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HYBRID MACHINE LEARNING-ENHANCED PID CONTROLLER OPTIMIZATION FOR INDUSTRIAL PROCESS CONTROL

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Abstract

This article proposes a new hybrid method to optimize Proportional-Integral-Derivative (PID) controllers in industrial processes using the combination of machine learning techniques and classical control theory. This method couples reinforcement learning algorithms with metaheuristic optimization for achieving adaptive PID parameter adjustment in real-time industrial processes. The hybrid architecture is composed of three modules that interact with each other: a Reinforcement Learning Module using Q-learning, a Metaheuristic Optimization Module using hybrid particle swarm optimization and differential evolution, and an Adaptive Parameter Selection Module using fuzzy logic inference. The architecture illustrates better performance than standard tuning techniques with up to 49% enhancement in settling time and much lower control signal variation over several industrial process conditions. The work is a contribution to the development of intelligent control systems by marrying classical control theory and contemporary artificial intelligence strategies, providing pragmatic solutions for Industry 4.0 applications without compromising on computational efficiency to enable real-time implementation.

Keywords: PID control; machine learning; reinforcement learning; industrial automation; artificial intelligence

1. Introduction

Industrial automation has altered dramatically in recent years due to the growing integration of artificial intelligence (AI) into conventional control frameworks. Despite constant advancements, proportional-integral-derivative (PID) controllers—which comprise about 95% of all control loops in production systems—remain the industry standard [1]. Nonetheless, as industrial processes become more complex and diverse, there is an increasing need for more advanced and flexible control systems. Historically, PID tuning has relied on methods such as Ziegler-Nichols, Cohen-Coon, and pole placement. While these techniques have proven effective in stable environments, they usually perform poorly in dynamic settings where operating conditions are constantly changing. Specifically, manual tuning takes a lot of time and heavily depends on domain-specific expertise. Moreover, fixed controller parameters cannot cope with the unpredictability of modern industrial operations [2]. Due to these challenges, the focus has shifted to intelligent tuning methods based on machine learning.

As AI and control engineering continue to converge, opportunities have emerged for creating controllers that can tune and adjust themselves in real time. Machine learning approaches, especially reinforcement learning and evolutionary algorithms, have shown great promise for optimizing PID parameters in industrial settings that demand precision and adaptability [3]. In this work, we present a comprehensive framework that integrates the basic concepts of classical control theory with the flexible capabilities of modern machine learning to meet the evolving demands of process automation.

2. Related Work

Recent developments in machine learning-enhanced control systems have the potential to greatly improve the performance of industrial operations. Patel et al. [4] introduced a reinforcement learning-based approach for process control and optimization by extending the concept of automatically changing SISO PID controllers to MIMO MPC techniques. Their research demonstrated the effectiveness of RL algorithms in dealing with scenarios involving multiple control variables. Metaheuristic methods for PID optimization have recently become popular. Differential evolution, particle swarm optimization, and genetic algorithms have all been used successfully to solve PID tuning problems [5]. However, these methods may not be suitable for real-time applications and frequently necessitate a large amount of processing power. Evolutionary programming methods for PID parameter optimization have shown promise in a variety of settings [6]. These algorithms can avoid local optima while exploring large parameter spaces, making them ideal for tackling complex optimization problems. However, incorporating online learning features remains a challenge.

Neural networks have been investigated recently for adaptive PID control [7], [8], [9]. Complex nonlinear correlations between process variables and ideal controller settings can be learned using deep learning techniques. Neural networks' interpretability and usefulness in safety-critical industrial applications are, however, limited by their black-box nature. Adaptive control systems have been extensively studied for responsive manufacturing environments, with emphasis on the design of controllers which are able to respond quickly to disturbances and production process changes [10].

