International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Adaptive Fuzzy-PID Based Speed Control and Feedback Mechanism for BLDC Motors.

Veena Vanamane
Dept. of electrical and electronics engineering
MVJ college of Engineering
Bengaluru, India

Yashawini U
Dept. of electrical and electronics engineering
MVJ college of Engineering
Bengaluru, India

Thanushree A
Dept. of electrical and electronics engineering
MVJ college of Engineering
Bengaluru, India

Hemanth R
Dept. of electrical and electronics engineering
MVJ college of Engineering
Bengaluru, India

Kishore S
Dept. of electrical and electronics engineering
MVJ college of Engineering
Bengaluru, India

Shivaraje Gowda R
Dept. of electrical and electronics engineering
MVJ college of Engineering
Bengaluru, India

***Abstract*— This paper presents an adaptive Fuzzy-PID based speed control and feedback mechanism for Brushless DC (BLDC) motors. BLDC motors are inherently nonlinear, multi-variable, and time-varying systems, which makes fixed-parameter PID control insufficient for achieving precise, stable performance across varying load conditions. To overcome these limitations, a Fuzzy-PID controller is designed where proportional (Kp), integral (Ki), and derivative (Kd) gains are dynamically tuned online using fuzzy inference rules derived from speed deviation (e) and its rate of change (ec). A Genetic Algorithm (GA) further optimizes the initial PID parameters as well as the fuzzy membership functions and rule base, reducing manual tuning effort and improving global search efficiency. The proposed GA-optimized Fuzzy-PID strategy is validated through MATLAB/Simulink simulations against traditional PID and standard Fuzzy-PID methods. Results demonstrate significantly reduced overshoot, faster settling time, smaller steady-state error, and superior disturbance rejection, establishing the proposed approach as a robust solution for BLDC motor speed control applications.**

***Keywords*— Brushless DC Motor (BLDCM); Fuzzy-PID Control; Genetic Algorithm Optimization; Speed Control; Adaptive Control; Membership Function.**.

1. INTRODUCTION

Brushless DC (BLDC) motors are increasingly favored in automotive, industrial automation, aerospace, and consumer electronics applications due to their high reliability, high power density, minimal maintenance, and efficient operation. Unlike conventional brushed DC motors, BLDCMs replace mechanical commutation with electronic switching, eliminating brush wear and reducing electromagnetic interference [1] [2] [3]. Despite these advantages, BLDC motors present complex control challenges. Their dynamic behavior is inherently nonlinear, multivariable, and time-varying, with parameters that shift significantly under varying load, temperature, and supply voltage conditions. Achieving tight speed regulation — with minimal overshoot, fast transient response, and robust disturbance rejection — requires controllers that can adapt to this complexity [4].

The classical Proportional-Integral-Derivative (PID) controller remains the dominant control strategy in industrial systems due to its straightforward structure, well-understood tuning procedures, and reliable steady-state performance. However, conventional PID controllers operate with fixed gain parameters and are tuned for a linearized operating point. When applied to the inherently nonlinear BLDC motor, fixed-gain PID performance degrades significantly with load changes, parameter variations, or speed setpoint steps, often resulting in

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

excessive overshoot, oscillations, or sluggish transient response [5] [6] [7].

Fuzzy logic control offers a model-free alternative, encoding expert knowledge as IF-THEN linguistic rules to handle nonlinearity and uncertainty. When combined with PID control — forming the Fuzzy-PID controller — the proportional, integral, and derivative gains can be dynamically adjusted online based on the real-time error state, achieving adaptive behavior without requiring a precise mathematical plant model. [8] [9] Nevertheless, conventional Fuzzy-PID controllers retain two key limitations: (1) the initial PID values are often set manually with limited optimality, and (2) the membership functions and fuzzy rule base are crafted from subjective expert knowledge that may not universally generalize

To overcome these limitations, this paper proposes a Genetic Algorithm (GA)-optimized Fuzzy-PID speed controller for BLDC motors. The GA performs a two-stage global optimization: first determining optimal initial PID gain values, and subsequently refining the fuzzy membership function parameters and the rule base encoding. This systematic optimization replaces ad hoc manual tuning with an objective, search-based approach guided by the ITAE (Integral of Time-weighted Absolute Error) performance criterion.

The paper is organized as follows. Section II presents the mathematical model of the BLDC motor. Section III describes the GA optimization of the Fuzzy-PID controller in detail. Section IV presents the simulation setup, comparative results, and analysis. Section V concludes the paper with observations and directions for future work.

