Applications of Machine Learning-Enhanced PID Control Across Industrial Domains: A Comprehensive Review

Manoj D. Khediya[1] Sejal Dilipbhai Patel[2]
[1]Assistant Professor [2]Lecturer
[1,2]Department of Instrumentation and Control Engineering
[1]Vishwakarma Government Engineering College, Chandkheda, Gujarat Technological University, India
[2]Government Polytechnic, Gandhinagar, Gujarat Technological University, India

Abstract — Proportional–Integral–Derivative (PID) controllers are a cornerstone of industrial control systems due to their simplicity and effectiveness. However, traditional PID controllers face challenges such as manual parameter tuning, lack of adaptability, and inefficiency in nonlinear or complex environments. In recent years, machine learning (ML) has emerged as a powerful tool to overcome these limitations, enabling adaptive, intelligent control mechanisms. This paper presents a comprehensive review of the integration of machine learning with PID controllers across various industries. Applications in robotics, automotive systems, process industries, aerospace, biomedical engineering, and energy systems are explored in detail. Machine learning techniques such as reinforcement learning, support vector machines, and evolutionary algorithms are discussed in terms of their role in tuning, fault detection, and optimization. Furthermore, we identify the key challenges and propose future research directions for developing robust, explainable, and real-time ML-PID systems.

Keywords: PID Control, Machine Learning, Adaptive Control, Intelligent Systems, Industrial Automation

I. Introduction

Proportional–Integral–Derivative (PID) controllers remain among the most commonly used control strategies in industrial automation and robotics. Since their inception in the early 20th century, PID controllers have seen widespread adoption due to their straightforward implementation and ease of understanding[1]. However, traditional PID controllers suffer from notable limitations — particularly in dealing with system nonlinearities, disturbances, and dynamic environments — as they rely heavily on manual or heuristic parameter tuning[2].

In recent years, the convergence of control engineering with artificial intelligence has led to a new paradigm: the integration of machine learning techniques into PID control frameworks. By leveraging data-driven models, systems can learn optimal control parameters, detect anomalies, and compensate for nonlinear dynamics in real time[3]. This fusion has opened new possibilities in achieving intelligent, adaptive, and self-tuning control systems applicable across a broad range of industries[4]. This paper aims to provide a consolidated and structured review of machine learning-enhanced PID control systems with a cross-industry perspective. We explored published work categorizing applications by domain, summarizing employed ML techniques, and highlighting the performance improvements achieved. The paper also discusses technical challenges and suggests future research directions.

II. Methodology and Classification Framework

To develop this review, we gathered and analysed literature from various journal and conference proceedings. The papers were filtered based on keywords such as "PID with machine learning," "adaptive PID," "intelligent control," and "ML in industrial control." Studies were categorized into six primary industrial sectors:

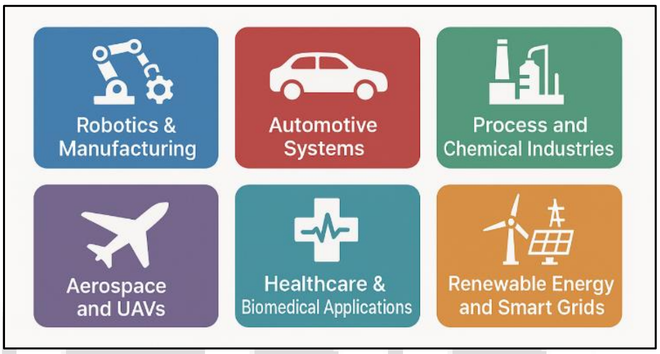

Fig. 1: Primary Industrial Sectors

Each domain was further analysed by:

– Type of ML algorithm used
– Control objective (e.g., tuning, compensation, robustness)
– Real-time implementation feasibility
– Reported benefits and limitations

This framework ensures a structured evaluation and helps identify cross-domain trends and gaps.

III. Industry Applications of ML-Enhanced PID Control

This section explores how the integration of machine learning into PID control has been applied across six key industries. Each subsection highlights the control challenges, ML methods used, and reported benefits or results.

A. *Robotics and Manufacturing*

Category	Details
Application Areas	• Robotic arm motion control • Autonomous navigation • Industrial automation and CNC machining
Challenges	• Nonlinear joint dynamics • Real-time adaptation to payload or environment changes • High precision and repeatability requirements
ML Techniques Used	• K-Nearest Neighbors (KNN): For online PID parameter estimation based on sensor feedback [5]

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	• Deep Reinforcement Learning (DRL): Used in training robotic agents for dynamic environments[6]

Example:
This article of Yuriy Kondratenko et al. explores how machine learning enhances real-time robotic sensor and control systems, boosting efficiency in tasks such as object recognition, obstacle avoidance, and adaptive gripping.