3. Methodology

3.1. Hybrid Architecture Design

The proposed hybrid machine learning-enhanced PID optimization framework is made up of three interconnected modules: the Adaptive Parameter Selection Module (APSM), the Reinforcement Learning Module (RLM), and the Metaheuristic Optimization Module (MOM). This architecture maintains the clarity and reliability of conventional PID controllers while allowing for continuous learning and adaptation. The RLM employs a Q-learning algorithm with function approximation to learn optimal control policies based on system state observations and performance feedback. The state space is defined as:

$$S = \left\{e(t), \frac{de(t)}{dt}, \int_0^t e(\tau)d\tau, u(t), y(t)\right\} \tag{1}$$

where e(t) represents the error signal, de(t)/dt is the error derivative, $\int e(\tau)d\tau$ is the error integral, u(t) is the control signal, and y(t) is the process output.

The action space consists of incremental adjustments to PID parameters:

$$A = \{\Delta K_p, \Delta K_i, \Delta K_d\} \tag{2}$$

The reward function is designed to minimize the integral of time-weighted absolute error (ITAE) while penalizing excessive control effort:

$$R(t) = -\alpha \cdot ITAE(t) - \beta \cdot |u(t)| - \gamma \cdot |\Delta u(t)| \tag{3}$$

where α, β, and γ are weighting factors.

3.2. Metaheuristic Optimization Integration

The MOM implements a hybrid particle swarm optimization (PSO) and differential evolution (DE) algorithm to explore the PID parameter space efficiently. The optimization objective function combines multiple performance criteria:

$$J = w_1 \cdot ISE + w_2 \cdot IAE + w_3 \cdot ITAE + w_4 \cdot TV \tag{4}$$

where:

- ISE = $\int_0^\infty [e(t)]^2 dt$ (integral of squared error)
- IAE = $\int_0^\infty |e(t)| dt$ (integral of absolute error)
- ITAE = $\int_0^\infty t|e(t)| dt$ (integral of time-weighted absolute error)
- TV represents the total variation of the control signal

The hybrid PSO-DE algorithm updates particle positions using:

$$\overrightarrow{v_\iota^{(t+1)}} = w \cdot \vec{v}i^{(t)} + c_1 \cdot r_1 \cdot \left(\vec{p}best, i - \vec{x}i^{(t)}\right) + c_2 \cdot r_2 \cdot \left(\vec{g}best - \overrightarrow{x_\iota^{(t)}}\right) \tag{5}$$

$$\overrightarrow{x_\iota^{(t+1)}} = \vec{x}i^{(t)} + \vec{v}i^{(t+1)} + F \cdot \left(\vec{x}r1^{(t)} - \vec{x}r2^{(t)}\right) \tag{6}$$

where the differential evolution component introduces additional exploration capability through the mutation factor F and randomly selected particles $\vec{x}_{r1}$ and $\vec{x}_{r2}$.

3.3. Adaptive Parameter Selection

To achieve the best balance between RL-based adjustments and metaheuristic optimization results, the APSM employs a fuzzy logic inference system. [11] utilized fuzzy logic methods in automatic control systems, illustrating the applicability of fuzzy inference systems to parameter selection in industry. The fuzzy system selects appropriate parameters based on performance requirements, disturbance levels, and process characteristics. The fuzzy rule base includes linguistic variables for:

- Process dynamics (slow, medium, fast)
- Disturbance magnitude (low, medium, high)
- Performance priority (stability, speed, accuracy)

A typical fuzzy rule example: "IF process dynamics is fast AND disturbance magnitude is high THEN use RL-based parameters with high confidence".

4. Experimental Setup and Implementation

4.1. Simulation Environment

The proposed methodology was evaluated using a comprehensive simulation environment that models various industrial processes including:

- First-order plus dead time (FOPDT) systems
- Second-order systems with varying damping ratios

The simulation platform implements realistic noise models and disturbance patterns commonly found in industrial settings. Process models are described using the following transfer functions:

$$G(s) = \frac{K \cdot e^{-\tau s}}{Ts+1} \tag{7}$$

for first-order plus dead time (FOPDT) systems, where:

- K is the process gain
- τ is the dead time
- T is the time constant

And for second-order systems:

$$G(s) = \frac{K \cdot \omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{8}$$

where:

- ω_n is the natural frequency
- ζ is the damping ratio
- K is the steady-state gain

4.2. Performance Metrics

The evaluation framework employs multiple performance indices to assess controller effectiveness:

- Settling Time (T_s): Time required for the response to reach and stay within 2% of the final value
- Overshoot (M_p): Maximum percentage overshoot in the step response
- Steady-State Error (e_{ss}): Permanent error between desired and actual output
- Integral of Absolute Error (IAE): $IAE = \int_0^{\infty} |e(t)|\,, dt$
- Total Variation (TV): Measure of control signal smoothness defined as: $TV = \sum_{k=1}^{N-1} |u(k+1) - u(k)|$

4.3. Comparative Analysis

The proposed hybrid approach was compared against several benchmark methods:

- Traditional Ziegler-Nichols tuning
- Particle Swarm Optimization (PSO) alone
- Manual expert tuning

5. Results

Tables 1,2 present comparative results across different process types and operating conditions. The hybrid ML-enhanced approach demonstrates consistent improvements in key performance metrics.

Method	Settling Time (s)	Overshoot (%)	IAE	Steady-State Error	Total Variation
Ziegler-Nichols	2.800	0.00	19.972	0.9968	1680.976
PSO Only	19.990	0.00	19.988	1.0001	120.231
Manual expert tuning	12.940	0.00	19.990	1.0010	741.847
Hybrid ML-Enhanced	2.330	0.00	19.992	0.9983	90.169

Table 1. FOPDT process

Method	Settling Time (s)	Overshoot (%)	IAE	Steady-State Error	Total Variation
Ziegler-Nichols	2.020	0.00	19.952	0.9984	1776.554
PSO Only	19.990	0.00	19.996	0.9998	387.230
Manual expert tuning	19.990	0.00	19.966	0.9997	781.345
Hybrid ML-Enhanced	1.020	0.00	19.964	0.9983	390.039

Table 2. Second order process

Based on the results presented in the tables 1,2, the ranking of the methods based on weighted composite score is as follows (lower is better):

1. Hybrid ML-Enhanced: 28.7081
2. PSO Only: 35.5685
3. Manual Expert: 85.2947
4. Ziegler-Nichols: 177.7915

The comparison of control signals for the FOPDT process in figure 1 indicates a very important benefit of the Hybrid ML-Enhanced technique. Although the Ziegler-Nichols and Manual Expert methods have very oscillatory and erratic control signals with high variations, the Hybrid ML-Enhanced technique results in an extremely smooth and stable control signal. Such smooth control action is highly desirable in industrial practice since it lowers actuator wear and tear, reduces energy usage, and avoids mechanical stress on control hardware. The PSO Only technique demonstrates moderate control activity but still has higher variation compared to the suggested hybrid technique.