I. MATHEMATICAL MODEL OF BRUSHLESS DC MOTOR

The BLDC motor is modeled using a three-phase Y-connected stator winding configuration with a trapezoidal back-EMF profile. The following standard simplifying assumptions are adopted: (1) three-phase windings are perfectly symmetric; (2) the air-gap magnetic field is square-wave; (3) stator current and rotor field distributions are symmetric; (4) cogging, commutation transients, and armature reaction effects are neglected; and (5) the magnetic circuit is linear (unsaturated), with eddy current and hysteresis losses excluded.

A. Voltage Equation

Under the symmetry conditions ($R_a = R_b = R_c = R$; $L_a = L_b = L_c = L$; $L_{ab} = L_{ac} = L_{ba} = L_{bc} = L_{ca} = L_{cb} = M$; $i_a + i_b + i_c = 0$),

the three-phase stator voltage equation reduces to:

[equation]

where Ua, Ub, Uc are phase voltages; ea, eb, ec are back-EMFs; ia, ib, ic are phase currents; R is the stator resistance; L is the self-inductance; and M is the mutual inductance between phases.

B. Electromagnetic Torque Equation

The electromagnetic torque Te is derived from the instantaneous power exchange between the back-EMF and phase currents as:

C. Mechanical Equation of Motion

The rotor dynamics are governed by Newton's second law for rotational systems:

$$J \cdot (d\omega/dt) = Te - TL - B \cdot \omega \ldots (3)$$

where J is the moment of inertia (kg·m²), TL is the load torque (N·m), and B is the viscous friction coefficient (N·m·s/rad). This coupled electromechanical model forms the basis of the simulation platform used in Section IV.

II. ALGORITHM GENERALIZATION OF FUZZY PID

The proposed control architecture employs a two-input, three-output Fuzzy-PID structure. The inputs are the speed deviation $e = nref - n$ and the error change rate $ec = de/dt$. The outputs are real-time gain increments ΔKp, ΔKi, and ΔKd, which are added to baseline PID values to yield the final control gains. The Genetic Algorithm is applied in two sequential rounds: (1) optimization of the initial PID gain set {Kp0, Ki0, Kd0}, and (2) optimization of the fuzzy membership function parameters and the rule base.

A. Stage 1 — Genetic Optimization of Initial PID Parameters

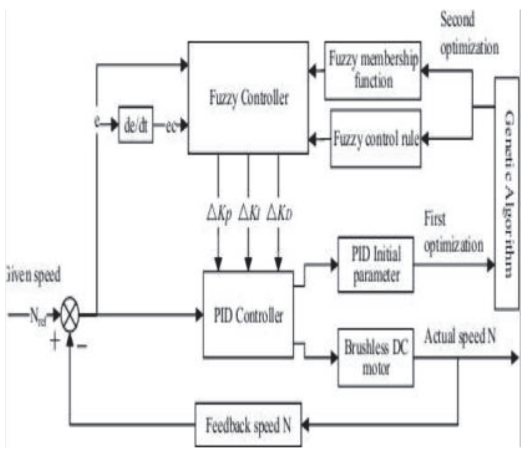

Fig 1.genetic optimization parametres

The initial PID gains significantly influence the operating

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

range of the fuzzy adaptation mechanism. A genetic population of N = 100 individuals is evolved over 50 generations, with search ranges: $K_p \in [0, 100]$, $K_i \in [0, 50]$, $K_d \in [0, 10]$. The ITAE performance index is adopted as the fitness criterion:

$$J(ITAE) = \int_0^t t \cdot |e(t)|\, dt \quad \ldots (4)$$

ITAE penalizes persistent errors more heavily than early transient errors, effectively balancing fast response with low steady-state error. Minimizing J yields optimal initial parameters. Convergence was observed by the 19th generation, yielding Kp = 98.2, Ki = 29.29, and Kd = 0.065.

B. Stage 2 — Genetic Optimization of Membership Functions and Fuzzy Rules

Each of the five fuzzy variables (e, ec, ΔKp, ΔKi,ΔKd) is represented by seven triangular membership functions covering seven linguistic labels: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZO), Positive Small (PS), Positive Medium (PM), and Positive Big (PB). For each variable, the five inner intersection points {x1, x2, x3, x4, x5} of adjacent triangular functions are encoded as optimization parameters, yielding 25 real-valued genes for membership function optimization.

Fuzzy rules for ΔKp, ΔKi, and ΔKd are each encoded as 7×7 = 49 linguistic values (integers 1–7), producing 147 rule genes. The combined chromosome length is 3 × 49 + 25 = 172 genes per individual. Decimal encoding is used for rule genes; real-number encoding is used for membership function genes.

