

An Improved Speed Controller for FOC IM Drive Using Fuzzy Logic

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ARTICLE INFO

Received: 01/01/2026
Revised: 11/05/2026
Accepted: 08/06/2026
Online First: 13/08/2026
Published:

KEYWORDS

Induction motor;
Field-oriented control;
Speed controller;
Proportional-integral;
Fuzzy logic.

ABSTRACT

The paper deals with employment of fuzzy logic (FL) to modify the proportional-integral (PI) speed controller in field-oriented control (FOC) for induction motor drive. First, the FOC strategy incorporating the PI speed controller is presented. The controller, which uses a fixed proportional gain and integral time constant, can achieve high performance if these parameters are properly tuned. However, tuning becomes difficult in cases where the load range and working speed change. The fuzzy logic technique is utilized to increase the adaptation of the proportional gain and integral time constant to variations in load and speed. Numerical simulations for the two speed controllers, fixed PI and fuzzy PI, are deployed in the MATLAB environment. Evaluations using overshoot, undershoot, integral of time multiplied by the absolute value of the speed error (ITAE), integral of the absolute value of the speed error (IAE), integral of time multiplied by the square of the speed error (ITSE), and integral of the square of the speed error (ISE), are carried out. Simulation results and assessments confirm that the fuzzy logic significantly improves the utilized criteria compared to the case without fuzzy logic.

Doi: <https://doi.org/10.54644/jte.2026.2065>

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1. Introduction

Methods using artificial intelligence (AI) in the speed controllers and observers of electric drives have been receiving attention over the past decades [1]–[4]. AI-based design, control, and maintenance of electric drives were presented in [2], [3]. The ability to implement machine learning approaches in real time for sensorless controls and speed controllers with DSPs was considered [4]. Among the AI techniques, fuzzy logic (FL) methods were developed and/or combined with other ones in problems of control systems [5]–[21].

A type-2 FL replaced the PI mechanism for sensorless full range IM [5]. For a Luenberger observer, the FL modified the proportional gain and integral time constant to improve sensorless IM control [6]. The FL was employed to adapt coefficients in both the sliding mode observer and sliding mode controller [7]. The FL, utilizing a combination of self-tuning and reinforcement learning techniques, reduced the number of rules and improved sensorless performance [8]. The FL was added to a nonlinear observer for disturbance removal in sensorless permanent magnet synchronous motor drive [9].

An online fuzzy controller adapted bandwidth of both controller and observer for improving the antidisturbance and control performances in bearingless IM drive [10]. Stochastic functions were processed by the FL to guarantee the convergence time and the robustness under variations of load and disturbance [11]. Ripples of thrust and flux were minimized by the FL algorithm in the predictive control of a linear IM [12]. The FL was employed to approximate the nonlinear functions for IM control [13]. To lower overshoot, limits of integral time constant were adjusted according to functions of speed error in PMSM drive [14]. To achieve asymptotic stability and reduce disturbance, a fuzzy controller was deployed in the case of packet loss for a generator-energy conversion system [15]. To obtain both high accuracy and stability, a type-2 fuzzy controller was applied to highly nonlinear magnetic levitation systems [16]. Order of nonlinear systems was reduced to one by the FL [17]. Multi-layer neural network was combined with the FL to achieve high performance in PMSM electric vehicles [18]. The load torque was estimated by the Kalman filter to adjust the parameters of the FL-PI speed controller [19]. To reduce

speed error and total harmonic distortion, the FL algorithm set up the PID parameters in electric vehicles using 6-phase IM [20]. A cerebellum controller was enhanced by the FL in case of inaccurate sensors for brushless DC motor drive system [21]. Through the above analysis, it can be seen that fuzzy logic can improve the quality of nonlinear systems. In the next section, the FOC-based IM drive integrated with the PI speed controller is presented. Then, the speed controller is adjusted by the FL. Simulations and discussions are carried out in the third section. Conclusions are presented in the last section.

2. Fuzzy Logic-Based Tuning Method for PI Speed Controller

The speed controller using a fixed PI or FL-adapted PI scheme for the FOC IM drive is presented in Figure 1. The motor mathematical model is expressed according to (1)–(5):

$$\frac{d\mathbf{X}}{dt} = \mathbf{A}\mathbf{X} + \mathbf{B}\mathbf{U} \quad (1)$$

$$\mathbf{X} = \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \\ \psi_{r\alpha} \\ \psi_{r\beta} \end{bmatrix}; \mathbf{U} = \begin{bmatrix} u_{s\alpha} \\ u_{s\beta} \end{bmatrix} \quad (2)$$

$$\mathbf{A} = \begin{bmatrix} k_1 \mathbf{I} & k_2 \mathbf{I} - k_3 \omega_r \mathbf{J} \\ \frac{R_r L_m}{L_r} \mathbf{I} & -\frac{R_r}{L_r} \mathbf{I} + \omega_r \mathbf{J} \end{bmatrix}; \mathbf{B} = \begin{bmatrix} \frac{1}{\sigma L_s} \mathbf{I} \\ \mathbf{0} \end{bmatrix}; \mathbf{I} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; \mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}; \mathbf{0} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (3)$$

$$k_1 = -\frac{(R_s L_r^2 + R_r L_m^2)}{\sigma L_s L_r^2}; k_2 = \frac{L_m R_r}{\sigma L_s L_r^2}; k_3 = \frac{L_m}{\sigma L_s L_r}; \sigma = \frac{L_r L_s - L_m^2}{L_r L_s} \quad (4)$$

