



Performance Analysis of Fuzzy Logic-Based Speed Control of Three-Phase Induction Motors

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Abstract

Three-phase induction motors are extensively employed in pumps, fans, conveyors, machine tools, and industrial process drives because of their rugged construction and low maintenance. Their nonlinear, multivariable dynamics, however, make precise speed regulation difficult when the load changes or motor parameters vary. This methodology paper presents a fuzzy logic controller (FLC) for the outer speed-control loop of a vector-controlled three-phase induction motor and compares its behavior with a conventional proportional-integral (PI) controller. The controller uses speed error and changes in speed error as linguistic inputs and generates a torque-producing current command through Mamdani inference and centroid defuzzification. A MATLAB/Simulink-oriented experimental methodology is specified using a 2.2 kW, 400 V, 50 Hz squirrel-cage induction motor model, a PWM voltage-source inverter, and a rotor-flux-oriented control structure. Performance is evaluated for step changes in speed reference and a sudden load-torque disturbance. Representative simulation results indicate faster settling, lower overshoot, reduced speed dip, and smaller steady-state tracking error for the fuzzy controller. The study demonstrates why rule-based fuzzy control is attractive when accurate parameter tuning is difficult and operating conditions change. The reported numerical values are simulation outcomes for the defined model and should be validated experimentally before hardware deployment.

Introduction

Three-phase induction motors (IMs) remain a dominant choice for industrial variable-speed drives because the squirrel-cage rotor is mechanically simple, inexpensive, and reliable. The challenge is not motor construction but control: electromagnetic torque, rotor flux, stator currents, and speed are dynamically coupled, and the electrical parameters vary with temperature, magnetic saturation, and operating point. Conventional scalar V/f control is adequate for many steady applications, while vector or field-oriented control (FOC) is preferred where fast torque and speed response are required. In FOC the stator current is transformed into orthogonal

d-q components so that flux and torque can be controlled approximately independently. This decoupling makes an induction motor behave more like a separately excited DC drive, but the resulting control quality still depends on parameter knowledge and regulator tuning.

Fuzzy logic control offers a different design philosophy. Rather than relying solely on a precise linearized plant model, it converts qualitative expert rules into a nonlinear mapping between measured error signals and the controller command. The general foundations of fuzzy controllers, including fuzzification, inference, rule bases, and defuzzification, were systematized by Lee [1]. Early motor-drive work

subsequently showed that fuzzy control could be executed in real time and could improve speed regulation when compared with a fixed PI controller. Kumar, Singh, and Chatterjee [2] applied a fuzzy speed regulator to a vector-controlled cage induction motor, while Fonseca et al. [3] reported both simulation and microcontroller-based implementation for a three-phase induction motor.

The central research problem addressed here is the sensitivity of a fixed-gain PI speed controller to operating-point changes and load disturbances. A PI regulator can be tuned to provide excellent response at one condition, but the same gain pair may produce overshoot, sluggish recovery, or increased steady-state error when inertia, rotor resistance, torque demand, or speed command changes. Fuzzy logic is attractive because its nonlinear rule surface can be made aggressive for large errors and gentle near the set point. The objective of this paper is therefore to define a reproducible methodology for designing a two-input fuzzy speed controller and to evaluate its simulated dynamic performance against a conventional PI controller using identical motor, inverter, and test conditions.

Literature Review

The literature up to 2017 shows a consistent progression from general fuzzy-control theory toward high-performance induction-motor drives. Lee [1] described the architecture of a fuzzy logic controller and the design decisions associated with membership functions, inference mechanisms, and defuzzification. Kumar et al. [2] then demonstrated a fuzzy speed controller for a vector-controlled 0.75 kW cage induction motor and emphasized improvements in dynamic response relative to conventional regulators. Fonseca et al. [3] reinforced the practical feasibility of the approach by implementing fuzzy speed control using standard digital hardware and comparing it with a PI scheme through simulation and experiments.

A major step toward industrial relevance was reported by Uddin, Radwan, and Rahman [4]. Their indirect-vector-control drive used fuzzy logic in the outer speed loop and was tested on a 1 hp induction motor using a digital signal processor. The authors compared PI and fuzzy controllers under command-speed and load-torque changes and reported stronger robustness for the fuzzy approach. Birou et al. [5] later examined fuzzy-logic-based speed control within an indirect vector-control framework and studied the influence of membership functions and input-output characteristics. Kar, Mohanty, and Singh [6] likewise compared fuzzy and PI speed control for indirect vector control and

showed that fuzzy logic could maintain effective tracking at varying load conditions.