The selection operator combines fitness-proportionate roulette wheel selection with elite preservation to balance population diversity against convergence. Adaptive crossover and mutation rates are initialized at 0.70 and 0.01, respectively, and decrease by 0.01 and 0.00045 per generation, preventing premature convergence while ensuring fine-grained exploitation in later iterations.

C. Fuzzy Rule Formulation Principles

The fuzzy inference rules governing the three gain adjustments are formulated based on well-established control heuristics:

(1) Large error |e|: The system is in the start-up / transient phase. Kp is set high for fast tracking. Ki is set to zero or very low to prevent integral windup. Kd is set small to avoid derivative kick.

(2) Medium |e| and |ec|: The system is in the rising phase. All three gains take moderate values balancing speed and overshoot prevention.

(3) Small |e|: The system is near steady state. Kp and Ki are increased for accuracy. Kd is reduced to prevent oscillation as the setpoint is approached.

The GA refines these expert-initialized rules by optimizing the rule chromosome against the ITAE objective, systematically improving upon the subjective expert baseline.

D. Defuzzification

The centroid (center-of-area) defuzzification method is used to convert the fuzzy output sets for ΔKp, ΔKi, and ΔKd into crisp scalar values. The final PID gains applied at each sampling instant are computed.

III. SIMULATION RESULTS AND DISCUSSION

A. Simulation Setup

The BLDC motor speed control system is modeled and simulated in MATLAB/Simulink. The motor parameters are listed in Table I. The double closed-loop structure is adopted: an outer speed loop implemented by the Fuzzy-PID controller generates a current reference, and an inner hysteresis current loop produces the inverter switching commands. A 20 kHz PWM switching frequency is used throughout. Three control strategies are evaluated under identical conditions: (1) Traditional PID, (2) Fuzzy-PID, and (3) GA-Fuzzy-PID (proposed).

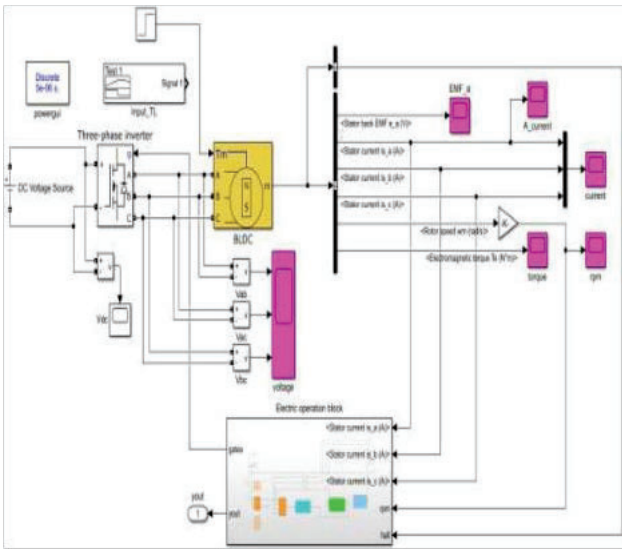

Fig 2.Simulation model

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

B. Simulation Model of BLDC Motor Drive System

The simulation model of the Brushless DC (BLDC) motor drive system is developed in MATLAB/Simulink to evaluate the performance of the control strategy. The overall model consists of a DC power supply, a three-phase inverter, a BLDC motor, and an electric operation subsystem responsible for signal processing and feedback control. A constant DC voltage source is used to supply power to the inverter. The inverter is implemented using a three-phase bridge configuration, which converts the DC input into a controlled three-phase AC output required for BLDC motor operation. The switching of the inverter is governed by gate signals generated from the control block.

The BLDC motor block represents the electrical and mechanical dynamics of the motor, including stator currents, back electromotive force (EMF), rotor speed, and electromagnetic torque. The motor operates based on trapezoidal back-EMF characteristics and electronic commutation. The electric operation block plays a crucial role in extracting and processing signals such as stator currents (ia,ib,ic)(i_a, i_b, i_c)(ia ,ib ,ic), back-EMF (ea,eb,ec)(e_a, e_b, e_c)(ea ,eb ,ec), rotor speed (ω)(\omega)(ω), and electromagnetic torque (Te)(T_e)(Te). These signals are used for monitoring and feedback purposes. The rotor speed is converted into revolutions per minute (RPM) for performance analysis. Additionally, voltage measurement blocks are used to monitor phase voltages

[equation]

and current measurement blocks are used to observe phase currents. The hall sensor signals provide rotor position information required for proper commutation of the inverter switches. The simulation also includes a load torque input, which allows the analysis of motor performance under varying load conditions. The discrete power Gui block is used to define the simulation type and solver configuration.

