The Open European Journal of Engineering and Scientific Research (OEJESR)
المجلة الأوروبية المفتوحة للهندسة والبحث العلمي

The Open European Journal of Engineering and Scientific Research (OEJESR)
E-ISSN: 3062-3383
Volume 2, Issue1, 2026, Pages: 01-16
Journal homepage*:*
https://easdjournals.com/index.php/oejesr/index

AI-Guided Adaptive Control Framework for Nonlinear Systems Under Uncertainty

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Article history	**Received**: 12-10-2025	**Accepted**: 25-12-2026	**Published**: 06-01-2026

Abstract
This paper proposes an AI-guided adaptive control framework for nonlinear systems operating under external disturbances, measurement noise, and parametric uncertainties. Unlike conventional adaptive controllers that rely solely on instantaneous tracking error or predefined rule-based mechanisms, the proposed approach integrates artificial intelligence–based awareness to evaluate the dynamic condition of the system in real time. The AI module analyzes the tracking error behavior and system response patterns to generate adaptive signals that regulate the controller parameters in a smooth and bounded manner.
The adaptive control law is designed to preserve the simplicity and reliability of classical control structures while enhancing robustness and transient performance. A Lyapunov-based stability analysis is developed to guarantee boundedness of all closed-loop signals and asymptotic convergence of the tracking error. The effectiveness of the proposed AI-guided controller is validated through numerical simulations on representative nonlinear benchmark systems. Simulation results demonstrate improved settling time, reduced overshoot, enhanced disturbance rejection, and smoother control effort compared to conventional PID and rule-based adaptive controllers.
A novel entropy-based awareness metric is introduced to quantify system uncertainty and modulate adaptation intensity accordingly.

Keywords: AI-guided control; Adaptive control; Nonlinear systems; Lyapunov stability; Robust control; Performance enhancement.

إطار تحكم تكيفي موجّه بالذكاء الاصطناعي للأنظمة غير الخطية تحت ظروف عدم اليقين

لطفي ميلاد اشتيوي [1*]، أكرم سعيد نصر أنخيلة [2] ، منصور الديب [3]
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الملخص
تقترح هذه الورقة إطارًا للتحكم التكيفي موجّهًا بالذكاء الاصطناعي للأنظمة غير الخطية التي تعمل تحت تأثير الاضطرابات الخارجية، وضوضاء القياس، وعدم اليقين في المعلمات. وعلى عكس المتحكمات التكيفية التقليدية التي تعتمد فقط على خطأ التتبع اللحظي أو على آليات قائمة على قواعد محددة مسبقًا، فإن النهج المقترح يدمج وعيًا قائمًا على الذكاء الاصطناعي لتقييم الحالة الديناميكية للنظام في الزمن الحقيقي. يقوم مكوّن الذكاء الاصطناعي بتحليل سلوك خطأ التتبع وأنماط استجابة النظام لتوليد إشارات تكيفية تعمل على تنظيم معاملات المتحكم بطريقة سلسة ومقيدة.
تم تصميم قانون التحكم التكيفي بحيث يحافظ على بساطة وموثوقية هياكل التحكم الكلاسيكية، مع تعزيز المتانة وتحسين الأداء الانتقالي. كما تم تطوير تحليل للاستقرار بالاعتماد على ليابونوف لضمان بقاء جميع إشارات الحلقة المغلقة ضمن حدود محددة وتحقيق تقارب خطأ التتبع إلى الصفر مع الزمن. وقد تم التحقق من فعالية المتحكم المقترح الموجّه بالذكاء الاصطناعي من خلال محاكاة عددية على أنظمة غير خطية معيارية تمثيلية. وتُظهر نتائج المحاكاة تحسنًا في زمن الاستقرار، وتقليلًا في نسبة التجاوز، وتعزيزًا في مقاومة الاضطرابات، إضافة إلى سلاسة أكبر في إشارة التحكم مقارنةً بمتحكمات PID التقليدية والمتحكمات التكيفية القائمة على القواعد.
كما تم تقديم مقياس جديد قائم على الإنتروبيا (Entropy) لقياس درجة عدم اليقين في النظام وضبط شدة التكيف بناءً عليها.

