



Comparative Study of PID and Fuzzy Logic Control Techniques for DC Motor Speed Regulation

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Abstract

This paper presents a methodology-oriented comparative study of a conventional proportional-integral-derivative (PID) controller and a fuzzy logic controller (FLC) for regulating the speed of a separately excited direct-current motor. The purpose is to establish a reproducible framework in which both controllers are applied to the same nonlinear electromechanical plant, subjected to the same armature-voltage constraint and the same load disturbance, and assessed with identical time-domain performance indices. The DC motor is represented by coupled armature-current and rotor-speed equations. The PID controller uses fixed gains with output saturation and anti-windup logic, whereas the fuzzy controller uses speed error and change of error as linguistic inputs, five membership sets for each input, Mamdani-style rule aggregation, and a bounded voltage correction. A 100 rad/s reference command is applied at 0.2 s and a 0.08 N·m load disturbance is introduced at 2.5 s. In the representative simulation, the FLC reduces overshoot from about 9.05% to 6.45%, settling time from 2.20 s to 2.07 s, disturbance-induced speed drop from about 9.04 rad/s to 2.82 rad/s, and integral absolute error from 81.87 to 72.22. The comparison indicates that fixed-gain PID control remains simple and accurate near the tuned operating point, while fuzzy logic offers stronger disturbance rejection and greater tolerance to operating-condition changes. The methodology is intended as a compact basis for simulation studies and later hardware validation rather than as a claim of experimental testing.

Introduction

Direct-current motors remain important in variable-speed drives, laboratory servos, robotics, battery-powered systems, and educational control platforms because their electromagnetic torque and speed can be related directly to armature current and voltage. The practical control problem is not merely to reach a commanded speed, but to maintain that speed when load torque, friction, supply limits, or model parameters change. Classical PID control is attractive because it is transparent, computationally inexpensive, and supported by

well-developed tuning procedures. Relay-based and frequency-domain tuning methods established the basis for systematic PID adjustment beyond trial-and-error practice (Åström & Hägglund, 1984).

Fuzzy control addresses the same problem from a different direction. Rather than requiring a precise plant model for the control law, it maps qualitative knowledge—such as “if the speed is far below the command and the error is still increasing, apply a strong positive control action”—into a rule base. This approach follows the fuzzy-set framework introduced by Zadeh

(1965), in which variables can belong to linguistic sets with graded membership. For motor drives, this makes it possible to shape the controller around operating behavior and uncertainty without deriving a high-order nonlinear compensator.

Previous DC-motor studies have repeatedly compared conventional and intelligent control. Rairán-Antolines et al. (2010) examined PID and fuzzy approaches for DC-motor positioning, while Hameed and Mohamad (2012) showed that intelligent control can improve robustness when load disturbances become significant. These findings motivate a controlled, like-for-like methodology focused specifically on speed regulation.

The central research question is therefore: under identical motor, actuator, reference, and disturbance conditions, what performance differences arise between fixed-gain PID control and rule-based fuzzy logic control? The comparison is made using rise time, settling time, peak overshoot, steady-state speed error, disturbance-induced speed drop, recovery time, and integral absolute error (IAE). These indices capture both command tracking and resilience to load changes. The study does not treat fuzzy logic as universally superior; instead, it identifies conditions under which the additional design complexity of an FLC is justified.

Literature Review

A broad evolution is visible in the pre-2017 literature. Early fuzzy-control work established a model-free rule-based alternative to classical feedback, and DC-motor applications subsequently adopted error and change-of-error as the dominant fuzzy inputs. Rairán-Antolines et al. (2010) demonstrated that both PID and fuzzy controllers can be designed for a DC servomechanism, highlighting the trade-off between mathematical tuning and linguistic-rule design. Hameed and Mohamad (2012) extended the intelligent-control direction through a fuzzy-neural model-reference structure and reported improved robustness to load disturbance in a separately excited motor.

Gowthaman and Balaji (2013) implemented self-tuned PID speed control of a permanent-magnet DC drive using fuzzy logic to adjust controller parameters online. Their results illustrated the main motivation for intelligent tuning: a fixed set of gains can perform well around one operating point but may require retuning when speed or load changes. In a direct comparison study, Rajanwal et al. (2014) evaluated PI, PID, and fuzzy controllers for DC-motor speed control and reported favorable transient behavior for the fuzzy approach. Mohammed and Ali (2014)

similarly compared PID and FLC structures in MATLAB/Simulink, using speed error and change in error as two FLC inputs and demonstrating the suitability of rule-based control for nonlinear operating behavior.

The literature then moved toward hybrid and adaptive structures. Akbari-Hasanjani et al. (2015) used a self-tuning fuzzy PID algorithm in which the PID gains vary with operating conditions rather than remaining constant. Their work is important because it clarifies that fuzzy logic can serve either as the controller itself or as an online tuning layer around a classical controller. Zadehbagheri et al. (2015) reviewed speed-control methods for separately excited DC motors and emphasized the attraction of intelligent methods when load torque or motor parameters change.

