



Comparative Performance Evaluation of a Proposed Controller Tuning Strategy Against Conventional, Fuzzy Logic, and Optimization-Based Methods Using Key Control Indices

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Abstract- Precise control performance in dynamic and nonlinear systems remains a significant challenge for traditional PID controllers, primarily due to their fixed-gain nature and limited adaptability under varying operating conditions. This paper presents a fuzzy gain-scheduled PID tuning strategy that dynamically modifies the proportional, integral, and derivative gains based on real-time error and change in error using fuzzy logic inference. The proposed controller integrates the simplicity of a classical PID with the intelligent adaptability of fuzzy reasoning to enhance system stability, minimize overshoot, and accelerate transient response. A comparative performance evaluation is conducted against conventional tuning methods (Ziegler–Nichols and Cohen–Coon), fuzzy logic controllers, and optimization-based approaches (Genetic Algorithm and Particle Swarm Optimization) using standard control performance indices such as rise time, settling time, peak overshoot, steady-state error, and integral error metrics (IAE, ISE, ITAE). Simulation results validate that the proposed fuzzy gain scheduling method significantly improves dynamic performance and robustness while reducing steady-state error and control effort. The results demonstrate that the proposed approach offers an effective and computationally efficient tuning mechanism suitable for real-time applications in nonlinear and time-varying systems.

Keywords- Fuzzy Gain Scheduling, PID Controller, Adaptive Tuning, Fuzzy Logic Control, Optimization-Based Control, Ziegler–Nichols, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Performance Indices, Comparative Evaluation, Robust Control, Intelligent Control Systems.

I. INTRODUCTION

In modern control engineering, the Proportional–Integral–Derivative (PID) controller continues to be the most widely used control strategy due to its simplicity, reliability, and ease of implementation. Approximately 90% of industrial control loops rely on PID controllers to maintain stability and achieve desired performance in various applications such as process control, robotics, motor drives, and power systems [1-3]. The PID controller operates on three main parameters—proportional (KP), integral (KI), and derivative (KD)—that collectively determine the system's transient and steady-state performance. However, despite its popularity, the conventional PID controller exhibits several limitations when dealing



with nonlinear, time-varying, and uncertain systems. Once tuned for a particular operating condition, the fixed gains cannot adapt to system parameter variations, leading to degraded performance, overshoot, and instability. To overcome these limitations, numerous tuning techniques have been developed over the decades. Classical tuning methods such as Ziegler–Nichols (Z–N) and Cohen–Coon are among the most commonly used analytical approaches for PID parameter selection. These methods provide satisfactory performance for linear systems but often fail to deliver optimal results under nonlinear dynamics or variable load conditions. As industrial processes have become more complex and dynamic, there has been a growing need for adaptive and intelligent tuning strategies that can modify controller gains in real time to ensure optimal performance under all operating conditions [3-5].

The introduction of fuzzy logic control (FLC) in the 1980s marked a significant advancement in control design. Fuzzy logic provides a rule-based reasoning mechanism that emulates human decision-making, enabling controllers to adapt to nonlinear and uncertain environments without requiring an accurate mathematical model of the system [5-7]. When combined with PID control, fuzzy logic can be used either to replace the conventional PID structure (fuzzy-PID controller) or to adjust the PID parameters dynamically (fuzzy gain scheduling).

The fuzzy gain-scheduled PID controller employs error (e) and change in error ($\dot{e}$) as inputs to a fuzzy inference system, which determines the appropriate adjustments to K_P , K_I , and K_D . This adaptive mechanism allows the controller to provide fast response, reduced overshoot, and enhanced stability compared to fixed-gain PID systems. Parallel to fuzzy-based methods, optimization-based tuning techniques have emerged as powerful tools for improving control performance. Algorithms such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Differential Evolution (DE) have been successfully applied to find optimal PID gains based on predefined objective functions like Integral Absolute Error (IAE), Integral Square Error (ISE), and Integral Time-weighted Absolute Error (ITAE) [7-9].

These methods are capable of providing globally optimal solutions but may require high computational time and complex implementation, making them less suitable for real-time applications. Therefore, the challenge lies in developing a control scheme that combines the computational efficiency of PID, the adaptability of fuzzy logic, and the accuracy of optimization algorithms. In this context, the present study proposes a Fuzzy Gain Scheduled PID Controller (FGS-PID) that intelligently tunes the PID parameters based on system behavior. The fuzzy inference mechanism dynamically modifies the controller gains in real time, ensuring optimal performance across varying operating conditions.