$$T_e = 1.5 \frac{L_m}{L_r} n_p (i_{s\beta} \psi_{r\alpha} - i_{s\alpha} \psi_{r\beta}); J_m \frac{d\omega_m}{dt} = T_e - T_L - B_m \omega_m \quad (5)$$

where, R_s and R_r – stator and rotor resistances; L_m, L_s , and L_r – magnetizing, stator, and rotor inductances; $u_{s\alpha}$ and $u_{s\beta}$, $i_{s\alpha}$ and $i_{s\beta}$ – components of stator voltage, stator current vectors; $\psi_{s\alpha}$ and $\psi_{s\beta}$, $\psi_{r\alpha}$ and $\psi_{r\beta}$ – ones of stator flux, rotor flux vectors; ω_r – rotor speed; n_p and ω_m – number of pole pairs and motor speed ($\omega_r = \omega_m \times n_p$); B_m and J_m – rotational damping coefficient and motor inertia; T_e and T_L – motor torque and load torque, ε – rotor position. Blocks including Clarke Transform, Park Transform and Inverse Park Transform compute:

$$\begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \frac{1}{\sqrt{3}} & \frac{2}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} i_{sa} \\ i_{sb} \end{bmatrix}; \begin{bmatrix} I_d \\ I_q \end{bmatrix} = \begin{bmatrix} \cos \gamma & \sin \gamma \\ -\sin \gamma & \cos \gamma \end{bmatrix} \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix}; \begin{bmatrix} u_{s\alpha,ref} \\ u_{s\beta,ref} \end{bmatrix} = \begin{bmatrix} \cos \gamma & -\sin \gamma \\ \sin \gamma & \cos \gamma \end{bmatrix} \begin{bmatrix} u_{sd,ref} \\ u_{sq,ref} \end{bmatrix} \quad (6)$$

The PWM block receives components of reference voltage vector $u_{s\alpha,ref}$, $u_{s\beta,ref}$ and utilizes the sinusoidal pulse width modulation technique with a 20 kHz carrier signal for generating 6 control pulses to the inverter. In the case of a FOC IM drive, a proportional-integral (PI) controller is used for the I_q Controller and the I_d Controller:

$$G_{pi,lq}(s) = K_{p,lq} + \frac{K_{i,lq}}{s} = K_{p,lq} \left(1 + \frac{1}{T_{i,lq}s} \right) \quad (7)$$

$$G_{pi,ld}(s) = K_{p,ld} + \frac{K_{i,ld}}{s} = K_{p,ld} \left(1 + \frac{1}{T_{i,ld}s} \right) \quad (8)$$

where, $K_{p,lq}$, $K_{i,lq}$, $T_{i,lq}$ and $K_{p,ld}$, $K_{i,ld}$, $T_{i,ld}$ – proportional gain, integral gain, integral time constant of the I_q Controller and the I_d Controller.

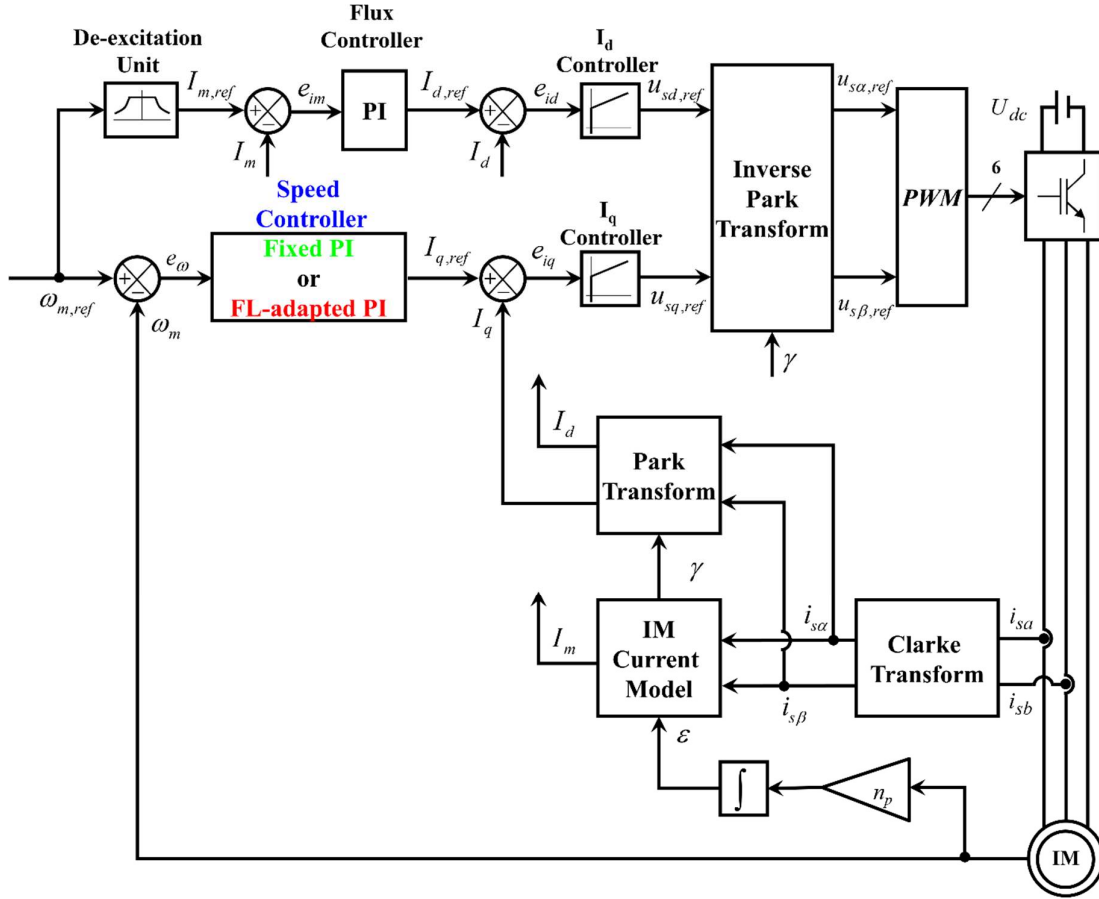


Figure 1. Speed controller using fixed PI or FL-adapted PI scheme for FOC IM drive.