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الكلمات المفتاحية : التحكم الموجّه بالذكاء الاصطناعي؛ التحكم التكيفي؛ الأنظمة غير الخطية؛ استقرار ليابونوف؛ التحكم المتين؛ تحسين الأداء.

1. Introduction

Adaptive control strategies have long played a central role in the regulation of nonlinear dynamic systems operating under uncertainty, external disturbances, and parameter variations. Classical control approaches, particularly proportional–integral–derivative (PID) controllers, remain widely adopted in industrial and engineering applications due to their simplicity, transparency, and ease of implementation. However, fixed-gain PID controllers often suffer from performance degradation when applied to nonlinear systems subjected to time-varying dynamics, modeling inaccuracies, and unknown disturbances.

To address these limitations, adaptive and intelligent control techniques have been extensively investigated. Conventional adaptive PID schemes typically adjust controller gains based on instantaneous tracking error, predefined adaptation laws, or heuristic tuning rules. While such methods improve flexibility compared to fixed-gain controllers, their performance remains sensitive to operating conditions, and their adaptation mechanisms often lack sufficient awareness of the underlying system uncertainty. As a result, excessive gain variation, oscillatory behavior, or slow convergence may occur, particularly in highly nonlinear or noisy environments.

In recent years, artificial intelligence (AI) techniques have emerged as powerful tools for enhancing control performance by enabling learning, pattern recognition, and data-driven decision-making. Neural networks, fuzzy logic systems, and reinforcement learning algorithms have been successfully integrated into control architectures to approximate unknown dynamics, tune controller parameters, or optimize performance objectives. Despite their advantages, fully AI-driven controllers may raise concerns related to stability guarantees, interpretability, and safe deployment, especially in safety-critical applications.

A promising alternative lies in hybrid control architectures, where AI components are employed as supervisory or assistive modules rather than direct control replacements. In such frameworks, classical controllers retain responsibility for real-time actuation, while AI-based mechanisms provide high-level adaptation, decision support, or performance enhancement. This hybrid philosophy preserves the robustness and reliability of conventional control structures while benefiting from the adaptability and learning capability of AI.

Motivated by these considerations, this paper introduces an AI-guided adaptive control framework for nonlinear systems operating under uncertainty. The proposed approach integrates an AI-based supervisory module with a classical adaptive control structure to regulate controller parameters in a bounded and smooth manner. Unlike conventional adaptive schemes that rely solely on tracking error signals, the proposed method incorporates additional system-awareness indicators to guide the adaptation process intelligently, thereby improving robustness and transient performance while avoiding excessive control effort.

The main contributions of this work can be summarized as follows:

A hybrid AI-guided adaptive control framework that enhances classical control structures without sacrificing stability or interpretability.

A bounded and safety-aware gain adaptation mechanism that prevents parameter drift and ensures smooth controller behavior.

A Lyapunov-based stability analysis guaranteeing boundedness of all closed-loop signals.

A comprehensive simulation study on nonlinear benchmark systems, demonstrating superior tracking performance and robustness compared to conventional PID and adaptive control methods.

The practical relevance of the proposed framework extends to numerous engineering domains where nonlinear systems operate under uncertainty. Potential application areas include:

Robotic Systems: Manipulators and mobile robots operating in unstructured environments with varying payloads and terrain conditions can benefit from the adaptive capability to maintain precise trajectory tracking despite unknown dynamics.

Autonomous Vehicles: Trajectory tracking and stability control under varying road conditions, wind disturbances, and sensor noise represent natural application scenarios where the entropy-based awareness can distinguish between transient maneuvers and genuine instability risks.

