference speed, while maintaining system stability and high control performance even under sudden variations of the reference signal.

5. CONCLUSIONS

In this paper, the dependency of the output torque on the switching time τ and the reference speed of the SRM was investigated and analyzed through digital simulation. A sample data table detailing the relationship between the switching time and the reference speed was constructed to serve as the basis for training the Fuzzy Logic System (FLS). The Takagi-Sugeno (TS) fuzzy model was selected to determine the appropriate switching time according to the reference speed for the commutation controller. The output of the TS fuzzy model is determined based on the SumMin principle and is trained offline. The TS fuzzy model, when integrated into the control scheme for the SRM, was analyzed both mathematically and through simulation, demonstrating a significant improvement in the torque characteristics. The research findings provide a scientific basis for improving the torque characteristics of the SRM through the refinement of the fuzzy control logic for the motor.

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TÓM TẮT

Giảm thiểu gợn sóng mô men đầu ra động cơ từ trở chuyển mạch bằng phương pháp điều chỉnh mờ thời gian chuyển mạch

Động cơ từ trở chuyển mạch (SRM) được biết đến với cấu trúc đơn giản và độ bền cao. Tuy nhiên, chúng thường gặp thách thức bởi hiện tượng gợn mô-men và hiệu suất thấp hơn so với các loại động cơ khác. Việc lựa chọn thời điểm chuyển mạch tối ưu giữa các pha của động cơ là yếu tố then chốt để khắc phục các vấn đề này, song cho đến nay chưa có phương pháp nào định hướng việc chọn thời gian chuyển mạch ứng với từng cấp tốc độ. Vì vậy, bài báo này đề xuất sử dụng hệ thống logic mờ để ra tìm ra thời gian chuyển mạch tối ưu, từ đó giảm thiểu hiện tượng gợn sóng mô-men. Khác với các phương pháp điều chỉnh thủ công, phương pháp đề xuất dựa vào logic mờ thích nghi để điều chỉnh theo thời gian thực, giảm sự phụ thuộc vào các tham số động cơ. Chiến lược này sử dụng mô phỏng số để xác định thời điểm chuyển mạch hợp lý cho SRM. Kết quả nghiên cứu được phân tích và tổng hợp thành một hệ chuyên gia mờ có khả năng tự động tối ưu hóa thời điểm chuyển mạch, từ đó nâng cao hiệu suất và khả năng vận hành của động cơ.

Từ khoá: Động cơ từ trở chuyển mạch; Hệ thống điều khiển mờ; Thời gian chuyển mạch; Tối ưu hoá; Mô hình mờ Takagi-Sugeno fuzzy model.