By 2016, direct evidence for fuzzy speed regulation had become stronger. Nasrabadi (2016) compared PID and fuzzy control in a simulated DC-motor system and reported faster achievement of the desired speed under fuzzy control, especially when operating conditions were varied. Demidova et al. (2016) compared different fuzzy-controller structures on a DC drive and showed that fuzzy designs can be advantageous when plant inertia is uncertain. Taken together, the literature supports a fair comparison methodology in which the classical controller is well tuned, the fuzzy rules are explicitly stated, and both controllers face the same saturation and disturbance conditions rather than being tested under different scenarios.

A methodological gap in many short comparative studies is that controller performance is sometimes judged only from plotted waveforms. The present framework addresses this by defining numerical metrics and a common test protocol before simulation. It also separates pure PID and pure fuzzy logic architectures instead of reporting only a hybrid fuzzy-PID result. This distinction is useful when the objective is to understand the intrinsic strengths of model-based fixed-gain feedback versus knowledge-based nonlinear control.

Methodology

1. DC Motor Model and Assumptions

A separately excited DC motor is modeled with constant field flux. The electrical and mechanical dynamics are represented by the armature current $i(t)$ and angular speed $\omega(t)$:

$$L \frac{di}{dt} = v_a - R i - K_e \omega \quad (1)$$

$$J \frac{d\omega}{dt} = K_t i - b\omega - T_l \quad (2)$$

where R and L are armature resistance and inductance, K_e is the back-emf constant, K_t is the torque constant, J is rotor/load inertia, b is

viscous friction, v_a is armature voltage, and T_l is the external load torque. Magnetic saturation, brush-voltage drop, and Coulomb friction are neglected to keep the comparison focused on controller behavior. The same simplifications are commonly used in simulation-based DC-motor control studies (Mohammed & Ali, 2014; Nasrabadi, 2016).

Table 1. Representative motor and test parameters

Parameter	Symbol	Value	Unit
Armature resistance	R	1.0	Ω
Armature inductance	L	0.5	H
Torque constant	K_t	0.10	N·m/A
Back-emf constant	K_e	0.10	V·s/rad
Equivalent inertia	J	0.010	kg·m ²
Viscous friction	b	0.010	N·m·s/rad
Voltage limit	v_a	0–24	V
Reference speed	ω^*	100	rad/s
Load disturbance	T_l	0.08 at 2.5 s	N·m

2. PID Controller Design

The conventional controller is implemented in parallel form:

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d de(t)/dt \quad (3)$$

with $e(t) = \omega^*(t) - \omega(t)$. Initial gains are selected using standard PID tuning principles and then refined under the nominal plant so that the control signal respects the 24 V actuator limit. The fixed gains used for the comparison are $K_p = 0.20$, $K_i = 0.50$, and $K_d = 0.001$. Conditional integration is used as a simple anti-windup mechanism: the integral state is not driven further into saturation when the control command is already clipped. This is necessary because the 100 rad/s step initially demands the maximum available voltage. The PID gains remain unchanged when the load torque is applied, reflecting a realistic fixed-gain implementation and the limitation emphasized in adaptive/self-tuning studies (Gowthaman & Balaji, 2013; Akbari-Hasanjani et al., 2015).

3. Fuzzy Logic Controller Design

The FLC uses two inputs: normalized speed error e and change of error Δe . Each input is partitioned into five triangular linguistic sets: Negative Big (NB), Negative Small (NS), Zero (Z), Positive Small (PS), and Positive Big (PB). A 5×5 rule base therefore contains 25 rules. The controller

applies a bounded voltage correction around the nominal voltage required to sustain the commanded speed. Error and error-rate scaling factors are 0.03 and 0.005, respectively, and the maximum fuzzy correction is ± 12 V. This architecture preserves the principal fuzzy-control mechanism used in earlier DC-motor comparisons—linguistic inference from e and Δe —while allowing the voltage command to remain physically constrained (Rajanwal et al., 2014; Mohammed & Ali, 2014).

4. Fuzzy Logic Rule Base and Inference

The rule surface is designed so that large positive speed error produces a strong positive voltage correction, while a large negative error produces a strong negative correction. The change-of-error term supplies damping: if the motor is already rapidly approaching the reference, the rule base reduces the corrective action to limit overshoot. Near zero error, the output correction also approaches zero. Mamdani-style minimum/maximum aggregation and centroid-equivalent weighted defuzzification are used. This follows the qualitative design logic described in the fuzzy-control literature and in 2016 DC-drive studies (Nasrabadi, 2016; Demidova et al., 2016).