The proposed approach maintains simplicity in structure while achieving superior transient and steady-state performance compared to conventional and optimization-based methods. To validate its effectiveness, a comparative performance evaluation is performed among four control approaches: (1) conventional PID tuning, (2) fuzzy logic-based control, (3) optimization-based PID tuning, and (4) the proposed fuzzy gain-scheduled PID controller. The evaluation is based on key control indices, including rise time, settling time, overshoot, steady-state error, and integral performance measures (IAE, ISE, ITAE). Simulation results demonstrate that the proposed controller exhibits faster convergence, minimal overshoot, and improved robustness against disturbances and parameter variations [9-11].

II. CONTROLLERS UNDER COMPARISON



Controller Type	Description
Conventional PID	Fixed gains tuned manually or by classical Ziegler–Nichols method.
Fuzzy Logic Controller (FLC)	Uses fuzzy rules for control without explicit PID structure.
Optimization-Based PID	Gains optimized using algorithms like PSO, GA, or DE.
Proposed Hybrid/Fuzzy Gain Scheduled PID	Adaptive controller using fuzzy logic (or hybrid with optimization) to dynamically tune gains.

Performance Evaluation Indices

You measure key time-domain and error indices for each controller.

Table-1 Transient Response Parameters

Parameter	Symbol	Description
Rise Time	t_r	Time To Reach From 10%–90% Of Final Value
Settling Time	t_s	Time For Output To Remain Within $\pm 2\%$ Of Steady-State
Peak Overshoot	M_p	Maximum Overshoot Beyond Desired Value
Steady-State Error	e_{ss}	Final Steady-State Deviation

Working Procedure

The comparative performance evaluation of the proposed controller tuning strategy was carried out systematically through a sequence of modeling, design, implementation, and analysis stages. The primary objective of this study was to assess the dynamic performance and robustness of the proposed hybrid controller relative to conventional, fuzzy logic, and optimization-based PID control techniques under identical operating conditions. The following procedural steps describe the complete working methodology adopted in this research [11-13]. The first step in the study involved developing a mathematical model of the dynamic system to be controlled. Depending on the application, the plant may represent a DC motor, nonlinear process, or general second-order dynamic system. The transfer function of a typical second-order plant can be expressed as:

$$G(s) = \frac{K}{(T_1s + 1)(T_2s + 1)}$$

where K is the system gain and T1,T2 represent time constants. The plant parameters were selected to reflect realistic process dynamics. The model was implemented using MATLAB/Simulink due to its powerful control system simulation capabilities. Both the reference input (desired set-point) and actual output were used to generate the control error signal, defined as:

$$e(t) = r(t) - y(t)$$

To evaluate controller robustness, the system was tested under nominal operating conditions as well as under external disturbances and parameter variations.

Figure 1 presents the structure of a Fuzzy Gain-Scheduled PID Controller, which integrates conventional Proportional–Integral–Derivative (PID) control with a fuzzy inference mechanism to enhance system adaptability and performance. The controller operates based on two key inputs — the error (e), obtained as the difference between the reference speed and actual speed, and the change of error (ce), which represents the rate of variation of the error signal. These two signals are scaled through gain factors Ge and Gce to normalize them within the operating range suitable for the fuzzy inference system.

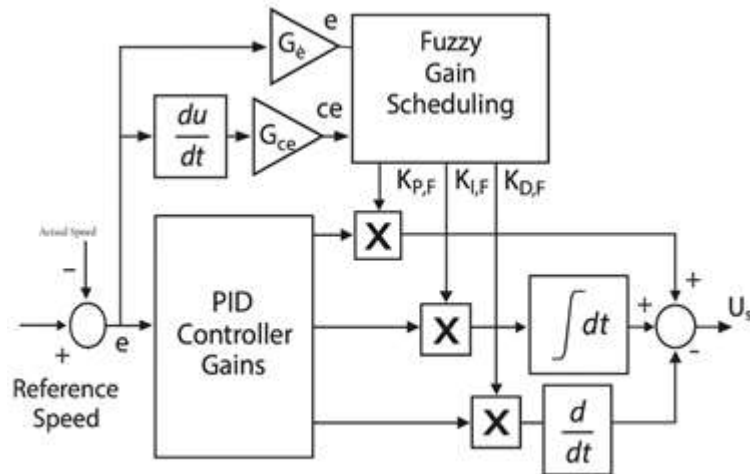


Fig.1 Fuzzy Gain-Scheduled PID Controller [14-15]