The rotor flux vector angle γ and the magnetizing current I_m are computed by the IM current model:

$$\begin{bmatrix} i_{m\varepsilon} \\ i_{m\xi} \end{bmatrix} = \frac{1}{T_r s + 1} \begin{bmatrix} \cos \varepsilon & \sin \varepsilon \\ -\sin \varepsilon & \cos \varepsilon \end{bmatrix} \begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} \quad (9)$$

$$\begin{bmatrix} i_{m\alpha} \\ i_{m\beta} \end{bmatrix} = \begin{bmatrix} \cos \varepsilon & -\sin \varepsilon \\ \sin \varepsilon & \cos \varepsilon \end{bmatrix} \begin{bmatrix} i_{m\varepsilon} \\ i_{m\xi} \end{bmatrix}; \gamma = \tan^{-1} \left(\frac{i_{m\alpha}}{i_{m\beta}} \right); I_m = \sqrt{i_{m\alpha}^2 + i_{m\beta}^2} \quad (10)$$

where, $i_{m\varepsilon}$, $i_{m\xi}$ – components of magnetizing current vector in the rotating reference frame $\varepsilon\xi$ whose ε -axis is the rotor axis; $T_r = L_r/R_r$ – rotor time constant. The flux-component current reference is calculated by the PI Flux Controller:

$$G_{pi,lm}(s) = K_{p,lm} + \frac{K_{i,lm}}{s} = K_{p,lm} \left(1 + \frac{1}{T_{i,lm}s} \right) \quad (11)$$

where, $K_{p,lm}$, $K_{i,lm}$, $T_{i,lm}$ – proportional gain, integral gain, integral time constant of the Flux Controller. In order to obtain torque-component current reference, the PI Speed Controller is employed as follows:

$$G_{pi}(s) = K_p + \frac{K_i}{s} = K_p \left(1 + \frac{1}{T_i s}\right) \quad (12)$$

where, K_p , K_i , T_i – proportional gain, integral gain, integral time constant of the Speed Controller. Next, the proportional gain and integral time constant are adapted according to the FL.

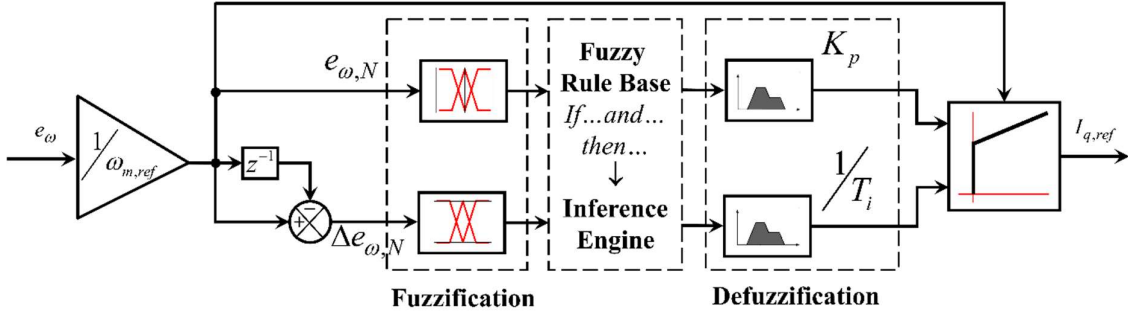


Figure 2. FL-adapted PI speed controller.

Figure 2 shows FL-adapted PI speed controller. Its algorithm consists of three main steps: fuzzification, fuzzy inference, defuzzification. The first one contains Γ -, Δ -, L - membership functions which are described for $e_{\omega,N}$ and $\Delta e_{\omega,N}$ respectively by (13)–(15) and (16)–(18):

$$\mu_P(e_{\omega,N}) = \begin{cases} 1, & \text{for } e_{\omega,N} \geq B_{e1} \\ \frac{e_{\omega,N}}{B_{e1}}, & \text{for } 0 \leq e_{\omega,N} < B_{e1} \\ 0, & \text{for } e_{\omega,N} < 0 \end{cases} \quad (13)$$

$$\mu_Z(e_{\omega,N}) = \begin{cases} 0, & \text{for } e_{\omega,N} \geq B_{e1} \\ \frac{B_{e1} - e_{\omega,N}}{B_{e1}}, & \text{for } 0 \leq e_{\omega,N} \leq B_{e1} \\ \frac{B_{e2} + e_{\omega,N}}{B_{e2}}, & \text{for } -B_{e2} \leq e_{\omega,N} \leq 0 \\ 0, & \text{for } e_{\omega,N} < -B_{e2} \end{cases} \quad (14)$$

$$\mu_N(e_{\omega,N}) = \begin{cases} 0, & \text{for } e_{\omega,N} \geq 0 \\ -\frac{e_{\omega,N}}{B_{e2}}, & \text{for } -B_{e2} \leq e_{\omega,N} < 0 \\ 1, & \text{for } e_{\omega,N} < -B_{e2} \end{cases} \quad (15)$$

