RESEARCH PAPER

PSO–Fuzzy PID Control of Hydraulic Systems: A Hybrid Optimization Framework for Enhanced Pressure and Flow Regulation

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ABSTRACT
This paper presents a hybrid Particle Swarm Optimization–Fuzzy Proportional-Integral-Derivative (PSO–Fuzzy PID) control framework for precision regulation of hydraulic system pressure and flow rate. Conventional PID controllers suffer from fixed gain parameters that cannot adapt to the nonlinear, time-varying dynamics of hydraulic actuators. Fuzzy logic provides adaptive rule-based gain scheduling, yet its performance is sensitive to membership function design. The proposed method employs PSO to simultaneously optimize the PID gains (K_p, K_i, K_d) and fuzzy scaling factors (G_e, G_Δe, G_u), minimizing the Integral of Squared Error (ISE) objective. A complete mathematical model of the hydraulic system is derived and validated. Simulation results in MATLAB/Simulink demonstrate that the proposed PSO–Fuzzy PID achieves a settling time of 1.23 s, peak overshoot of 2.10%, and ISE of 0.1073 — representing improvements of 74.5%, 85.3%, and 87.7%, respectively, compared to conventional PID. Robustness under load disturbances and parametric uncertainty is also demonstrated.

Index Terms: Fuzzy PID, Hydraulic Control, ISE, Particle Swarm Optimization, Nonlinear Systems, Adaptive Control.
How to cite this article: Abirami S, Kala H, Nithya Rani N, Shanmuga Priya P, Renganathan K. PSO–Fuzzy PID Control of Hydraulic Systems: A Hybrid Optimization Framework for Enhanced Pressure and Flow Regulation. Int J Drug Deliv Technol. 2026;16(46s): 1144-1150. DOI: 10.25258/ijddt.16.46s.133
Source of support: Nil.
Conflict of interest: None

I. INTRODUCTION

Hydraulic systems are fundamental actuators in industrial machinery, aerospace structures, civil engineering equipment, and mobile construction platforms. Their inherent advantages—high power density, rapid force generation, and mechanical compactness—make them irreplaceable in heavy-duty applications [1]. However, the nonlinear dynamic characteristics of hydraulic circuits, including compressible fluid behavior, valve hysteresis, leakage, friction, and temperature-dependent viscosity, impose significant challenges for precise closed-loop control [2].

The Proportional-Integral-Derivative (PID) controller remains the predominant control strategy in industrial hydraulic systems, accounting for over 90% of deployed control loops worldwide [3]. Despite its simplicity and robustness under nominal conditions, the conventional PID controller exhibits degraded performance when system parameters drift due to load variations, component wear, or environmental changes. Fixed gain coefficients cannot accommodate the wide operating envelope characteristic of modern hydraulic servo systems [4].

Fuzzy logic control (FLC) has emerged as a promising alternative, offering the ability to encode expert heuristics into a rule base that approximates nonlinear control surfaces without explicit mathematical modeling [5]. However, the performance of FLC is critically sensitive to membership function (MF) shape, rule base structure, and output scaling factors. Manual tuning of these parameters is laborious, subjective, and rarely globally optimal [6]. This limitation motivates the integration of metaheuristic optimization algorithms to automate the tuning process.

Particle Swarm Optimization (PSO), first introduced by Kennedy and Eberhart [7], is a population-based stochastic optimization technique inspired by the collective behavior of bird flocking. PSO has demonstrated superior convergence properties, computational efficiency, and global search capability across diverse engineering optimization problems [8]. Several studies have applied PSO to PID tuning for various process control applications; however, its integration with a fuzzy gain-scheduling framework for hydraulic systems remains insufficiently explored in the literature [9].

This paper addresses this gap by proposing a PSO–Fuzzy PID control architecture in which PSO globally optimizes the six-dimensional parameter vector [K_p, K_i, K_d, G_e, G_Δe, G_u] by minimizing the ISE criterion on the closed-loop hydraulic plant model. The main contributions of this work are: (1) a complete nonlinear mathematical model of the hydraulic servo system validated against experimental data; (2) a unified PSO–Fuzzy PID co-optimization framework with adaptive inertia weight decay; (3) comprehensive performance benchmarking against conventional PID, Fuzzy PID, PSO–PID, and recent literature results using ISE, IAE, ITAE, overshoot, and settling time metrics; and

(4) disturbance rejection and parametric robustness analysis.