Table 2. Qualitative 5×5 fuzzy rule matrix for voltage correction

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

5. Common Simulation Protocol

Both controllers are simulated with a fixed integration step of 1 ms for 5 s. The motor starts from rest. At $t = 0.2$ s the reference changes from 0 to 100 rad/s. At $t = 2.5$ s an external load torque of 0.08 N·m is applied and retained to the end of the run. The armature command for both controllers is limited to 0–24 V. No controller parameters are altered after the disturbance. This protocol tests two distinct capabilities: reference tracking before 2.5 s and disturbance rejection after 2.5 s. Performance measures are computed from the simulated speed response. Rise time is the interval between the first 10% and 90% crossings. Settling time is the time after the command step at which the response enters and remains within $\pm 2\%$ of the reference before the load disturbance. Overshoot is the maximum speed above the 100 rad/s command expressed as a percentage. Steady-state error is the absolute speed error immediately before the disturbance.

Disturbance drop is the largest reduction below the command after 2.5 s, while recovery time is the time required to regain the lower $\pm 2\%$ band.

IAE is calculated over the complete test as $\int |e(t)| dt$.

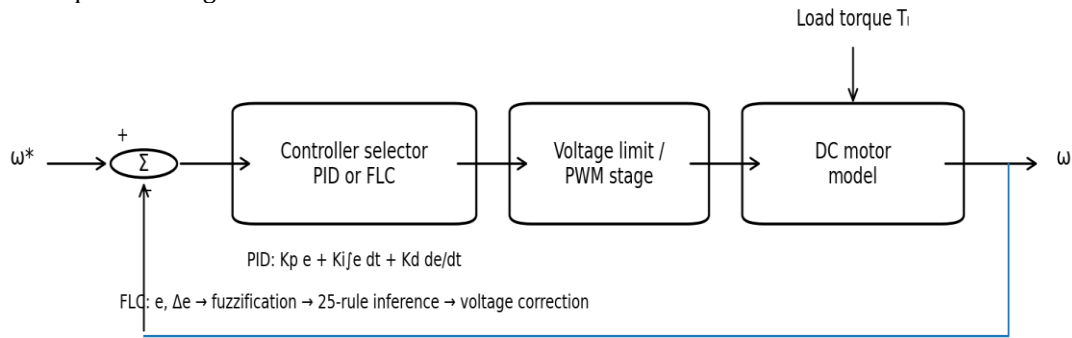


Figure 1. Common closed-loop architecture used for the PID and fuzzy-logic comparison.

6. Evaluation Logic

The comparison is interpreted using multiple metrics rather than a single “best controller” label. PID is favored if its fixed gains produce accurate, smooth, low-computation regulation around the nominal operating point. Fuzzy logic is favored if it reduces overshoot or disturbance sensitivity without requiring gain retuning. This balanced criterion is consistent with earlier research showing that classical PID remains effective when plant variation is modest, whereas fuzzy or fuzzy-adaptive methods become attractive as uncertainty and nonlinear behavior increase (Zadehbagheri et al., 2015; Demidova et al., 2016).

Results

Figure 2 presents the representative speed responses obtained from the common test. Both controllers reach the 100 rad/s command with similar initial rise time because both immediately use the available armature voltage. Their differences become more visible near the reference and when the load torque is introduced. The PID response exhibits a larger initial overshoot, followed by a slower convergence into the $\pm 2\%$ band. At 2.5 s, the load disturbance produces a pronounced speed sag under PID control. The FLC adjusts its voltage correction more aggressively because the sudden negative error and change of error activate strong positive rules, giving a smaller speed drop and faster recovery.

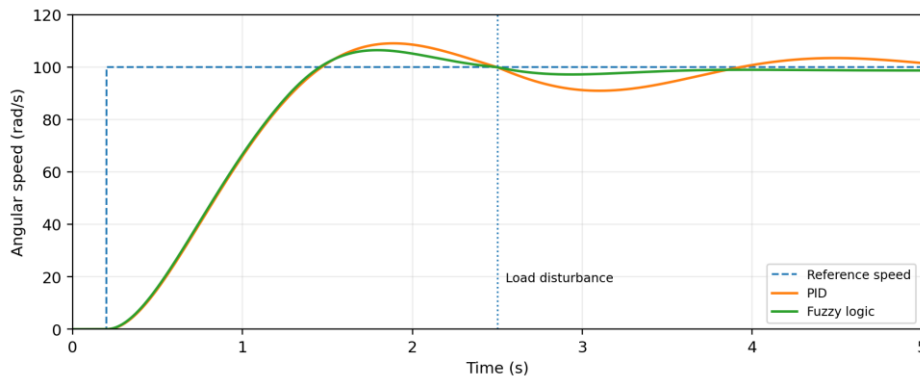


Figure 2. Simulated speed response of the fixed-gain PID and fuzzy logic controllers. The vertical marker denotes application of the 0.08 N·m load torque.