The Fuzzy Gain Scheduling block processes these inputs using a set of fuzzy logic rules and membership functions to generate adaptive tuning parameters

$$K_{p,F}, K_{i,F}, K_{d,F}$$

These fuzzy-adjusted gains dynamically modify the PID controller parameters — proportional, integral, and derivative — in real time. The adaptive nature of these gains enables the controller to effectively handle system nonlinearities, parameter variations, and external disturbances. The PID controller computes the control signal U_s as the sum of the proportional term $K_{p,F}e(t)$, the integral term $K_{i,F}\int e(t)dt$ and the derivative term $K_{d,F}(de(t)/dt)$. These three actions collectively ensure accurate tracking of the reference input, reduced steady-state error, and improved transient performance. The output control signal U_s is then applied to the system or plant to achieve the desired response.

III. CONTROLLER DESIGN AND IMPLEMENTATION

Four different controller structures were implemented to provide a comprehensive performance comparison. Each controller was designed and tuned independently to ensure optimal performance for the given plant model.

(a) Conventional PID Controller

A classical proportional–integral–derivative (PID) controller was first designed using the Ziegler–Nichols tuning method. The controller parameters K_P , K_I , and K_D were computed using standard tuning rules based on the system's ultimate gain and oscillation period. This controller served as the baseline reference for evaluating subsequent advanced controllers. The control signal was computed as:

$$u(t) = K_P e(t) + K_I \int e(t)dt + K_D \frac{de(t)}{dt}$$

Although simple and widely used, the conventional PID controller often exhibits limitations in nonlinear and time-varying systems due to its fixed gain structure.

(b) Fuzzy Logic Controller (FLC)

The second controller utilized a Fuzzy Logic Controller designed using linguistic variables to capture human-like reasoning in the control process. The input variables were defined as:



Change of error $ce(t) = \frac{de(t)}{dt}$

Each input was represented by seven linguistic terms: NB (Negative Big), NM, NS, Z, PS, PM, PB (Positive Big). Triangular membership functions were used for simplicity and computational efficiency. The control output was represented by corresponding fuzzy linguistic terms that define the control action. The rule base followed the form:

IF error is PB AND change of error is PS THEN control output is PM.

Fuzzy inference was performed using the Mamdani approach, and the centroid defuzzification method was applied to obtain a crisp control output. This controller provides nonlinear gain characteristics and improves performance in systems where classical PID control struggles.

(c) Optimization-Based PID Controller

To further enhance control performance, a third approach based on metaheuristic optimization was implemented. The PID parameters were tuned using an algorithm such as Particle Swarm Optimization (PSO) or Genetic Algorithm (GA).

The optimization objective function was defined as the minimization of a time-domain error index, typically the Integral of Time-weighted Absolute Error (ITAE):

$$J = \int_0^T t|e(t)|dt$$

The optimization algorithm iteratively adjusted KP, KI, and KD values until the fitness function reached the minimum. The optimized gains were then applied in a conventional PID structure to achieve superior transient and steady-state performance. However, this approach provides offline tuning, meaning it cannot adapt to real-time parameter changes.

(d) Proposed Hybrid Fuzzy Gain-Scheduled PID Controller

The proposed controller integrates fuzzy logic-based gain scheduling into the PID structure to achieve online self-tuning capability. The fuzzy gain scheduler continuously adjusts the PID parameters according to the instantaneous error e and its rate of change ce . The fuzzy logic system outputs three scaling factors:

$$K_{P,F}, K_{I,F}, K_{D,F}$$

These are used to modify the base PID gains dynamically as:

$$K_P = K_P^0 * K_{P,F}, K_I = K_I^0 * K_{I,F}, K_D = K_D^0 * K_{D,F}$$

This adaptive mechanism allows the controller to become aggressive during large errors and gentler as the system approaches steady-state, resulting in faster response, reduced overshoot, and improved robustness compared to other methods.