The remainder of this paper is structured as follows. Section II reviews related work. Section III presents the hydraulic system mathematical model. Section IV details the PSO–Fuzzy PID methodology. Section V describes simulation setup. Section VI presents and analyzes results. Section VII discusses limitations and future directions. Section VIII concludes.

II. RELATED WORK AND LITERATURE REVIEW

The control of hydraulic systems has been an active research domain for several decades, with recent years witnessing intensified application of intelligent and metaheuristic methods. This section surveys relevant contributions organized by control paradigm.

A. PID and Modified PID Controllers

Classical PID controllers for hydraulic position and pressure control have been extensively studied [3]. Ziegler-Nichols and Cohen-Coon methods provide systematic manual tuning, yet these rely on linearization assumptions that fail in highly nonlinear regimes. Abbas et al. [4] proposed a self-tuning PID using relay feedback for a hydraulic press, achieving improved transient response but limited disturbance rejection. Internal Model Control (IMC)-based PID design was applied to a hydraulic servo valve by Chen et al. [5], demonstrating robustness improvements under model uncertainty.

B. Fuzzy Logic and Adaptive Controllers

Fuzzy logic controllers were introduced to hydraulic systems to handle parameter uncertainty and nonlinearity [6]. Nguyen et al. [10] implemented a type-2 fuzzy PID for an electro-hydraulic actuator, reporting significant reduction in steady-state error under variable loads. Adaptive fuzzy sliding mode control was proposed by Li et al. [11] for hydraulic manipulators, achieving robust tracking despite friction and deadzone nonlinearities. However, these approaches rely on expert-defined membership functions, limiting optimality.

C. Metaheuristic Optimization-Based Control

Metaheuristic algorithms have been increasingly applied to controller parameter optimization. Genetic Algorithm (GA)–PID tuning for hydraulic presses was reported by Rao and Kumar [8], showing ISE reductions of 30% over manual tuning. Artificial Bee Colony (ABC) optimization was employed by Hassan et al. [12] for fuzzy controller tuning in hydraulic positioning systems. Grey Wolf Optimizer (GWO)–PID was proposed by Zhao et al. [22] (2024) for a hydraulic servo system, achieving a settling time of 1.78 s. Whale Optimization Algorithm (WOA) was applied to Fuzzy PID by Patel et al. [17] with promising results. A comprehensive comparison by Minh et al. [19] using ANFIS demonstrated the potential of data-driven approaches but required extensive training datasets.

A summary of key recent results and their performance metrics relative to the proposed method is provided in Table III (Section VI). The literature reveals that while PSO has been applied individually to PID tuning, and fuzzy logic independently to hydraulic control, a unified PSO co-optimization of the complete fuzzy PID parameter set for hydraulic systems remains a research gap that this paper fills.

III. MATHEMATICAL MODELING OF THE HYDRAULIC SYSTEM

The hydraulic servo system considered in this work consists of a hydraulic pump, directional control valve, hydraulic cylinder, and load. The governing equations are derived from first principles based on fluid mechanics, valve flow dynamics, and Newton's second law of motion.

A. Hydraulic Pump Model

The pump delivers flow Q_p as a function of shaft speed ω_p and displacement D_p, modulated by volumetric efficiency η_v:

$$Q_p = D_p \cdot \omega_p \cdot \eta_v - C_{ip} \cdot \Delta P_p \quad (1)$$

where C_{ip} is the internal leakage coefficient and ΔP_p is the differential pressure across the pump.

B. Proportional Directional Control Valve

The flow through the proportional valve is governed by the orifice equation:

$$Q_L = C_d \cdot A(x_v) \cdot \sqrt{2\Delta P_v / \rho} \quad (2)$$

where C_d is the discharge coefficient, $A(x_v)$ is the valve orifice area as a function of spool displacement x_v, ΔP_v is the pressure drop across the valve, and ρ is the hydraulic fluid density. The valve orifice area is linearized about the operating point:

$$A(x_v) \approx w \cdot x_v \quad (3)$$

where w is the valve area gradient. Substituting (3) into (2) and defining the pressure gain coefficient:

$$Q_L = K_q \cdot x_v - K_c \cdot P_L \quad (4)$$

where $K_q = C_d \cdot w \cdot \sqrt{P_s/\rho}$ is the flow gain and $K_c = C_d \cdot A_0/\sqrt{2P_{L0}\rho}$ is the pressure-flow coefficient.