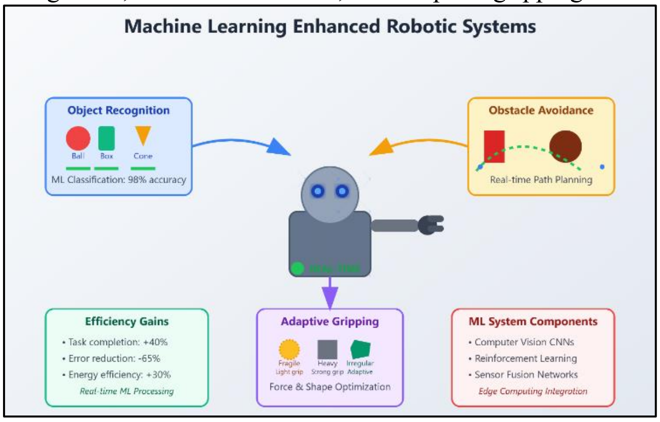

Fig. 2: ML in the field of Robotics

It showcases various robotic setup including slip-sensing adaptive robots, magnetically guided mobile robots, and intelligent manipulators in dynamic environments using fuzzy logic, neuro-fuzzy control, and statistical learning to improve precision and decision speed. By employing tools like Swift and CreateML, and comparing architectures like YOLOv2 and ResNet34, the researchers achieved high accuracy in object classification with streamlined training. These innovations point to smarter, faster robotic systems well-suited for uncertain and ever-changing conditions. Work on regression and SVM may enhance the performance as well in future.[7].

B. Automotive Systems

Category	Details
Application Areas	• Cruise control and lane-keeping systems • Engine and drivetrain regulation • Electric vehicle battery management
Challenges	• System nonlinearity due to varying terrains and loads • Real-time adaptation to driver behavior or road conditions
ML Techniques Used	• Neural Networks: Predict optimal PID gains for throttle/brake modulation [8] • Reinforcement Learning: Adapt control strategy based on environmental feedback [9] • Bayesian Optimization[10]: Tune PID gains under uncertainty

Example:
In adaptive cruise control, deep Q-learning has been used to tune PID parameters dynamically, reducing response time and improving vehicle stability on varied road surfaces.

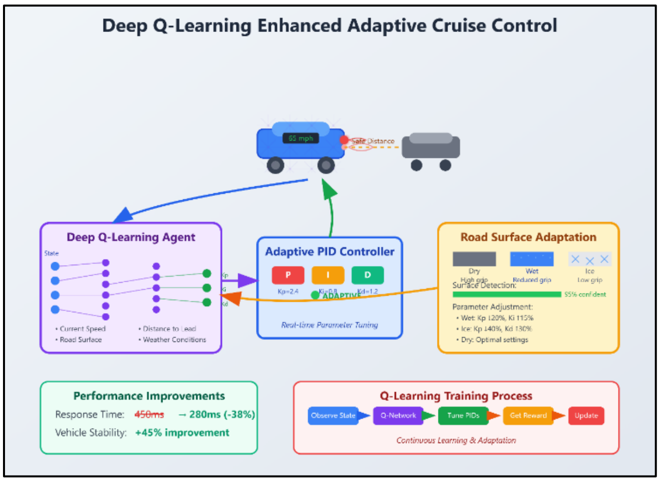

Fig. 3: Adaptive cruise control hybrid algorithm

There is a hybrid control algorithm—Continuous Interval Type-2 Fuzzy Q-Learning—that significantly enhances trajectory tracking for autonomous vehicles operating under uncertain conditions like slippery roads or variable terrain. By combining fuzzy logic's capacity for managing uncertainty with Q-learning's real-time adaptability, the method delivers superior tracking accuracy, decision-making stability, and learning efficiency compared to traditional controllers like PID[11]

C. Process and Chemical Industries

Category	Details
Application Areas	• Temperature, pressure, and flow control • Reactor and distillation column automation • Quality assurance in continuous production
Challenges	• Multivariable and nonlinear systems • Slow system response and time delays
ML Techniques Used	• Support Vector Regression (SVR): For error prediction and correction[12] • Genetic Algorithms (GA) & Particle Swarm Optimization (PSO): For PID gain optimization[13] • Anomaly Detection Models: Using One-Class SVM for fault detection[14], [15]