$$\mu_P(\Delta e_{\omega,N}) = \begin{cases} 1, & \text{for } \Delta e_{\omega,N} \geq B_{\Delta e1} \\ \frac{\Delta e_{\omega,N}}{B_{\Delta e1}}, & \text{for } 0 \leq \Delta e_{\omega,N} < B_{\Delta e1} \\ 0, & \text{for } \Delta e_{\omega,N} < 0 \end{cases} \quad (16)$$

$$\mu_Z(\Delta e_{\omega,N}) = \begin{cases} 0, & \text{for } \Delta e_{\omega,N} \geq B_{\Delta e1} \\ \frac{B_{\Delta e1} - \Delta e_{\omega,N}}{B_{\Delta e1}}, & \text{for } 0 \leq \Delta e_{\omega,N} \leq B_{\Delta e1} \\ \frac{B_{\Delta e2} + \Delta e_{\omega,N}}{B_{\Delta e2}}, & \text{for } -B_{\Delta e2} \leq \Delta e_{\omega,N} < 0 \\ 0, & \text{for } e_{\omega,N} < -B_{\Delta e2} \end{cases} \quad (17)$$

$$\mu_N(\Delta e_{\omega,N}) = \begin{cases} 0, & \text{for } \Delta e_{\omega,N} \geq 0 \\ -\frac{\Delta e_{\omega,N}}{B_{\Delta e2}}, & \text{for } -B_{\Delta e2} \leq \Delta e_{\omega,N} < 0 \\ 1, & \text{for } \Delta e_{\omega,N} < -B_{\Delta e2} \end{cases} \quad (18)$$

where, the $e_{\omega,N}$ and $\Delta e_{\omega,N}$ own linguistic values of P , N , Z ; boundaries $0 < B_{e1}, B_{e2}, B_{\Delta e1}, B_{\Delta e2} < 1$. Table 1 presents fuzzy 9-rule base and inference engine for the second step, where three linguistic values large, medium, small, of the proportional gain and integral time constant are denoted as L , M , S . Unlike [14], [19], the linguistic values of K_p and $1/T_i$ in Table 1 are chosen as odd functions that pass through the origin ($e_{\omega,N}; \Delta e_{\omega,N}$) = ($Z; Z$). The centroid method [22], [23] is deployed with triangle membership functions (19)–(21) and (22)–(24) to obtain the crisp values of K_p and $1/T_i$:

$$\mu_S(K_p) = \begin{cases} 0, & \text{for } K_p \leq 0 \text{ or } K_p \geq P_M \\ \frac{K_p}{P_S}, & \text{for } 0 < K_p < P_S \\ \frac{P_M - K_p}{P_M - P_S}, & \text{for } P_S < K_p \leq P_M \end{cases} \quad (19)$$

$$\mu_M(K_p) = \begin{cases} 0, & \text{for } K_p \leq P_S \text{ or } K_p \geq P_L \\ \frac{K_p - P_S}{P_M - P_S}, & \text{for } P_S < K_p \leq P_M \\ \frac{P_L - K_p}{P_L - P_M}, & \text{for } P_M < K_p < P_L \end{cases} \quad (20)$$

$$\mu_L(K_p) = \begin{cases} 0, & \text{for } K_p \leq P_M \text{ or } K_p \geq (2P_L - P_M) \\ \frac{K_p - P_M}{P_L - P_M}, & \text{for } P_M < K_p \leq P_L \\ \frac{2P_L - P_M - K_p}{P_L - P_M}, & \text{for } P_L < K_p < (2P_L - P_M) \end{cases} \quad (21)$$

$$\mu_S\left(\frac{1}{T_i}\right) = \begin{cases} 0, & \text{for } \frac{1}{T_i} \leq 0 \text{ or } \frac{1}{T_i} \geq T_M \\ \frac{\frac{1}{T_i}}{T_S}, & \text{for } 0 < \frac{1}{T_i} < T_S \\ \frac{T_M - \frac{1}{T_i}}{T_M - T_S}, & \text{for } T_S < \frac{1}{T_i} \leq T_M \end{cases} \quad (22)$$

$$\mu_M\left(\frac{1}{T_i}\right) = \begin{cases} 0, & \text{for } \frac{1}{T_i} \leq T_S \text{ or } \frac{1}{T_i} \geq T_L \\ \frac{\frac{1}{T_i} - T_S}{T_M - T_S}, & \text{for } T_S < \frac{1}{T_i} \leq T_M \\ \frac{T_L - \frac{1}{T_i}}{T_L - T_M}, & \text{for } T_M < \frac{1}{T_i} < T_L \end{cases} \quad (23)$$

$$\mu_L\left(\frac{1}{T_i}\right) = \begin{cases} 0, & \text{for } \frac{1}{T_i} \leq T_M \text{ or } \frac{1}{T_i} \geq (2T_L - T_M) \\ \frac{\frac{1}{T_i} - T_M}{T_L - T_M}, & \text{for } T_M < \frac{1}{T_i} \leq T_L \\ \frac{2T_L - T_M - \frac{1}{T_i}}{T_L - T_M}, & \text{for } T_L < \frac{1}{T_i} < (2T_L - T_M) \end{cases} \quad (24)$$

Where, $P_L > P_M > P_S > 0$, $T_L > T_M > T_S > 0$,

Table 1. Fuzzy 9-rule base and inference engine.