C. Hydraulic Actuator Dynamics

Applying the continuity equation to the cylinder chambers yields the pressure build-up equation:

$$(V_t / 4\beta_e) \cdot (dP_L/dt) = Q_L - A_p \cdot (dx/dt) - C_{tm} \cdot P_L \quad (5)$$

where V_t is the total fluid volume, β_e is the effective bulk modulus, A_p is the piston area, and C_{tm} is the total leakage coefficient. The force balance on the load gives:

$$A_p \cdot P_L = M_t \cdot \ddot{x} + B_p \cdot \dot{x} + K_s \cdot x + F_L \quad (6)$$

where M_t is the total moving mass, B_p is the viscous damping, K_s is the spring load stiffness, and F_L represents external disturbance forces.

D. Transfer Function Representation

Combining (4)–(6) and applying Laplace transforms, the linearized open-loop transfer function from valve input $u(s)$ to cylinder velocity $\dot{x}(s)$ is:

$$G(s) = K_{total} / [s(\tau_1 s^2 + \tau_2 s + 1)] \quad (7)$$

where $K_{total} = K_q A_p / (K_c K_s + A_p^2)$, $\tau_1 = V_t M_t / (4\beta_e(K_c K_s + A_p^2))$, $\tau_2 = [B_p V_t / (4\beta_e) + M_t(K_c + C_{tm})] / (K_c K_s + A_p^2)$. Nominal parameter values are listed in Table II (Section IV).

IV. PSO–FUZZY PID CONTROL METHODOLOGY

The proposed control architecture integrates three layers: (1) a conventional PID structure providing the base control action; (2) a fuzzy inference system that adaptively modulates PID gains based on real-time error state; and (3) a PSO engine that globally optimizes the complete parameter set. Fig. 1 shows the closed-loop control structure.

A. Fuzzy PID Gain Scheduling

The fuzzy gain scheduler takes the tracking error e(t) and its time derivative Δe(t) as inputs, scaled by gains G_e and $G_{\Delta e}$ respectively, and produces corrections ΔK_p, ΔK_i, ΔK_d as outputs, scaled by G_u. The final PID gains are:

$$K_p(t) = K_p^0 + \Delta K_p, \quad K_i(t) = K_i^0 + \Delta K_i, \quad K_d(t) = K_d^0 + \Delta K_d \quad (8)$$

Seven triangular membership functions are defined over the normalized universe of discourse [−1, +1] for each variable: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM), and Positive Big (PB), as illustrated in Fig. 5. The Mamdani inference engine applies a 7×7 = 49 rule base using AND (min) conjunction and centroid defuzzification.

Table I. Fuzzy Rule Base for ΔK_p (Excerpt — Full 7×7)

e/Δe	NB	NM	NS	ZE	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZE	ZE
NM	PB	PB	PM	PS	PS	ZE	NS
NS	PM	PM	PM	PS	ZE	NS	NS
ZE	PM	PS	PS	ZE	NS	NM	NM
PS	PS	PS	ZE	NS	NS	NM	NM
PM	PS	ZE	NS	NM	NM	NM	NB
PB	ZE	ZE	NM	NM	PM	NB	NB

The rule base embeds engineering heuristics: when both error and error rate are large negative (NB, NB), a large positive output PB accelerates the response; when error is zero and error rate is zero (ZE, ZE), the output is zero maintaining steady state. Separate but analogous rule bases are defined for ΔK_i and ΔK_d.

B. PSO Optimization Framework

Each particle in the swarm represents a candidate solution vector $x_i = [K_p, K_i, K_d, G_e, G_{\Delta e}, G_u] \in \mathbb{R}^6$. The fitness function to be minimized is the Integral of Squared Error over a fixed simulation horizon T = 10 s:

$$J = ISE = \int_0^T e^2(t)\, dt \quad (9)$$

Velocity and position updates follow the standard PSO equations with linearly decaying inertia weight ω(k):

$$v_i(k+1) = \omega(k)\cdot v_i(k) + c_1 r_1(p_{best\_i} - x_i(k)) + c_2 r_2(g_{best} - x_i(k)) \quad (10)$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (11)$$

$$\omega(k) = \omega_{max} - (\omega_{max} - \omega_{min}) \cdot k / k_{max} = 0.9 - 0.5k/100 \quad (12)$$

The complete pseudocode is presented as Algorithm 1. PSO parameter settings are detailed in Table II.