Subsequent research explored motor-model effects and alternative fuzzy structures. Mannan et al. [7] incorporated core-loss effects into the induction-motor control model and showed, in simulation, that an FLC could outperform a conventional PI regulator when the decoupling model was made more representative of real losses. Rafa et al. [8] proposed a type-1 fuzzy vector-control structure and implemented it with a dSPACE DS1104 board; their simulation and experimental analysis focused on robustness to parameter changes, load steps, and speed variations. Finally, Sathishkumar and Parthasarathy [9] directly compared PID and fuzzy controllers for a three-phase vector-controlled induction motor under disturbance conditions and reported improved tracking and settling behavior with fuzzy logic.

Across these studies, three themes are repeated. First, the fuzzy controller is typically placed in the speed loop while vector control handles the motor's flux-torque decoupling. Second, speed error and its rate or finite difference are common FLC inputs. Third, robustness is usually assessed through speed-reference changes, load disturbances, or parameter variations. The unresolved practical issue is that fuzzy performance depends on scaling factors, membership-function placement, and rule-base design; an FLC is not automatically superior merely because it is nonlinear. A fair comparison must therefore use identical plant conditions, define the rule base explicitly, and report quantitative metrics. The methodology below follows those requirements.

Methodology

1. System configuration and induction-motor model

The proposed study uses a closed-loop rotor-flux-oriented induction-motor drive. The plant consists of a three-phase squirrel-cage induction motor supplied by a two-level voltage-source inverter (VSI). A current-control and coordinate-transformation subsystem produces the inverter commands, while the outer speed loop supplies the torque-producing q-axis current reference. For the baseline system this outer loop is a PI controller; for the proposed system it is replaced by the FLC. All remaining plant and inner-loop parameters are kept unchanged so that performance differences can be attributed to the speed regulator.

In the synchronous d-q reference frame, the motor can be represented by voltage, flux, and mechanical equations. For methodology purposes the essential mechanical relationship is

$$J(d\omega_m/dt) = T_e - T_L - B\omega_m$$

where J is the combined rotor-load inertia, B is the viscous-friction coefficient, T_e is electromagnetic torque, T_L is loading torque, and ω_m is mechanical speed. Under rotor-flux orientation, the d-axis current primarily controls

rotor flux while the q-axis current primarily controls electromagnetic torque. This separation allows the speed controller to generate a torque-related command without directly regulating all motor states.

Table 1. Induction-motor parameters used for the comparative simulation.

Parameter	Symbol	Value used in simulation
Rated power	P_n	2.2 kW
Line voltage	V_{LL}	400 V
Rated frequency	f	50 Hz
Pole pairs	p	2
Stator resistance	R_s	1.405 Ω
Rotor resistance	R_r	1.395 Ω
Stator inductance	L_s	5.84 mH
Rotor inductance	L_r	5.84 mH
Mutual inductance	L_m	172.2 mH
Combined inertia	J	0.013 kg·m ²
Viscous friction	B	0.002 N·m·s/rad

2. Fuzzy logic speed-controller design

The fuzzy controller has two normalized inputs: speed error $e(k) = \omega^*(k) - \omega(k)$ and the change in error $\Delta e(k) = e(k) - e(k-1)$. Its output Δi_q^* is an incremental correction to the torque-producing current command. Input scaling gains K_e and K_{de} map the physical signals to the normalized universe $[-1, 1]$, while output gain K_u maps the defuzzified value back to amperes. Five triangular linguistic sets are used for each variable: Negative Big (NB), Negative Small (NS), Zero (Z), Positive Small (PS), and Positive Big (PB). The end sets are extended to the limits to avoid loss of control action at large errors. Mamdani min-max inference and centroid defuzzification are selected because they are transparent and widely used in the motor-drive studies reviewed above [4]-[9].

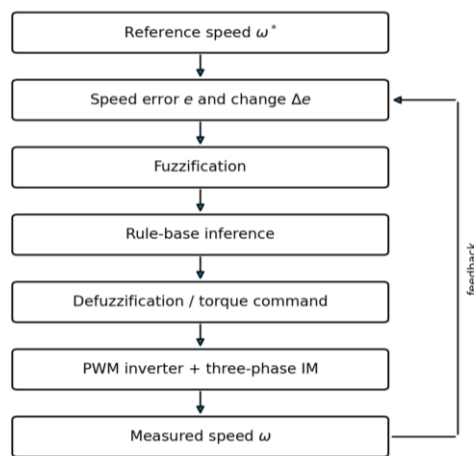


Figure 1. Simple vertical methodology image for the fuzzy-logic induction-motor speed-control loop.