$\Delta e_{\omega, N}$	$e_{\omega, N}$		
	P	Z	N
P	L, S	M, S	S, L
Z	L, M	M, M	L, M
N	S, L	M, S	L, S

3. Simulations and Discussions

Two PI speed controllers are simulated in the MATLAB environment. Parameters of the motor and the FOC are listed in Table 2. The control parameters of the Fixed PI Speed Controller (FPI) are $K_{p,FPI} = 0.25$ A/rpm, $T_{i,FPI} = 0.02$ s. In the case of the FL-adapted PI controller (FLA), the fuzzy membership boundaries and parameters are empirically chosen: $B_{e1} = B_{e2} = 0.001$, $B_{\Delta e1} = B_{\Delta e2} = 2 \times 10^{-4}$; $P_S = 0.1$, $P_L = 0.4$, $P_M = K_{p,FPI} = 0.25$; $T_S = 25$, $T_L = 75$, $T_M = 1/T_{i,FPI} = 50$. The selection is explained as follows: when $e_{\omega, N}$ and $\Delta e_{\omega, N}$ are zero, these parameters are the same for both controllers. If the distance between the two boundaries ($P_L - P_S$) is too small, then when the load torque changes, the motor

speed will fluctuate greatly. This fluctuation decreases as $(P_L - P_S)$ increases; however, when the deviation increases too high, the system will oscillate. The current limit of the speed controllers is ± 7.92 A. The jump in the utilized load torque L_J is 9 N·m.

Table 2. Parameters of the motor and the FOC.

Parameter	Quantity	Value
Nominal motor torque	$T_{e,n}$	14 N·m
Nominal stator current	$I_{s,n}$	5.6 A
Pole pairs number	n_p	2
Inertial moment	J_m	0.0047 kg·m ²
Rotational damping constant	B_m	0.007 N·m·s
Stator resistance	R_s	3.179 Ω
Rotor resistance	R_r	2.119 Ω
Magnetizing inductance	L_m	192 mH
Stator inductance	L_s	209 mH
Rotor inductance	L_r	209 mH
Proportional gain of I_q controller	$K_{p,Iq}$	5 V/A
Integral time constant of I_q controller	$T_{i,Iq}$	0.05 s
Proportional gain of I_d controller	$K_{p,Id}$	100 V/A
Integral time constant of I_d controller	$T_{i,Id}$	0.01 s
Proportional gain of flux controller	$K_{p,Im}$	100
Integral time constant of flux controller	$T_{i,Im}$	0.01 s

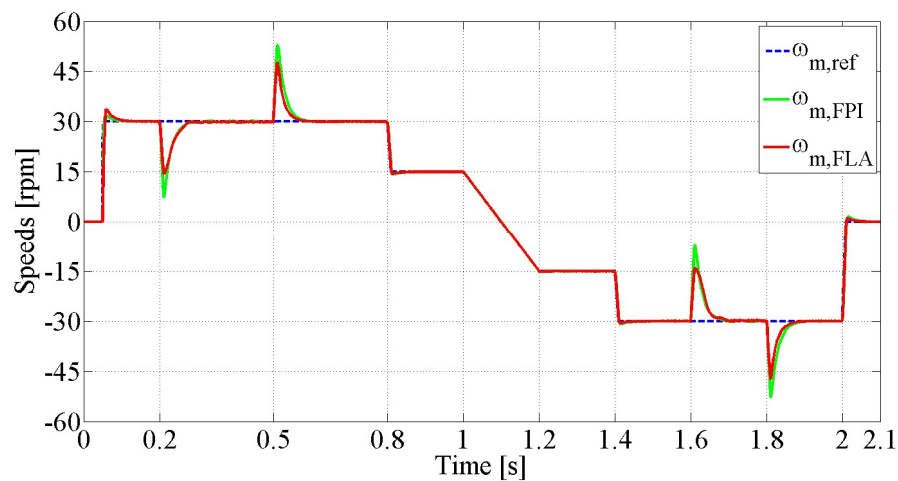


Figure 3. Speed responses.

The diagrams of speeds, torques, currents, reference currents, and magnetizing currents are shown in Figures 3–7. Except at starting, there is a lower overshoot/undershoot of approximately 22.7%–32.5% of the speed response for FLA compared to FPI (see Table 3). The reason for this is that the fuzzy logic brings faster responses of torque or torque-component currents (see Figures 4–6) by updating the proportional gain and integral time constant (see Figures 7–8). The response of the magnetization current remains smooth (see Figure 9). In order to evaluate the entire speed response, integral performance

indices including ITAE, IAE, ITSE, ISE are utilized [24]. The FLA gives a reduction of 18%–38.6% in the indices compared to the FPI (see Table 4). To adapt the proportional gain and integral time constant, artificial intelligence methods such as neural network [2] can be utilized to replace the FL one. For enhancing the control performance, the proposed controller can be combined with reinforcement learning [8], adaptive neuro techniques [18], [21], particle swarm optimization [24].