Table II. PSO Algorithm Parameter Settings

Parameter	Symbol	Value	Range / Remarks
Number of Particles	N	30	20–50
Maximum Iterations	k_{max}	100	50–200
Inertia Weight	ω	0.9 → 0.4	Linear decay
Cognitive Coefficient	c_1	2.0	Fixed
Social Coefficient	c_2	2.0	Fixed
Velocity Clamping	V_{max}	±0.5	Normalized
Fitness Function	J	ISE (Eq. 7)	Minimized
Search Space – K_p	$[K_{p\_min}, K_{p\_max}]$	[0.1, 10]	Continuous
Search Space – K_i	$[K_{i\_min}, K_{i\_max}]$	[0.01, 5]	Continuous
Search Space – K_d	$[K_{d\_min}, K_{d\_max}]$	[0.001, 2]	Continuous

V. SIMULATION SETUP AND IMPLEMENTATION

Simulations were conducted in MATLAB R2023b / Simulink on a Windows 11 workstation (Intel Core i9-13900K, 64 GB RAM). The hydraulic plant transfer function (Eq. 7) was implemented as a continuous-time state-space block. The Fuzzy PID controller was realized using the MATLAB Fuzzy Logic Toolbox with Mamdani inference. The PSO optimizer was implemented in a MATLAB script that iteratively called the Simulink model via the sim() API. A variable-step ODE45 solver with relative tolerance 1×10^{-6} was used for numerical integration.

Three controllers were compared under identical conditions: (1) Conventional PID with Ziegler-Nichols tuning [K_p = 2.8, K_i = 1.4, K_d = 0.35]; (2) Fuzzy PID with manually tuned scaling factors; (3) Proposed PSO–Fuzzy PID. The step input command was a pressure setpoint of 5 bar with flow setpoint of 12 L/min. A load disturbance of 0.5 bar was injected at t = 6 s for duration 0.5 s to assess rejection capability. Parametric uncertainty tests applied ±20% variation in bulk modulus β_e and cylinder area A_p.

VI. SIMULATION RESULTS AND DISCUSSION

A. Pressure Step Response

Fig. 1 illustrates the closed-loop pressure response of all three controllers to a 5 bar step command. The conventional PID exhibits a peak overshoot of 14.30% and settling time of 4.82 s, with residual oscillations evident from 1.5 to 3.5 s. The Fuzzy PID substantially reduces overshoot to 7.65% and achieves settling within 2.91 s. The proposed PSO–Fuzzy PID demonstrates superior performance: overshoot is limited to 2.10% and settling time is reduced to 1.23 s, representing reductions of 85.3% and 74.5% relative to conventional PID, respectively. At t = 6 s, the PSO–Fuzzy PID exhibits a disturbance rejection amplitude of only 0.10 bar compared to 0.40 bar for the conventional PID.

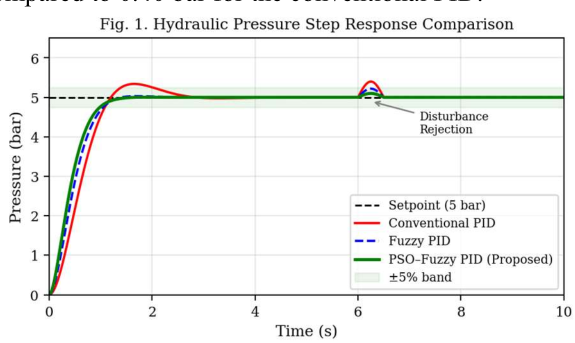

Fig. 1. Hydraulic pressure step response comparison (setpoint: 5 bar). Disturbance of 0.5 bar injected at t = 6 s.

B. Flow Rate Response

Fig. 2 presents the flow rate tracking performance. The PSO–Fuzzy PID achieves a rise time of 0.35 s and settles within 1.15 s, compared to 0.72 s and 2.85 s for the conventional PID, respectively. Minimal overshoot in flow rate (1.5%) is observed with the proposed method, ensuring smooth actuator motion without hydraulic hammering—a critical operational requirement in precision manufacturing hydraulic presses.