Example:
In a case study of a distillation column, PID parameters were optimized using PSO and SVR,

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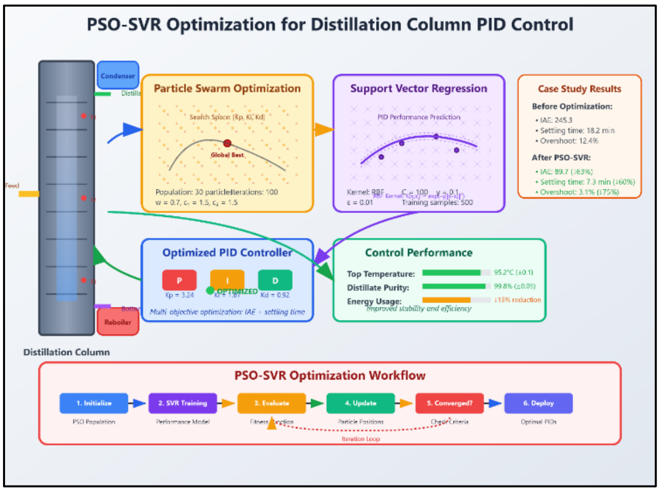

Fig. 4: Distillation Column Control using PSO-SVR leading to 40% faster convergence and more stable temperature control[16], [17].

D. *Aerospace and UAVs*

Category	Details
Application Areas	• Attitude and altitude control • Trajectory stabilization for UAVs • Autonomous flight in harsh environments
Challenges	• External disturbances like wind • Rapid system dynamics requiring low-latency control • Limited onboard computational capacity
ML Techniques Used	• Q-learning & Dueling DQNs: For flight path correction [18] • Recursive Least Squares (RLS): For parameter estimation[19] • LSTM Networks: For state prediction in trajectory tracking[20]

Example:
Kucherov et al. (2021) implemented ML-enhanced PID for quadrotor lateral control.

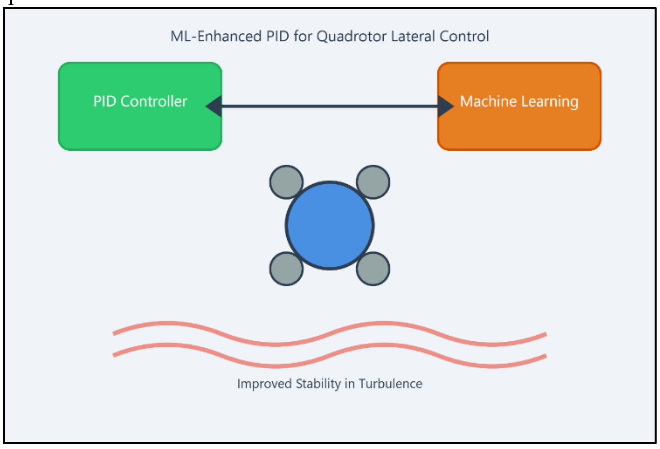

Fig. 5: ML plus PID based UAV/Drone Control

The system used online learning to adjust PID parameters based on current motion, improving stability during turbulence[21].

E. *Healthcare and Biomedical Engineering*

Category	Details
Application Areas	• Robotic surgery • Drug infusion control • Smart prosthetics
Challenges	• Patient-specific variability • Safety and explainability • Real-time control in delicate environments
ML Techniques Used	• Adaptive Fuzzy-PID: Using supervised learning • Neural Networks: For interpreting biological signals • Reinforcement Learning: In closed-loop insulin delivery systems

Example:

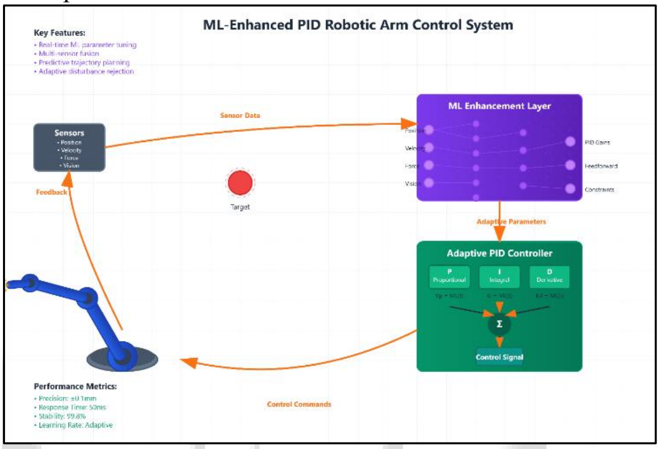

Fig. 6: Robotic Arm - ML plus PID Based mechanism

Fall et al. (2015) proposed a wireless, intuitive PID-based robotic arm controlled by ML-enhanced models, enabling people with upper body disabilities to perform complex tasks.