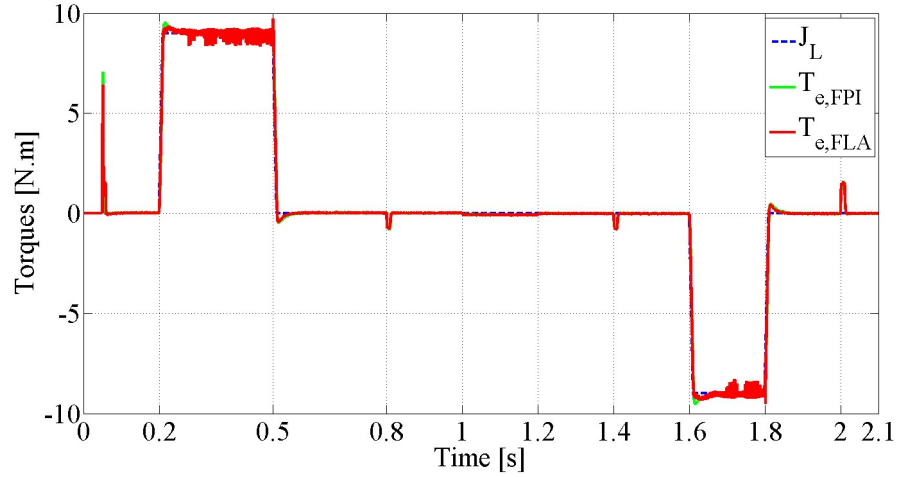


Figure 4. Torque responses.

Table 3. Overshoots/Undershoots [rpm].

Controller	Starting	After loading at 0.2s	After unloading at 0.5s	After Loading at 1.6s	After unloading at 1.8s	Stopping
FPI	1.76	22.65	22.94	22.80	22.81	1.60
FLA	3.72	15.70	17.74	15.89	17.39	1.08

Table 4. Integral performance indices.

Controller	ITAE [$s^2.rpm$]	IAE [$s.rpm$]	ITSE [$s^3.rpm$]	ISE [$s.rpm^2$]
FPI	2.71	2.60	32.34	31.46
FLA	2.13	2.13	19.86	19.97

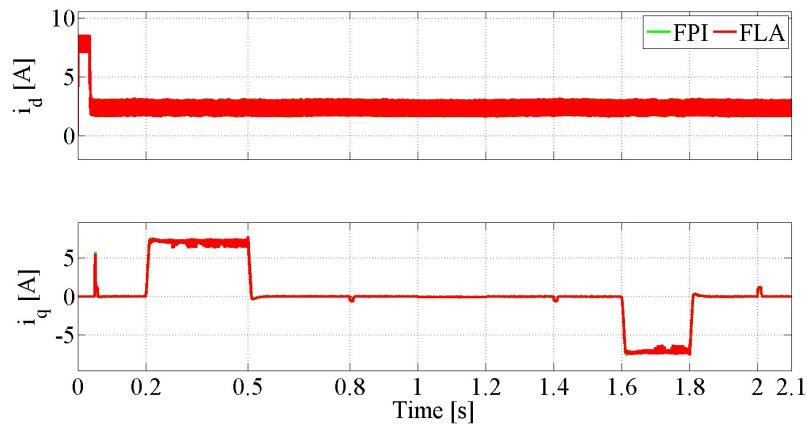


Figure 5. Flux-component and torque-component currents.

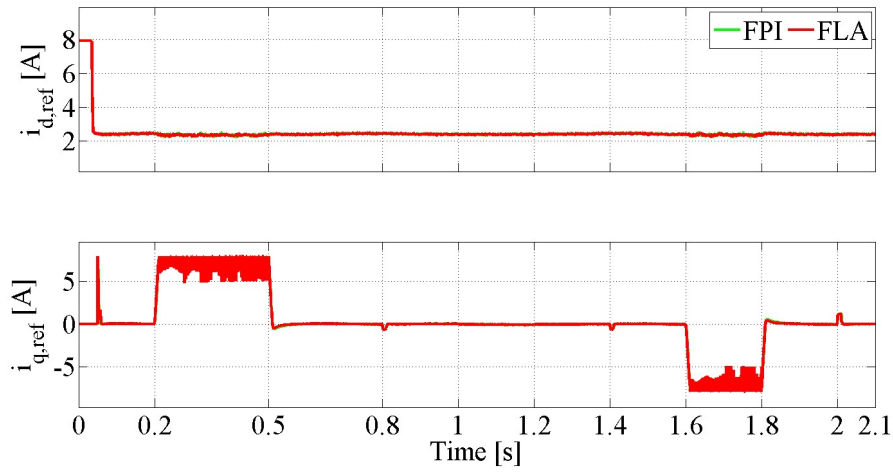


Figure 6. Reference flux-component and torque-component currents.

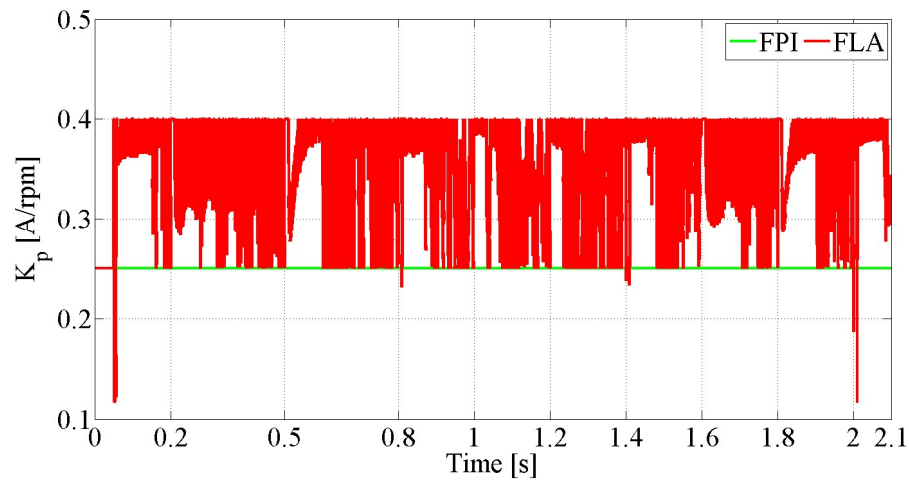


Figure 7. Proportional gains.