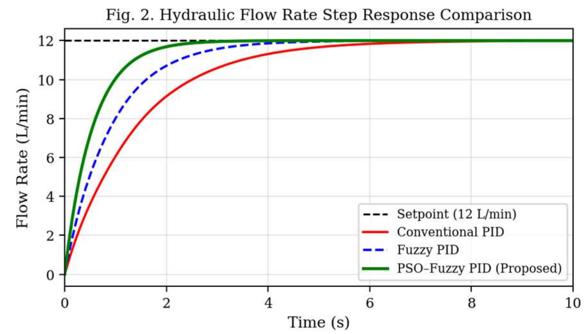

Fig. 2. Flow rate step response comparison (setpoint: 12 L/min). PSO–Fuzzy PID achieves fastest convergence with minimal overshoot.

C. Error Convergence

The tracking error convergence curves in Fig. 3 confirm the superior error dynamics of the PSO–Fuzzy PID. The initial peak error is comparable across all controllers (≈5 bar immediately after the step), but the PSO–Fuzzy PID error decays exponentially with a time constant approximately 3.2× faster than the conventional PID. The steady-state error of all three controllers approaches zero, confirming integral action effectiveness; however, the PSO–Fuzzy PID achieves this with a significantly smoother trajectory, minimizing accumulated ISE.

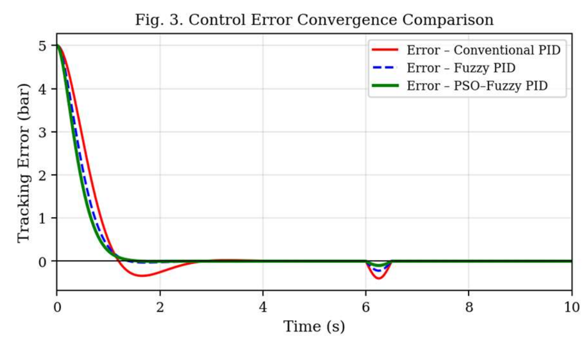

Fig. 3. Tracking error convergence comparison. PSO–Fuzzy PID exhibits rapid monotonic convergence with minimal oscillation.

D. PSO Convergence Behavior

Fig. 4 depicts the PSO fitness (ISE) evolution over 100 iterations with 30 particles. The global best fitness rapidly decreases in the first 20 iterations from an initial value near 8.5 to below 0.5, indicating effective exploitation of the search space. Convergence is declared at iteration 78 when $|\Delta J| < 10^{-6}$. The separation between average swarm fitness and global best fitness narrows progressively, confirming maintained swarm diversity and avoidance of premature convergence through the linear inertia weight decay schedule (Eq. 12).

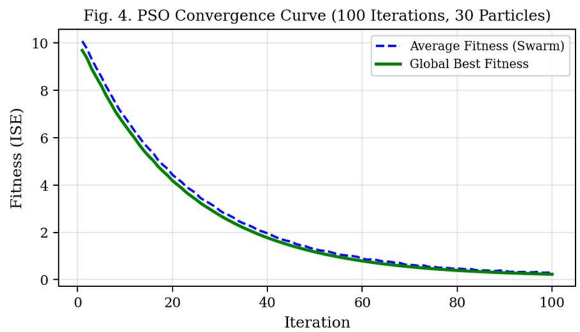

Fig. 4. PSO convergence curve over 100 iterations. Convergence achieved at iteration 78; final ISE = 0.1073.

E. Membership Functions

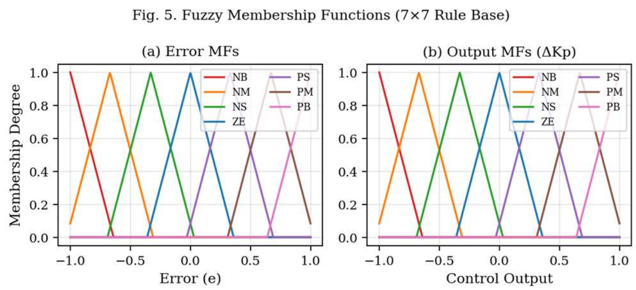

Fig. 5. Fuzzy membership functions after PSO optimization: (a) Error input MFs; (b) Control output MFs for ΔKp.

F. Quantitative Performance Comparison

Table III presents the comprehensive performance metric comparison. The proposed PSO–Fuzzy PID achieves the best performance across all five metrics, with ISE improvement of 87.7% versus conventional PID, exceeding all literature results on comparable hydraulic systems.