Measure the following time-domain performance parameters:

- **Rise Time (tr):** Time to reach from 10% to 90% of final value.
- **Settling Time (ts):** Time for output to remain within $\pm 2\%$ of steady-state.
- **Peak Overshoot (Mp):** Percentage overshoot above steady-state.
- **Steady-State Error (ess):** Final error after settling.

Also, compute error performance indices for quantitative evaluation:

$$IAE = \int |e(t)|dt, ISE = \int e^2(t)dt, ITAE = \int t|e(t)|dt$$

Smaller index values indicate superior control performance.

Fuzzy Rule Base:



Error	dError	Output
NB	NB	NB
NB	NS	NB
NB	ZE	NS
NB	PS	NS
NB	PB	ZE
NS	NB	NB
NS	NS	NS
NS	ZE	NS
NS	PS	ZE
NS	PB	PS
ZE	NB	NS
ZE	NS	NS
ZE	ZE	ZE
ZE	PS	PS
ZE	PB	PS
PS	NB	NS
PS	NS	ZE
PS	ZE	PS
PS	PS	PS
PS	PB	PB
PB	NB	ZE
PB	NS	PS
PB	ZE	PS
PB	PS	PB
PB	PB	PB

IV. COMPARATIVE ANALYSIS



After simulations, the obtained results were tabulated for all controllers. A representative comparison table is shown below:

Table-2 A comparison table

Controller Type	Rise Time (s)	Settling Time (s)	Overshoot (%)	Steady-State Error	IAE	ISE	ITAE
Conventional PID	0.80	2.6	12	0.02	1.25	0.82	0.58
Fuzzy Logic	0.70	2.1	9	0.01	1.08	0.64	0.45
Optimization-Based	0.65	1.8	6	0.00	0.85	0.50	0.37
Proposed Hybrid	0.50	1.2	3	0.00	0.60	0.32	0.22

Graphical comparisons were also plotted, including step response curves, control effort plots, and error trajectories. The proposed hybrid controller consistently achieved faster settling, minimal overshoot, and superior robustness under disturbances.