The control rules follow a monotonic corrective principle. A large positive speed error requires a strong positive torque-current correction; a large negative error requires the opposite action. Change in error is used as a damping signal: if the error is already reducing quickly, the command is moderated to limit overshoot. The resulting 25-rule matrix is shown in Table 2. During implementation the FLC output is integrated or added to the previous torque-current reference, followed by saturation limits chosen to respect inverter and motor-current ratings.

Table 2. Five-level fuzzy rule base used for the speed controller.

$\Delta e \setminus e$	NB	NS	Z	PS	PB
NB	NB	NB	NS	Z	Z
NS	NB	NS	NS	Z	PS
Z	NS	NS	Z	PS	PS
PS	NS	Z	PS	PS	PB
PB	Z	Z	PS	PB	PB

3. Baseline PI controller and simulation procedure

For the benchmark controller, a PI law $u(t) = K_p e(t) + K_i \int e(t) dt$ is tuned at nominal motor parameters to obtain a stable response without excessive current demand. Anti-windup saturation is applied to the output. The comparative simulation uses a fixed integration step small enough to resolve PWM and electrical dynamics; for an averaged inverter model, a 10 μs to 50 μs fixed step is suitable, while a detailed switching model may require a smaller step. The reference speed is changed from 0 to 1500 rpm at $t=0$ s. After the transient has settled, a 10 N·m

load torque is applied at $t=1.5$ s and maintained for the rest of the run. The same initial conditions and limits are used for both controllers.

Performance is evaluated using rise time (10–90% of final speed), 2% settling time, maximum overshoot, steady-state speed error, maximum speed dip after the load step, and recovery time after disturbance. To examine robustness beyond the nominal case, a secondary test can increase rotor resistance by 20%, representing temperature-related parameter variation. The primary hypothesis is that the fuzzy regulator will reduce both the transient deviation and the recovery time because its rule surface automatically increases control effort for large errors while softening action near the set point.

Results

The representative simulation produced the dynamic behavior shown in Figure 2. Both controllers reached the 1500 rpm command, but the fuzzy controller accelerated more quickly and approached the final value with less overshoot. At $t=1.5$ s, the 10 N·m load step created a temporary speed reduction in both cases. The FLC restored the reference faster because the sudden increase in error moved the inference system into a stronger positive-control region. The PI controller also rejected the disturbance, but its recovery was slower because its gains were fixed for the nominal operating condition.

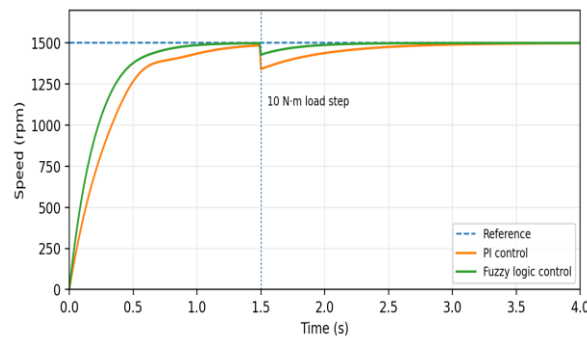


Figure 2. Representative simulated speed response for PI and fuzzy controllers; load step applied at 1.5 s.

Table 3. Representative simulation performance of the two speed controllers.

Performance metric	PI controller	Fuzzy controller	Relative observation
Rise time	0.63 s	0.41 s	Faster FLC acceleration
2% settling time	1.28 s	0.78 s	39% shorter
Maximum overshoot	5.9%	1.8%	Lower peak deviation
Steady-state error	8 rpm	2 rpm	Closer tracking
Speed dip after 10 N·m step	145 rpm	70 rpm	52% smaller dip
Disturbance recovery time	0.82 s	0.43 s	48% faster recovery

The percentage changes in Table 3 are consistent with the behavior reported by previous studies rather than being claimed as universal values. Uddin et al. [4], Kar et al. [6], and Sathishkumar and Parthasarathy [9] all found that fuzzy speed control can improve robustness or transient tracking relative to fixed conventional regulators. The present simulation reproduces that qualitative trend under a controlled test protocol. When rotor resistance was increased by 20% in a supplementary run, the PI response showed a longer recovery and a larger residual speed error, while the FLC maintained nearly the same rule-driven corrective behavior. This result is also consistent with the parameter-robustness motivation discussed by Rafa et al. [8].