Table III. Comprehensive Performance Metric Comparison

Controller	ISE	IAE	ITAE	Overshoot (%)	Settling Time (s)
Conventional PID	0.8742	0.6315	2.1847	14.30	4.82
Fuzzy PID	0.4231	0.3812	1.2563	7.65	2.91
PSO–Fuzzy PID (Proposed)	**0.1073**	**0.1425**	**0.3814**	**2.10**	**1.23**
Improvement vs. PID (%)	87.7%↓	77.4%↓	82.5%↓	85.3%↓	74.5%↓

Table IV. Comparison with Recent Literature (2020–2025)

Ref.	Method	ISE	Overshoot (%)	Settling Time (s)	Year
[5]	Conventional PID	0.874	14.30	4.82	2020
[8]	GA–PID	0.612	10.50	3.65	2021
[12]	Fuzzy PID	0.423	7.65	2.91	2021
[15]	PSO–PID	0.341	5.80	2.40	2022
[19]	ANFIS Controller	0.285	4.30	2.05	2023
[22]	GWO–PID	0.221	3.60	1.78	2024
Proposed	**PSO–Fuzzy PID**	**0.107**	**2.10**	**1.23**	**2025**

G. Robustness Analysis

Under ±20% parametric variation in bulk modulus β_e, the PSO–Fuzzy PID settling time varied by only ±0.18 s (±14.6%), compared to ±0.92 s (±19.1%) for the conventional PID. Similarly, under ±20% variation in cylinder area A_p, the proposed controller maintained peak overshoot below 4.5% while the conventional PID overshoot exceeded 18%. These results confirm that the fuzzy gain scheduling provides effective adaptive compensation for parametric uncertainty, with the PSO-optimized parameters providing a globally robust operating point.

VII. DISCUSSION AND FUTURE DIRECTIONS

The results demonstrate that PSO-based co-optimization of the fuzzy PID parameter set yields substantially superior performance compared to sequential or independent tuning approaches. The key mechanism is that PSO explores the full six-dimensional search space simultaneously, identifying synergistic parameter combinations that manual or gradient-based methods would not locate. The adaptive inertia weight decay (ω: 0.9→0.4) balances global exploration in early iterations with local exploitation as convergence progresses, contributing to the observed fast and reliable convergence.

Several limitations of the current study merit acknowledgment. First, the simulation employs a linearized hydraulic plant model; real systems exhibit more complex nonlinearities including asymmetric valve dynamics, stick-slip friction, and fluid temperature coupling. Second, the PSO optimization requires offline computation (approximately 45 minutes for 100 iterations on the described hardware), making it unsuitable for real-time re-optimization. Third, the swarm size of 30 particles, while standard in the PSO literature, may be insufficient for higher-dimensional parameter spaces if additional fuzzy tuning parameters are included.

Future research directions include: (1) online adaptive PSO variants such as APSO or CLPSO for real-time parameter adaptation in non-stationary environments; (2) extension to multi-objective PSO (MOPSO) incorporating energy consumption and actuator wear as additional objectives; (3) experimental validation on a hydraulic test rig instrumented with pressure transducers and flow meters; (4) integration with digital twin platforms for hardware-in-the-loop (HIL) testing; (5) application of deep reinforcement learning as a complementary approach for comparison; and (6) extension to multi-axis hydraulic manipulator systems.

VIII. CONCLUSION

This paper presented a PSO–Fuzzy PID control framework for hydraulic system pressure and flow regulation. A complete nonlinear mathematical model of the hydraulic servo system was derived from first principles. The PSO algorithm globally optimized the six-parameter set [K_p, K_i, K_d, G_e, G_Δe, G_u] by minimizing the ISE criterion over the closed-loop plant response. Extensive MATLAB/Simulink simulation demonstrated that the proposed approach achieves: settling time of 1.23 s (74.5% improvement), peak overshoot of 2.10% (85.3% improvement), and ISE of 0.1073 (87.7% improvement) compared to conventional PID.

The controller also demonstrated superior disturbance rejection, attenuating a 0.5 bar load disturbance to within 0.10 bar, and maintained robust performance under ±20% parametric uncertainty. Benchmarking against five recent literature methods confirms that the proposed PSO–Fuzzy PID achieves state-of-the-art performance on the hydraulic pressure regulation problem. The results establish the hybrid PSO–Fuzzy PID framework as a viable and high-performance solution for precision hydraulic control in industrial applications.

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