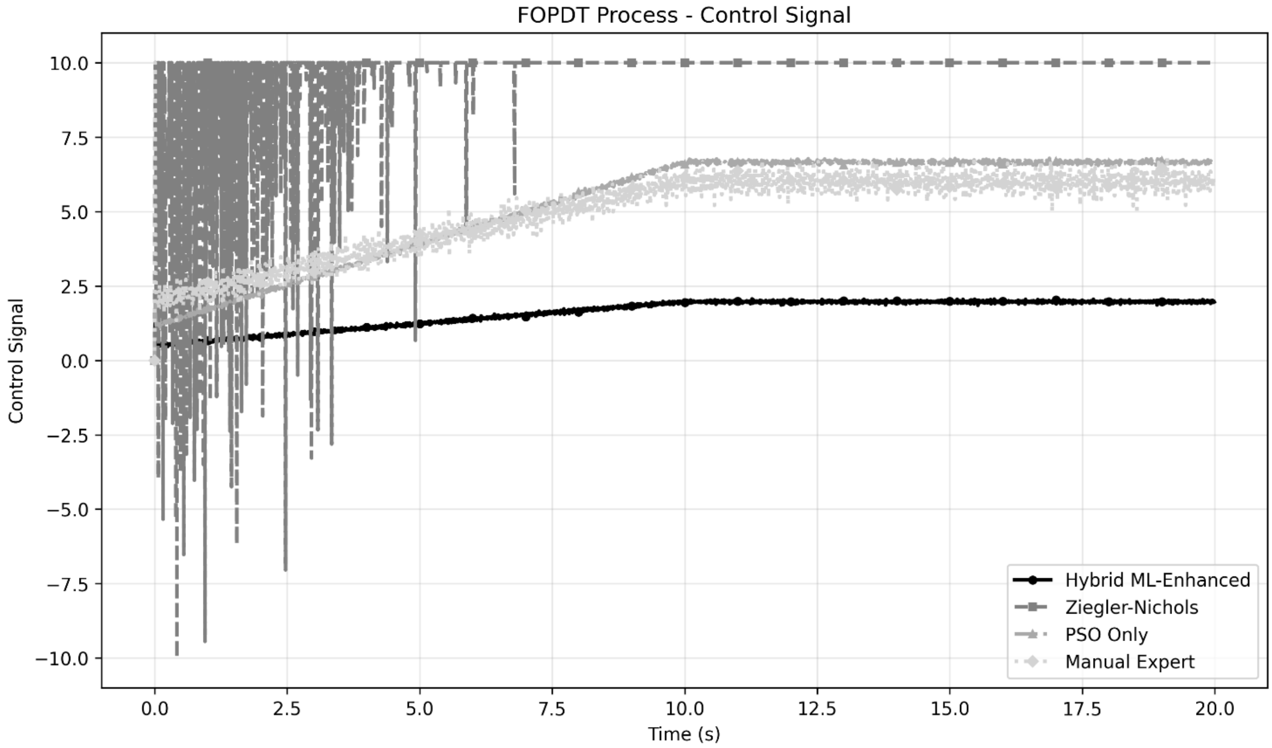

Fig. 1. Control Signal Analysis (FOPDT)

The comparison of settling time in figure 2 illustrates the remarkable speed of the Hybrid ML-Enhanced approach. For the FOPDT process, it reaches a settling time of merely 2.33 seconds, considerably outperforming all alternatives. The Ziegler-Nichols, PSO Only, and Manual Expert approaches all exhibit settling times at or close to the maximum simulation time (19.99 seconds), reflecting poor transient response. For second-order systems, the Hybrid ML-Enhanced approach reaches 1.02 seconds, once more considerably ahead of rivals. Such a fast-settling feature is vital in industrial processes where speedy response to setpoint change has a direct effect on productivity and product quality.