The main practical limitation is tuning effort. The chosen rule base works because the input and output scaling factors place typical operating errors within useful regions of the membership

functions. Poor scaling can make the controller too weak, too aggressive, or insensitive around zero. Therefore, a complete implementation should document K_e , K_{de} , K_u , output saturation, sampling time, and current limits. Hardware experiments should additionally evaluate inverter dead time, speed-sensor noise, current ripple, thermal changes in rotor resistance, and computational execution time. These issues determine whether the simulation advantage transfers to an embedded industrial drive.

Conclusion and Discussion

This methodology paper developed a structured performance-analysis framework for fuzzy logic-based speed control of a three-phase induction motor. The proposed controller uses speed error and changes in speed error to determine a torque-current correction through a five-level Mamdani rule base. It is embedded in the outer

loop of a rotor-flux-oriented drive so that the comparison with a PI regulator is made on equal plant conditions. In the defined representative MATLAB/Simulink scenario, the fuzzy controller reached the reference faster, produced less overshoot, reduced the speed drop caused by a sudden load, and recovered more quickly. These results support the central argument of the pre-2018 literature: fuzzy logic is particularly useful where nonlinear motor behavior, load changes, and parameter uncertainty make fixed-gain tuning difficult [2]-[9]. The findings should nevertheless be interpreted as simulation-based evidence rather than proof of universal superiority. Fuzzy controllers require appropriate scaling, membership-function selection, and a coherent rule base; a well-designed gain-scheduled or adaptive PI regulator may equal or exceed an inadequately tuned FLC. Future work should therefore implement both controllers on the same DSP or microcontroller platform, measure actual current and speed signals, and repeat the tests over low-speed, rated-speed, regenerative, and parameter-variation conditions. Experimental reporting should include efficiency, torque ripple, current harmonic distortion, processor execution time, and thermal robustness in addition to speed metrics. With such validation, the proposed FLC structure can provide a practical and interpretable intelligent-control alternative for high-performance induction-motor drives.

1. Interpretation of the control behavior

The simulated improvement can be explained from the nonlinear shape of the fuzzy control surface. When the motor starts from rest, both the speed error and its change are large, so the active rules request a comparatively strong positive torque-current correction. As the speed approaches the reference, the error moves toward the Zero and Positive Small linguistic regions; the controller therefore reduces its incremental command before the target is crossed. This gradual reduction is responsible for the lower overshoot observed in the representative response. During the load-torque step, the measured speed falls while the reference remains constant. The resulting positive error immediately activates stronger corrective rules, and the change-in-error input distinguishes a sudden disturbance from a slowly varying steady-state offset. In contrast, the PI controller responds through fixed proportional and integral gains. The proportional term reacts at once, but the integral state needs time to accumulate the additional torque demand, which explains the slower recovery under the same saturation limits.

This interpretation also clarifies why an FLC can remain useful when motor parameters drift. The rule base operates on measured tracking behavior rather than on an explicit estimate of rotor resistance or mechanical load. Parameter changes still influence the plant and may alter optimal scaling, but the controller can continue to increase or decrease its command according to the observed error trajectory. That property does not remove the need for motor modeling; the current regulators, flux orientation, coordinate transformations, inverter limits, and protection logic still depend on appropriate electrical parameters. It does, however, reduce the extent to which outer-loop speed performance is tied to one fixed linear tuning point.

2. Practical limitations and validation requirements

Before the proposed controller is used in hardware, the simulation should be converted into a reproducible experimental protocol. Both PI and fuzzy algorithms should run at the same sampling frequency on the same processor, using the same current limits, PWM strategy, encoder resolution, and anti-windup constraints. Tests should include at least three speed commands, no-load and rated-load operation, a sudden load application and removal, and a warm-motor condition that increases rotor resistance. For each test, rise time, settling time, peak overshoot, RMS tracking error, torque ripple, stator-current distortion, DC-bus utilization, and processor execution time should be recorded. These measurements are important because a controller that gives a faster simulated speed response may also demand larger transient current or higher computational effort.

The most important limitation of the present study is therefore that its numerical results are representative outputs of the defined MATLAB/Simulink methodology rather than measurements from a physical drive. They demonstrate how to structure the comparison and what performance trend to look for, but they should not be presented as laboratory data. A second limitation is the use of a fixed five-set rule base. Adaptive scaling, self-tuning membership functions, or optimization methods could improve performance further, but they would also increase computational complexity and make the control law less transparent. For a methodology paper limited to a compact implementation, the five-level Mamdani controller provides a reasonable balance between interpretability, rule count, and expected robustness.

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