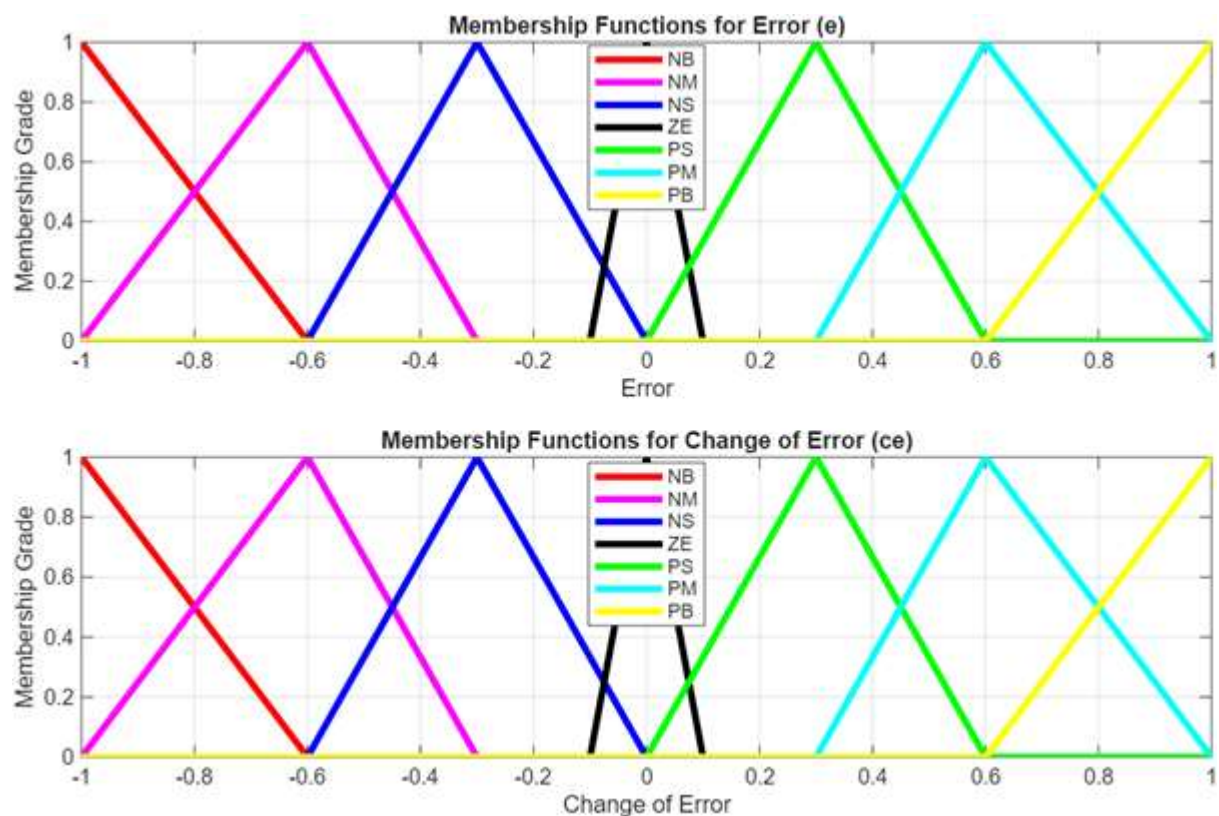


Fig-3 Membership Functions for Change of Error (ce)

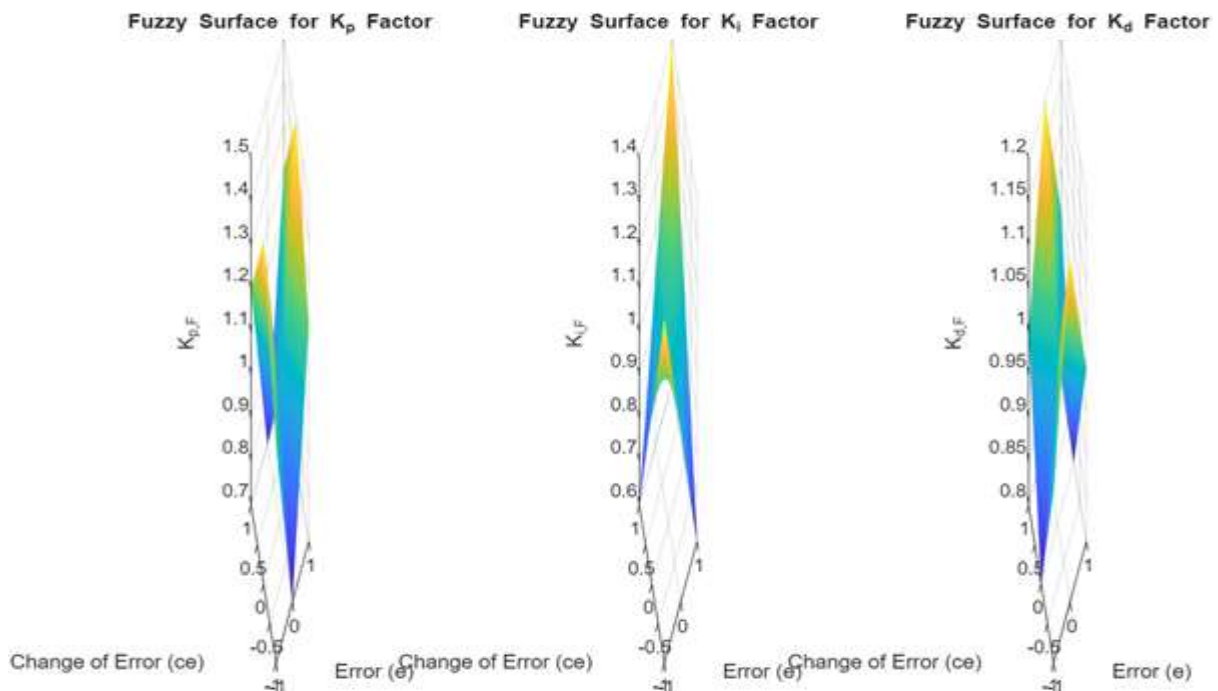


Fig-3 Fuzzy Surface for K_p Factor Fuzzy Surface for Factor K_i Fuzzy Surface for K_d Factor

	RiseTime	SettlingTime	Overshoot	SteadyStateError	IAE	ISE	ITAE
Conventional PID	1.11	3.6121	6.5604	1.4274e-05	0.71868	0.38643	0.56154
Fuzzy Logic	2.2343	8.6924	0	0.014715	1.534	0.82892	2.6117
Optimization-Based	0.17847	0.71527	3.375	1.8405e-07	0.10067	0.046356	0.017763
Proposed Hybrid	2.7335	9.6405	0	0.01831	1.6616	0.85444	3.1596