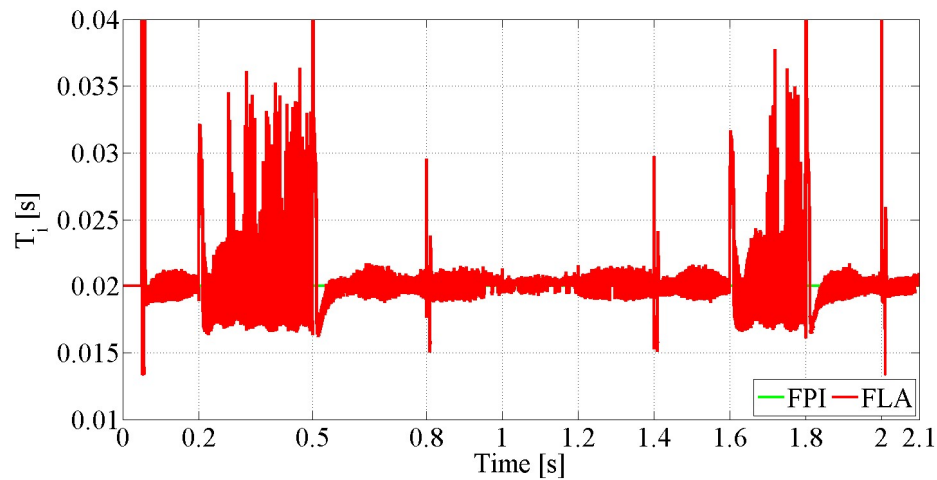


Figure 8. Integral time constants.

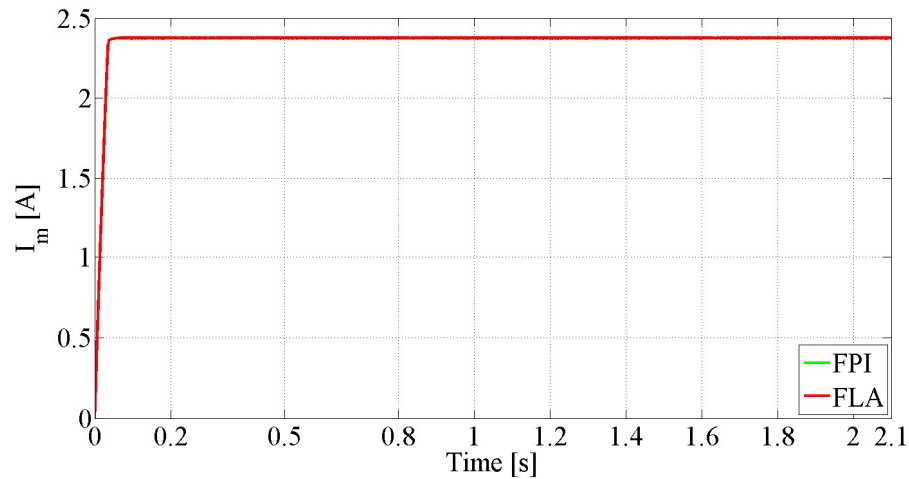


Figure 9. Magnetizing currents.

4. Conclusions

The FOC drive integrating the fixed PI and fuzzy logic-adapted PI speed controllers for the IM was presented and simulated. Based on the simulations and evaluations, the FLA yielded performance indices that were up to 38% lower than those of the FPI. The FOC drive performance for the FLA is supported by the smooth magnetizing current response. The type-2 or type-3 fuzzy logic can be utilized to increase the robustness at lower speed commands under load disturbance and machine parameters uncertainty. In these cases, load and parameter estimation can be incorporated to increase flexibility, transforming traditional fuzzy control into type-2 or type-3 one. Due to changes in the IM's operating conditions, such as load disturbances, parameter uncertainty of the stator resistance and rotor time constant, and stator current noise, stability and robustness analysis according to Lyapunov's theorem, and sensitivity testing should be developed. Finally, hardware implementation should be deployed for verification of the performance of the advanced fuzzy controllers.

Acknowledgments

This work is part of a project funded by Ton Duc Thang University, Vietnam, in 2026.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

- [1] B. K. Bose, "Control and Estimation of Induction Motor Drives," in *Modern Power Electronics and AC Drives*. Upper Saddle River, NJ, USA: Prentice Hall, 2002, ch. 8, sec. 4, pp. 333–387.
- [2] H. H. Vo, P. Brandstetter, C. S. T. Dong, and T. C. Tran, "Speed estimators using stator resistance adaptation for sensorless induction motor drive," *Adv. Electr. Electron. Eng.*, vol. 14, no. 3, pp. 267–273, Sep. 2016.
- [3] W. Qiu, X. Zhao, A. Tyrrell, S. Perinpanayagam, S. Niu, and G. Wen, "Application of artificial intelligence-based techniques in electric motors: A review," *IEEE Trans. Power Electron.*, vol. 39, no. 10, pp. 13543–13568, Oct. 2024.
- [4] H. A. G. Al-Kaf, K. B. Lee, and F. Blaabjerg, "Overview of DSP-based implementation of machine learning methods for power electronics and motor drives," *J. Power Electron.*, vol. 25, no. 2, pp. 271–288, Feb. 2025.
- [5] A. Khemis, T. Boutabba, M. Kaddache, L. Laggoun, and G. Boukhalfa, "A new approach of sensorless control of induction motor using Type-2 fuzzy logic observer," in *Proc. 5th Int. Conf. Electr. Eng. Control Appl.*, 2022, pp. 217–231, doi: 10.1007/978-981-97-0045-5.
- [6] Q. T. Nguyen *et al.*, "Fuzzy Luenberger observer for sensorless control of induction motor drive," in *Proc. AETA 2022—Recent Advances in Electrical Engineering and Related Sciences: Theory and Application*, 2022, doi: 10.1007/978-981-99-8703-0.
- [7] X. Zou, H. Ding, and J. Li, "Sensorless control strategy of permanent magnet synchronous motor based on fuzzy sliding mode controller and fuzzy sliding mode observer," *J. Electr. Eng. Technol.*, vol. 18, no. 3, pp. 2355–2369, May 2023.
- [8] Q. Abdullah *et al.*, "Sensorless speed control of induction motor drives using reinforcement learning and self-tuning simplified fuzzy logic controller," *IEEE Access*, vol. 12, pp. 136485–136501, 2024.