Parameter	Value	Parameter	Value
Rated Voltage (V)	330	Number of Poles	4
Stator Resistance Rs (Ω)	2.875	Moment of Inertia J (kg·m²)	8×10^{-4}
Stator Inductance Ls (H)	8.5×10^{-3}	Damping Coefficient B (N·m·s)	1×10^{-5}
Flux Linkage (Wb)	0.12	PWM Frequency (kHz)	20

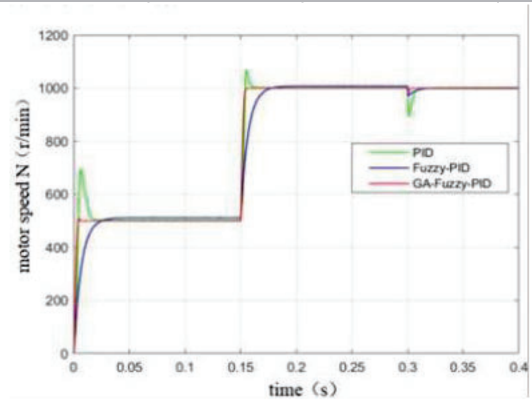

Fig 3.speed comparison

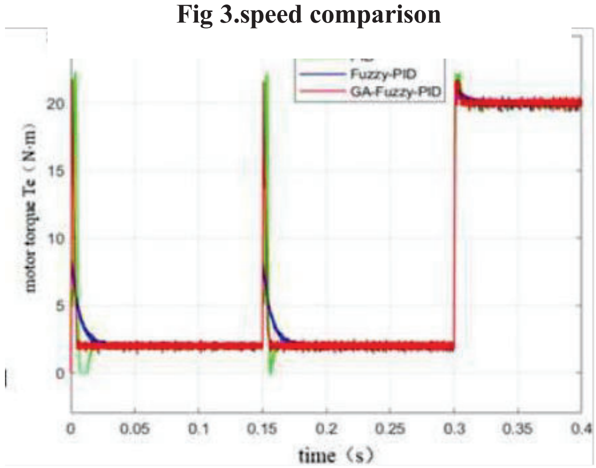

Fig 4. Torque comparison

C. Working Principle

The DC source supplies power to the inverter, which generates a three-phase voltage waveform based on switching signals. These signals are synchronized with rotor position information obtained from hall sensors. The BLDC motor converts electrical energy into mechanical energy, producing torque and rotational motion. The feedback signals such as speed, current, and torque are continuously monitored and can be used for implementing advanced control strategies such as Fuzzy-PID control. This enables improved dynamic response, reduced oversho [1]ot, and enhanced stability, as discussed in recent literature.

D. Test Scenario

The motor is started under an initial load torque of Te = 2 N·m with a reference speed of 500 r/min. At t = 0.15 s, the

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

reference speed is stepped up to 1000 r/min. At t = 0.30 s, a sudden additional load of 20 N·m is applied to test disturbance rejection capability. Speed and torque response curves are recorded for all three controllers.

E. Performance Comparison

Quantitative performance metrics are summarized in Table II. The GA-Fuzzy-PID controller achieves the fastest settling time (0.005 s vs. 0.025 s for the other two), the lowest speed overshoot on load disturbance (20.61 r/min), and an essentially zero steady-state error (0.1 r/min), confirming the effectiveness of the dual-stage GA optimization.

Algorith m	Speed Overshoo t (r/min)	Settlin g Time (s)	Steady - State Error (r/min)	Sudden Load Overshoo t (r/min)
Traditiona l PID	195.6	0.025	3.3	108.45
Fuzzy-PID	0.0	0.025	7.5	30.10
GA-Fuzzy-PID (Proposed)	8.1	0.005	0.1	20.61