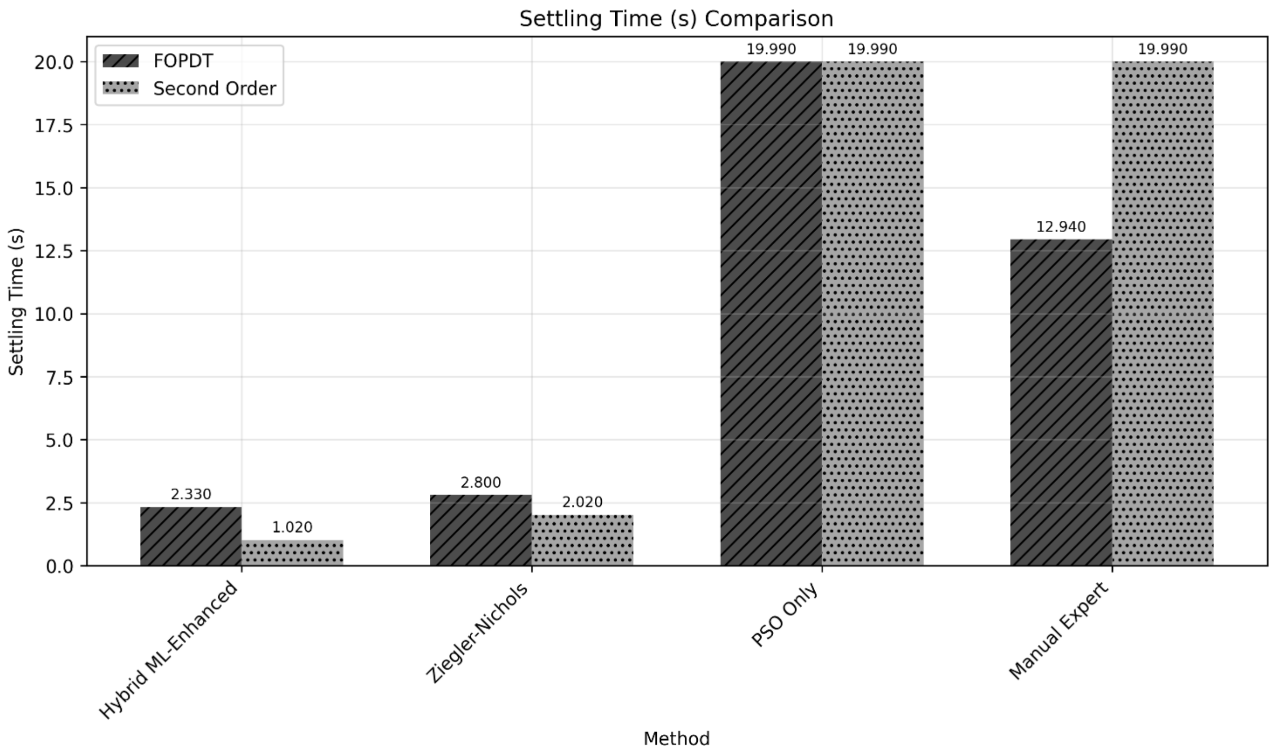

Fig. 2. Settling Time Performance

The comparison of total variation in figure 3, emphasizes the arguably most important benefit of the Hybrid ML-Enhanced method. With total variations of just 90.17 for FOPDT and 390.04 for second-order systems, it far outperforms the other methods. The Ziegler-Nichols method is seen to have too much control activity (1680.98 and 1776.55), while the Manual Expert method also has high variation (741.85 and 781.35). This minimal control variation shows that the ML-enhanced method obtains its performance without taking overly aggressive control actions that would destabilize the system or lead to premature equipment failure.