- [9] X. Wang, Q. Wang, Z. Yang, and Y. Li, "Sensorless control of permanent magnet synchronous motorized spindles with parameters adjustment based on fuzzy control algorithm," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 13, no. 4, pp. 5262–5272, Aug. 2025.
- [10] Z. Yang, J. Jia, X. Sun, and T. Xu, "A fuzzy-ELADRC method for a bearingless induction motor," *IEEE Trans. Power Electron.*, vol. 37, no. 10, pp. 11803–11813, Oct. 2022.
- [11] P. Ma, J. Yu, Q. G. Wang, and J. Liu, "Filter- and observer-based finite-time adaptive fuzzy control for induction motor systems considering stochastic disturbance and load variation," *IEEE Trans. Power Electron.*, vol. 38, no. 2, pp. 1599–1609, Feb. 2023.
- [12] L. Tang *et al.*, "Model predictive thrust control for linear induction machine: A fuzzy optimization approach," *IEEE Trans. Ind. Appl.*, vol. 59, no. 2, pp. 2532–2545, Mar./Apr. 2023.
- [13] J. Yu, Q. G. Wang, G. Wang, P. Ma, and J. Liu, "Command-filtered adaptive fuzzy control for induction motors with iron losses and stochastic disturbances via reduced-order observer," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, vol. 70, no. 4, pp. 1525–1529, Apr. 2023.
- [14] H. H. Vo and P. Brandstetter, "Modified fuzzy logic PI speed controller with scheduling boundaries of integral time constant for PMSM drive," *Przegld Elektrotechniczny*, vol. 99, no. 11, pp. 175–179, Nov. 2023.
- [15] R. Datta and Y. H. Joo, "Fuzzy memory sampled-data controller design for PMSG-based WECS with stochastic packet dropouts," *IEEE Trans. Fuzzy Syst.*, vol. 31, no. 12, pp. 4421–4434, Dec. 2023.
- [16] T. L. Le *et al.*, "Intelligent controller design for precise trajectory control in magnetic levitation systems," *J. Tech. Educ. Sci.*, vol. 19, Special Issue 02, pp. 14–23, Apr. 2024.
- [17] D. Perdukova, P. Fedor, M. Sobek, and J. Bacik, "A simple linearization method of nonlinear systems based on fuzzy logic," *IEEE Access*, vol. 12, pp. 165441–165457, 2024.
- [18] D. D. Hoang, T. T. Minh, and V. T. Ha, "Torque control of an in-wheel axial flux permanent magnet synchronous motor using adaptive neuro-fuzzy inference system (ANFIS) for electric vehicle applications," *J. Tech. Educ. Sci.*, vol. 19, no. 4, pp. 43–54, Aug. 2024.
- [19] D. Q. Nguyen, H. H. Vo, and P. Brandstetter, "Modified fuzzy speed controller of induction motor drive using extended Kalman filtering," *MM Sci. J.*, vol. 17, no. 6, pp. 7888–7896, Dec. 2024.
- [20] M. I. Abdelwanis, "Optimizing the performance of six-phase induction motor-powered electric vehicles with fuzzy-PID and DTC," *Neural Comput. Appl.*, vol. 37, no. 16, pp. 9721–9734, Jun. 2025.
- [21] M. R. Velpula, "A novel fuzzy cerebellar adaptive neuro-intelligent controller for high-performance brushless DC motor drives," *Int. J. Dyn. Control*, vol. 13, no. 2, Art. no. 82, Jan. 2025.
- [22] H. T. Nguyen, N. R. Prasad, C. L. Walker, and E. A. Walker, "Fuzzy Logic for Control," in *A First Course in Fuzzy and Neural Control*. Boca Raton, FL, USA: CRC Press, 2003, ch. 3, sec. 9, pp. 120–123.
- [23] P. X. Minh and N. D. Phuoc, *Fuzzy Control Theory*. Hanoi, Vietnam: Science and Technics Publishing House, 2006. (in Vietnamese).
- [24] M. H. Ramadhan, I. Setiawan, and S. Handoko, "Performance evaluation of PSO-optimized PI controller for quadratic boost converter: A comparative study of ITAE, IAE, ITSE, and ISE objective functions," in *Proc. 12th Int. Conf. Inf. Technol., Comput., Electr. Eng. (ICITACEE)*, Semarang, Indonesia, 2025, pp. 1–7, doi: 10.1109/ICITACEE66165.2025.11232570.

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