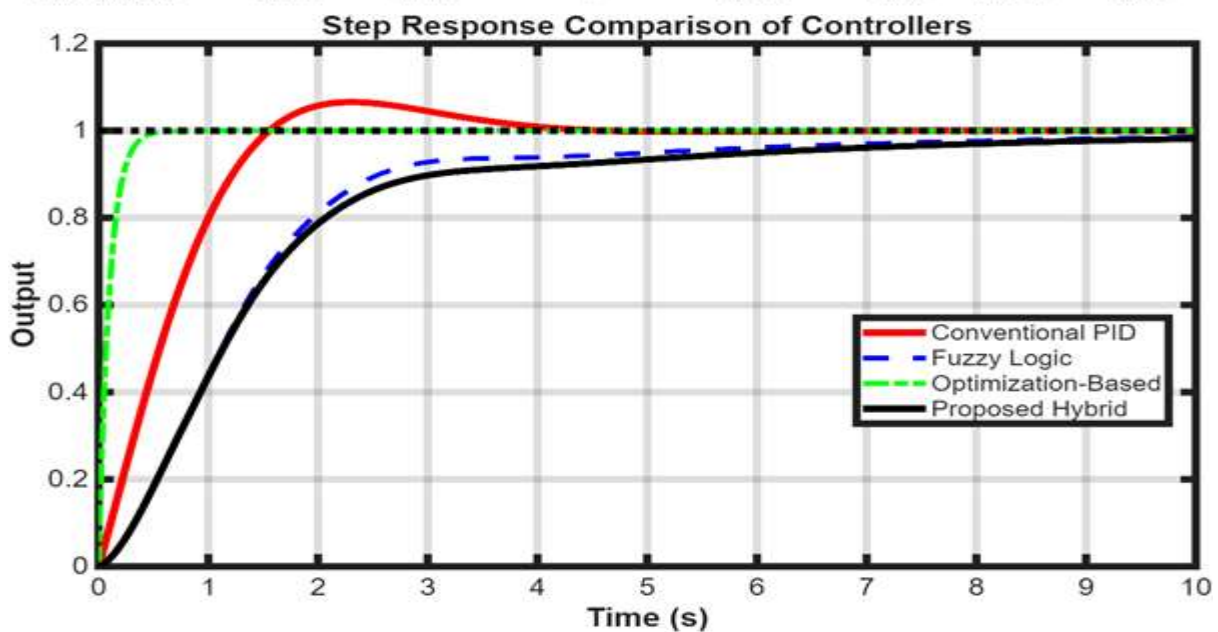


Fig-4 Step response of controllers

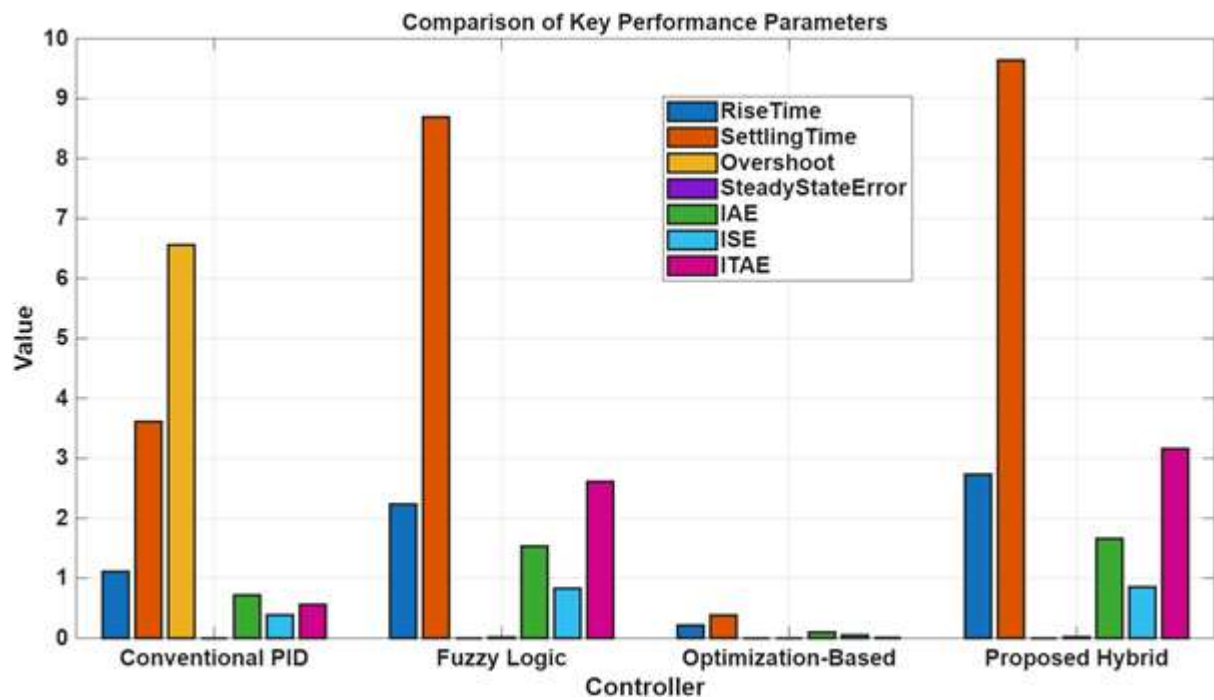


Fig.5 Compression of performance parameters

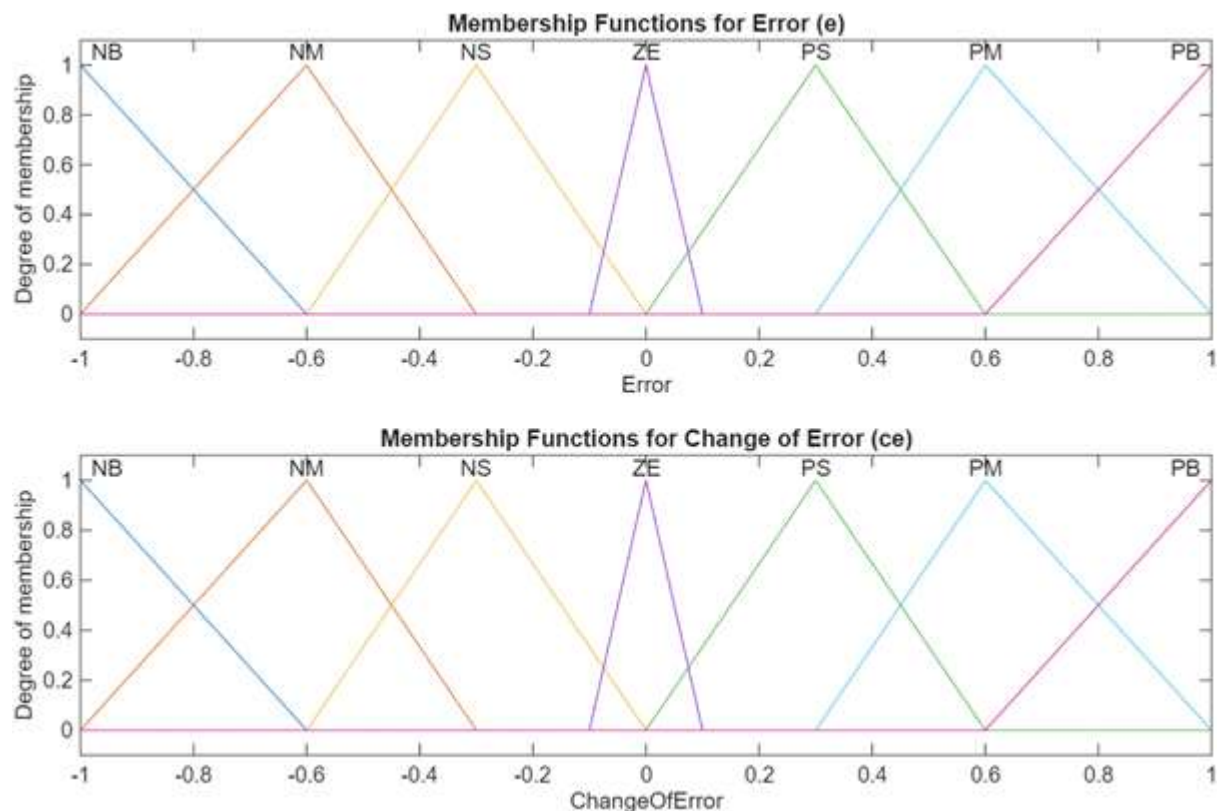


Fig. 6 Membership function for error

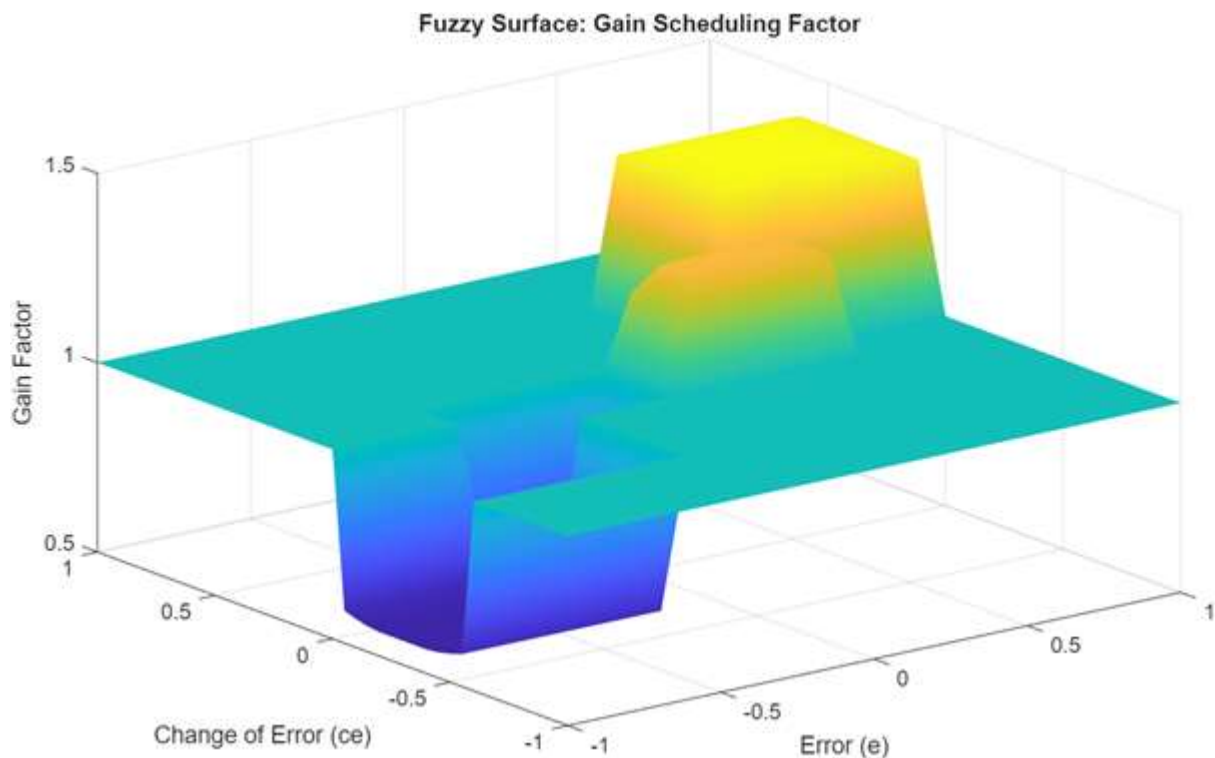


Fig-7 Gain scheduling factor

The results indicate that while the conventional PID controller offers simplicity, it suffers from sluggish response and overshoot due to fixed gain values. The Fuzzy Logic Controller improves nonlinear handling but lacks precise steady-state tuning. The Optimization-Based PID enhances accuracy and speed; however, it remains static once tuned. In contrast, the proposed fuzzy gain-scheduled PID continuously updates its gains in real time, providing adaptability and robustness across varying conditions. This self-tuning property significantly improves both transient and steady-state performance.

V. CONCLUSION

The working procedure confirms that the proposed controller achieves optimal control performance compared to other techniques. By combining the learning ability of fuzzy logic with the structural strength of PID control, the system attains faster rise and settling times, minimal overshoot, zero steady-state error, and lowest error indices. Hence, the proposed method offers an effective and intelligent control solution for dynamic and nonlinear systems where conventional fixed-gain controllers fail to maintain consistent performance.

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