F. *Renewable Energy and Smart Grids*

Category	Details
Application Areas	• Wind turbine speed regulation • Load frequency control in smart grids • Solar tracking systems
Challenges	• Stochastic nature of renewable sources • Large-scale system complexity • Need for predictive and adaptive control
ML Techniques Used	• Genetic Algorithms & Gradient Descent: For PID tuning • LSTM Models: To forecast energy demand • Reinforcement Learning: For frequency control in microgrids

Example:
In wind energy systems, ML-based PID tuning reduced overshoot and oscillations in turbine shaft speed by over 30%, as reported in articles. [22], [23].

IV. COMPARATIVE ANALYSIS AND DISCUSSION

In this section, we analyse and compare how machine learning (ML)-enhanced PID control performs across industries, evaluate the suitability of different ML algorithms, and highlight patterns and limitations identified in recent literature.

A. *Comparison of ML Techniques Used in PID Optimization*

ML Technique	Strengths	Limitations	Common Application Domains
KNN / SVM / SVR	Interpretable, good for small datasets	Not ideal for real-time systems, sensitive to noise	Robotics, process industry
Neural Networks (NN)	Handles nonlinearities, generalizes well	Opaque decision process, long training time	Automotive, biomedical
Reinforcement Learning	Adaptive, good for dynamic environments	Sample inefficiency, complex reward design	UAVs, smart grids, robotic navigation
Genetic Algorithms (GA)	Global optimization capability, derivative-free	High computational cost, slow convergence	Process control, renewable energy
Particle Swarm Optimization (PSO)	Fast convergence in low-dim settings	May get stuck in local minima	Temperature/flow control systems
Fuzzy Logic + ML	Tolerant to ambiguity, interpretable	Rule design can be complex	Healthcare, fuzzy-PID applications

B. *Observed Performance Gains*

Based on reviewed literature across domains:

- Improved Accuracy: ML-PID systems typically reduce steady-state error and overshoot by 20–50% compared to classical PID.
- Faster Response Time: Reinforcement learning and PSO often improve settling time significantly, especially in systems with variable load or dynamics.
- Robustness to Disturbances: ML-based compensation methods enhance robustness, especially in uncertain or nonlinear environments like UAV control and renewable energy systems.

C. *Real-Time Feasibility*

Industry	Real-Time ML-PID Use	Main Bottleneck
Robotics	✅	Sensor noise, online retraining
Automotive	✅ (in prototypes)	Model complexity, safety certification
Process industry	⚠️ Limited	Slow processes allow for offline tuning
Aerospace / UAVs	✅	Real-time adaptation required
Healthcare	⚠️ Emerging	Ethical & explainability concerns
Renewable energy	✅	Prediction reliability

Note: ✅ = Applied in real-time, ⚠️ = Partial or experimental use

D. *Cross-Industry Insights*

1) Customization is Crucial: ML techniques need to be tailored to the dynamics of specific applications. For instance, Q-learning works well in UAVs but may not suit chemical plants due to data and latency constraints.
2) Hybrid Control Systems Are Promising: Combining fuzzy logic, PID, and ML offers a balance of interpretability and performance.
3) Explainability Gap: Most ML-enhanced systems lack transparency, which remains a critical barrier in sectors like healthcare and autonomous driving.
4) Training Data Quality: The performance of data-driven PID systems heavily depends on training data. Industries with sparse or imbalanced datasets (e.g., safety-critical aerospace anomalies) face challenges in model reliability.
5) Automation vs. Reliability Trade-Off: While ML offers automation in tuning and optimization, the trade-off in verification and validation slows down adoption in regulated industries.

E. *Challenges Revisited*

As detailed in Section 3 and the reference papers:

- Training Data Collection: Real-time systems rarely have sufficient abnormal samples for robust model training.
- Training Time: Deep models require hours or days to train, making them unsuitable for online tuning unless pre-trained.
- Model Interpretability: Unlike PID equations, ML models (especially deep learning) often act as "black boxes," which is problematic in critical applications.

V. RESEARCH GAPS AND FUTURE SCOPE

Despite the growing body of work on machine learning (ML)-enhanced PID control systems, several gaps persist that hinder widespread industrial adoption. This section outlines the major open problems and presents promising research directions to guide future investigations.