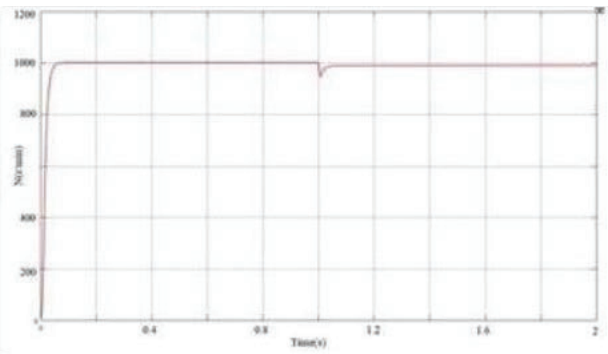

Fig 6.speed simulation using fuzzy PID Controller

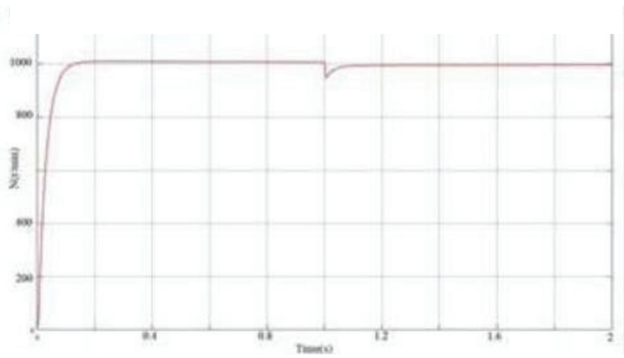

Fig 5.Rotate speed simulation on PID Controller

F. *Discussion*

The traditional PID controller exhibits the fastest initial rise time owing to its high proportional gain, but generates a large speed overshoot of 195.6 r/min and a substantial post-disturbance oscillation of 108.45 r/min. These characteristics confirm the known limitation of fixed-gain PID in handling nonlinear plant dynamics and external disturbances.

The standard Fuzzy-PID controller eliminates startup overshoot entirely (0.0 r/min) and reduces load-disturbance deviation to 30.10 r/min. However, its steady-state error of 7.5 r/min is the largest among the three controllers, attributable to the suboptimal expert-designed initial PID values and non- optimized membership function distribution.

The proposed GA-Fuzzy-PID achieves the best overall performance across all metrics. The GA-optimized initial gains provide a well-centered adaptation range for the fuzzy inference, while the optimized membership functions and rule base ensure more precise and context-aware gain scheduling. The result is an 80% reduction in settling time, near-zero steady-state error, and the smallest disturbance- induced speed deviation (20.61 r/min)— a 81% improvement over traditional PID and a 31% improvement over standard Fuzzy-PID. Torque ripple is also visibly reduced, contributing to smoother mechanical operation.

IV. CONCLUSION AND FUTURE CONSIDERATION

This paper has presented an adaptive Fuzzy-PID speed control strategy for BLDC motors, enhanced by a two-stage Genetic Algorithm optimization framework. The first GA stage searches globally for optimal initial PID gain values; the second stage simultaneously optimizes fuzzy membership function parameters and the fuzzy rule base, replacing subjective expert design with an objective, criterion-driven search. MATLAB/Simulink simulation results validate the superior performance of the proposed GA-Fuzzy-PID controller over both traditional PID and standard Fuzzy-PID approaches. The proposed method achieves an 80% reduction in settling time, near-zero steady-state error, and significantly improved load disturbance rejection. These results confirm that the integration of genetic algorithm optimization with fuzzy-adaptive PID control constitutes a robust and practically viable strategy for

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

high-performance BLDC motor speed regulation.

Future work will focus on hardware-in-the-loop validation, real-time implementation on embedded control platforms (DSP/FPGA), investigation of particle swarm optimization (PSO) and reinforcement learning as alternative tuning methods, and extension of the adaptive framework to sensorless BLDC motor drives.

REFERENCES

[1] DC motor," Control,, vol. 12, pp. 254-259, 2008.
[2] motor," Journal of Electrical Technology, pp. 159-165, 2011.
[3] PID control based on Q-learning opt neural network," pp. 2256–2260, 2015.".
[4] ultrasonic motor based on improv genetic algorithm," *(Engineering and Technology Edition),*
(Engineering Edition), vol. 51, pp. 2280- 2021.

[4] MICROMOTORS, vol. 53, pp. 72-78, 2020. [5] Y
[5] Control Engineering, vol. 25, pp. 915-919, 2018.
[6] based on genetic algorithm," Normal University (Natural Science), 35-40, 2022.
[7] GA," Journal of Jilin University (Science Edition p. pp. 1421–1428, 2020.
[8] X. M. C. S. a. X. N. W. Zhu, "Design of fuzzy- speed controller for brushless DC motor,"
[9] IEEE Int. Conf, pp. 1038-1042, 2019.
1990-1996, 2021.
[10] and fuzzy PID," MICROMOTORS , vol. 54, pp. 92- 98, 2021.
[11] based on genetic fuzzy PID algorithm," Science (IC2ECS), pp. 866-872, 2023.
[12] motor speed control based- algorithm,"
and Automation (ICMA), Harbin, China, pp. 287- 292, 2016.
[13] pp. 2256–2260, 2015.".
[14] ultrasonic motor based on improv genetic algorithm,"
(Engineering and Technology Edition),