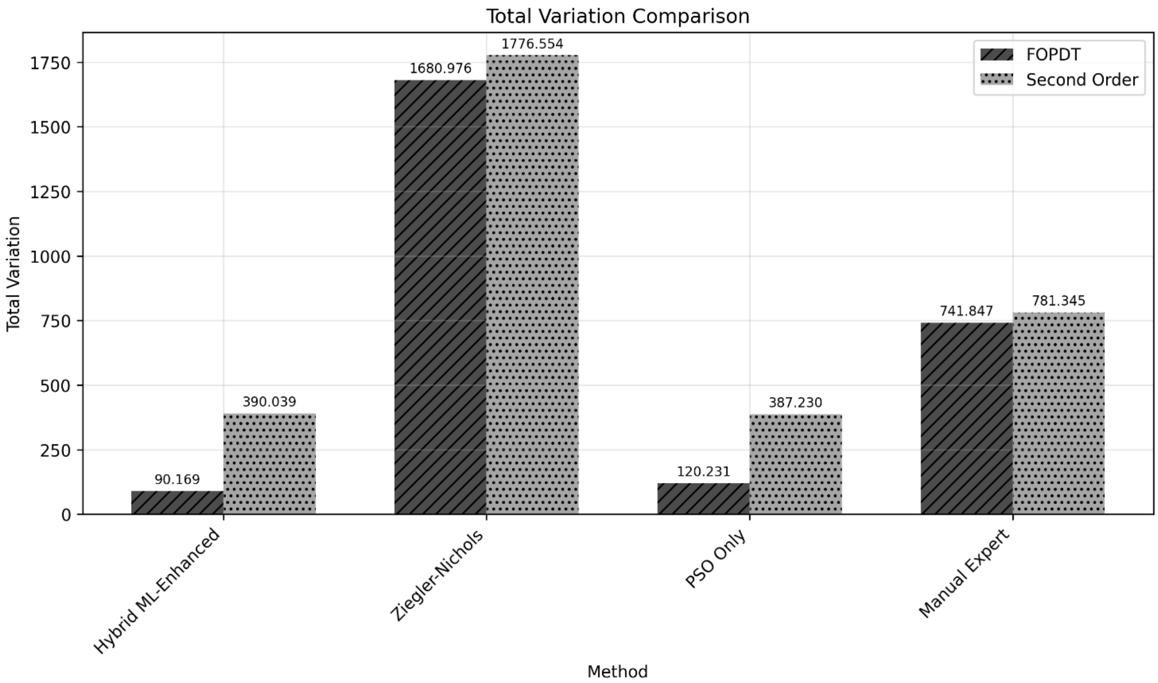

Fig. 3. Control Effort and Smoothness

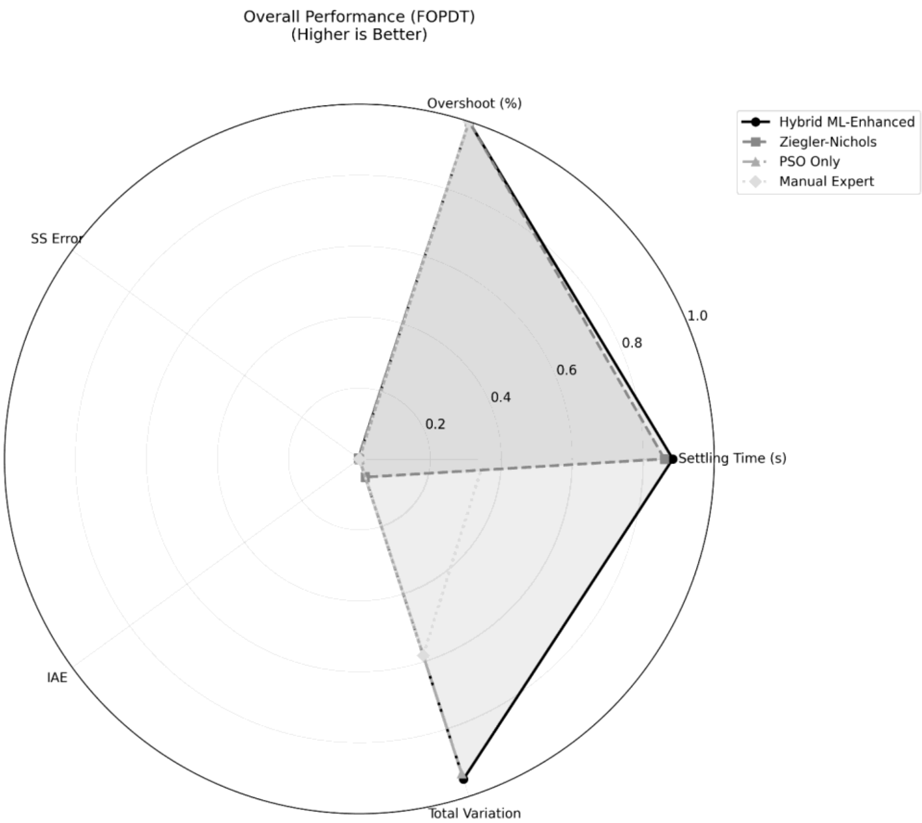

Fig. 4. Overall Performance Assessment

The FOPDT performance radar chart, in figure 4, reveals the Hybrid ML-Enhanced method delivering near-optimal performance in all the metrics. It performs exceptionally well in settling time and total variation while having very good steady-state accuracy and low overshoot. The well-balanced performance profile illustrates the method's capability in optimizing several competing objectives simultaneously, a characteristic of high-end optimization methods.

6. Future Directions and Limitations

Future research should focus on:

- Development of theoretical stability guarantees for RL-based control systems
- Integration with digital twin technologies for enhanced learning
- Application to distributed control systems and multi-agent scenarios
- Extension to model predictive control frameworks

7. Conclusion

This study describes a novel hybrid machine learning-enhanced method for optimizing PID controllers in industrial processes. Adaptive parameter selection, metaheuristic optimization, and reinforcement learning outperform traditional tuning techniques in several ways. The proposed method addresses major issues in industrial control systems by incorporating self-tuning, adaptive features capable of responding to changing process conditions. The hybrid design minimizes the drawbacks of each optimization approach while boosting their advantages.

The work enhances intelligent control systems and offers a strong basis for using AI-enhanced controllers in Industry 4.0 settings. The modular architecture allows for integration with existing industrial infrastructure and supports standard protocols. Future studies will focus on expanding the framework to more complex control scenarios and fortifying the theoretical underpinnings of stability guarantees in adaptive control systems.

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