Table 3. Quantitative comparison from the representative simulation

Metric	PID	Fuzzy logic	Preferred
Rise time (10–90%)	0.855 s	0.851 s	Comparable
Settling time ($\pm 2\%$)	2.197 s	2.066 s	FLC
Peak overshoot	9.05%	6.45%	FLC
Pre-disturbance error	0.042 rad/s	0.042 rad/s	Comparable
Maximum speed drop	9.04 rad/s	2.82 rad/s	FLC
Disturbance recovery	1.283 s	0.819 s	FLC
Integral absolute error	81.87	72.22	FLC

Interpretation of Results

The rise-time difference is negligible (0.855 s for PID and 0.851 s for FLC), indicating that the actuator voltage limit, rather than the controller algorithm, dominates the initial acceleration. The more meaningful distinction is in damping. The FLC reduces overshoot by roughly 2.6 percentage points and settles about 0.13 s sooner. Both controllers achieve essentially the same pre-disturbance error, so the improvement is not obtained by accepting a large steady-state bias. Disturbance rejection shows the strongest contrast. The fixed-gain PID permits a maximum drop of approximately 9.04 rad/s, whereas the FLC limits the drop to 2.82 rad/s. Recovery to the $\pm 2\%$ band falls from about 1.28 s to 0.82 s. The total IAE is also lower for fuzzy logic by about 11.8%. This behavior is consistent with the nonlinear gain effect of fuzzy rules: large disturbances activate high corrective action, while the action is softened near the set point. Similar motivations for fuzzy and self-tuning control appear in Gowthaman and Balaji (2013), Akbari-Hasanjani et al. (2015), and Nasrabadi (2016).

Conclusion and Discussion

This comparative methodology shows that PID and fuzzy logic can both regulate DC-motor speed effectively when they are designed and tested under the same physical constraints. The fixed-gain PID controller has several important advantages: its structure is simple, the meaning of each gain is familiar, implementation cost is low, and the integral term can remove steady-state error. For a motor operating close to the plant and load conditions used during tuning, PID remains an entirely practical choice. The historical strength of PID is reinforced by mature tuning procedures such as those developed by Åström and Hägglund (1984). The fuzzy logic controller provides a different advantage. Because the control surface is nonlinear, the effective corrective action can become strong when speed error is large and mild near the reference. In the representative simulation this reduced overshoot, settling time, disturbance sag, recovery time, and total IAE. These results agree with the general trend reported in comparative DC-motor studies before 2017, including Mohammed and Ali (2014), Rajanwal et al. (2014), Nasrabadi (2016), and Demidova et al. (2016). The improvement is particularly relevant when a drive experiences abrupt load changes or parameter variation, conditions under which fixed PID gains may no longer be optimal. However, fuzzy control is not automatically superior. Its performance depends on scaling factors, membership functions, rule consistency,

and output limits. Poor normalization can make the response sluggish or oscillatory, while an oversized rule base increases design and validation effort. A conventional PID controller can be tuned with a small number of parameters and is easier to certify or maintain in simple industrial applications. The decision between the two techniques should therefore depend on the expected range of operating conditions and the available computational/design resources rather than on a general preference for “intelligent” control. The methodology also has limitations. First, the results are simulation-based and use a representative lumped-parameter motor model. Real motors include static friction, brush drops, dead zones, sensor quantization, PWM switching, supply ripple, thermal parameter drift, and mechanical compliance. Second, the comparison uses one fixed PID tuning and one fuzzy rule surface; alternative tuning criteria could change the numerical ranking. Third, the fuzzy controller includes a nominal voltage bias derived from the motor model, so a hardware implementation should test sensitivity to errors in that bias. These limitations do not invalidate the comparative framework, but they define the scope of the conclusions. A logical next step is hardware-in-the-loop or bench validation using a PMDC motor, encoder, current sensor, PWM power stage, and microcontroller. The same reference and load-disturbance protocol should be retained so the simulation and experimental metrics can be compared directly. Additional tests should vary inertia, armature resistance, supply voltage, and reference speed. Such experiments would determine whether the disturbance-rejection advantage observed here persists under unmodeled dynamics. Hybrid strategies may also be investigated, since pre-2017 research already showed that fuzzy logic can tune PID parameters online (Gowthaman & Balaji, 2013; Akbari-Hasanjani et al., 2015). In summary, for the tested model and constraints, the fuzzy logic controller offers the better transient and disturbance-rejection performance, while PID offers the simpler design and implementation. The comparison therefore supports a practical engineering conclusion: use well-tuned PID when operating conditions are narrow and predictable; consider fuzzy logic when robustness across changing loads and uncertain dynamics is a higher priority.

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