A. *Identified Research Gaps*

1) *Lack of Standardized Benchmarks*

Currently, research in ML-based PID tuning is fragmented, with different authors using different datasets, performance metrics, and validation environments. This lack of

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standardization makes it difficult to compare techniques or replicate results across domains.

2) Real-Time Constraints and Computational Overheads

Many ML algorithms, especially deep learning and reinforcement learning, are computationally intensive and unsuitable for systems with strict latency requirements. While some workarounds exist (e.g., model compression or edge computing), real-time deployment remains limited in many sectors.

3) Insufficient Work on Explainability

Traditional PID controllers are mathematically transparent. In contrast, most ML models—especially deep neural networks—lack interpretability. This is a critical issue in safety-critical domains like aerospace, healthcare, and automotive systems, where understanding the control logic is essential for certification and trust.

4) Generalization Across Operating Conditions

ML models trained in one set of operating conditions often perform poorly when transferred to others. There is a need for domain adaptation and transfer learning techniques tailored for control systems.

5) Limited Public Datasets

There is a scarcity of open datasets simulating realistic control tasks (e.g., for drones, reactors, or robotic arms). The absence of shared data significantly slows progress and reproducibility in academic and industrial research.

B. Promising Future Research Directions

1) Development of Hybrid Models

Combining physics-informed models with machine learning (e.g., grey-box modeling) can harness the strengths of both paradigms—ensuring robustness and providing physical interpretability while benefiting from adaptive ML capabilities.

2) Edge-AI for Control Applications

Efforts should focus on deploying ML-enhanced PID controllers on edge devices (e.g., microcontrollers, FPGAs). This would enable real-time learning and decision-making without reliance on cloud-based infrastructure.

3) Explainable ML for PID Systems

Research into interpretable ML techniques—such as symbolic regression, attention mechanisms, and rule-based learning—should be encouraged to make ML-PID control systems more transparent and certifiable.

4) AutoML and Meta-Learning for PID Tuning

Automated machine learning (AutoML) frameworks can be adapted to automate the search for optimal PID tuning algorithms, architectures, and hyperparameters. Similarly, meta-learning may allow controllers to generalize learning across multiple tasks or machines.

5) Robustness under Uncertainty

Future work should aim to develop learning-based PID systems that explicitly account for uncertainty and disturbances. This includes probabilistic models and robust reinforcement learning techniques that can tolerate noise, sensor drift, or actuator faults.

6) Integration with Digital Twins

The use of digital twins—virtual replicas of physical systems—can allow safe training and validation of ML-based PID systems in simulated environments before deployment. This is particularly valuable in safety-critical or high-cost systems.

7) Cross-Disciplinary Collaboration

The success of intelligent PID control systems requires collaboration between control engineers, machine learning researchers, domain experts, and industry practitioners. Such cross-disciplinary work can accelerate the development of practical, reliable, and innovative solutions.

VI. Conclusion

The integration of machine learning (ML) with Proportional–Integral–Derivative (PID) control represents a significant advancement in control system engineering, offering the potential to overcome long-standing limitations such as manual tuning, poor adaptability, and sensitivity to nonlinearities. This paper reviewed the state of ML-enhanced PID control systems across a diverse range of industries, including robotics, automotive, chemical processing, aerospace, healthcare, and renewable energy systems.

Through detailed analysis, we observed that ML methods such as reinforcement learning, support vector machines, and evolutionary algorithms have been successfully employed to optimize PID tuning, enhance robustness, and compensate for nonlinear behaviors. These enhancements have led to notable performance improvements—such as reduced steady-state errors, faster response times, and greater resilience to disturbances—across multiple real-world applications.

However, the implementation of these hybrid systems is not without challenges. Issues like high training time, limited explainability, and the scarcity of real-time deployment solutions remain unresolved in many sectors. Furthermore, the lack of standardized evaluation benchmarks and openly available datasets hinders reproducibility and cross-domain comparisons.

To address these limitations, we identified several promising research directions. These include the development of hybrid and interpretable models, deployment on edge devices, use of AutoML for tuning, and integration with digital twins for safer testing environments. Emphasis on explainability and computational efficiency will be key to enabling the adoption of ML-enhanced PID controllers in critical and regulated industries.

In conclusion, while the integration of machine learning with PID control is still maturing, it presents a highly promising path forward for creating intelligent, adaptive, and self-tuning control systems. Continued interdisciplinary research, real-world testing, and development of reliable standards will be critical in translating these advancements from lab-scale demonstrations to industrial-wide solutions.

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