Electromechanical Systems: Precision motion control in CNC machines and industrial automation, where friction, backlash, and thermal effects introduce nonlinearities, can leverage the smooth adaptation mechanism to extend component lifetime while maintaining accuracy.

Aerospace Applications: Attitude and position control of unmanned aerial vehicles (UAVs) under atmospheric disturbances and parameter variations due to fuel consumption or payload changes align well with the framework’s robustness features.

Process Control: Chemical reactors and distillation columns with time-varying dynamics, unmeasured disturbances, and stringent safety constraints can benefit from the bounded adaptation and stability guarantees.

The lightweight neural network architecture (approximately 28 floating-point operations per step) makes the proposed controller suitable for implementation on standard industrial microcontrollers and embedded platforms, facilitating technology transfer from simulation to practical deployment.

The remainder of this paper is organized as follows. Section 2 reviews related work on adaptive and AI-assisted control strategies. Section 3 presents the proposed AI-guided adaptive control framework. Stability and safety considerations are discussed in Section 4. Section 5 describes the simulation setup and benchmark systems, followed by comparative performance evaluation and discussion in Sections 6 and 7, respectively. Finally, Section 8 concludes the paper and outlines directions for future research.

2. Related Work

Research on control of nonlinear systems has produced a wide spectrum of methodologies ranging from classical linear controllers to advanced adaptive and intelligent schemes. This section reviews the most relevant contributions related to classical PID control, adaptive control strategies, and AI-assisted control frameworks, with emphasis on identifying existing limitations and research gaps addressed by this work.

2.1 Classical and Adaptive PID Control

PID controllers remain the most widely used control structures in industrial practice due to their simplicity, robustness, and ease of tuning. Numerous studies have investigated PID-based solutions for nonlinear systems by employing gain scheduling, heuristic tuning rules, and model-based linearization techniques. While these approaches improve performance over fixed-gain PID controllers, their effectiveness strongly depends on accurate system modeling and operating point selection [1], [8]

Adaptive PID control methods have been proposed to address parameter variations and environmental uncertainties. Such methods typically rely on error-driven adaptation laws, gradient-based tuning, or rule-based mechanisms to update controller gains online. Although adaptive PID controllers provide improved flexibility, many reported approaches suffer from excessive gain oscillations, slow convergence, or sensitivity to measurement noise, particularly in highly nonlinear or time-varying systems. Moreover, stability guarantees are often established under restrictive assumptions, limiting their practical applicability [3], [6].

2.2 Intelligent and Fuzzy-Based Control Approaches

To overcome the limitations of classical adaptive schemes, intelligent control techniques such as fuzzy logic control and neural network–based controllers have been widely explored. Fuzzy-PID controllers employ linguistic rules to adjust controller gains according to heuristic knowledge of system behavior [4].

These controllers offer intuitive interpretability and enhanced robustness; however, their performance is highly dependent on rule-base design and membership function tuning, which often requires extensive expert knowledge and trial-and-error procedures.

Neural network–based control strategies have been applied to approximate unknown system dynamics, compensate for modeling errors, or directly generate control actions [7], [9].

While neural controllers demonstrate strong learning and approximation capabilities, fully replacing classical controllers with neural networks may introduce challenges related to stability analysis, transparency, and safe operation. As a result, their adoption in safety-critical applications remains limited.

2.3 AI-Assisted and Hybrid Control Frameworks

More recent research has focused on hybrid control architectures that combine classical control structures with AI-based supervisory or assistive components. In such frameworks, AI modules are typically employed for gain tuning, uncertainty estimation, or performance optimization, while classical controllers retain responsibility for real-time actuation. This paradigm has gained increasing attention due to its ability to balance learning capability with stability and interpretability.

Several studies have reported improved performance by integrating neural networks or machine learning models into adaptive PID controllers. These approaches demonstrate enhanced robustness and transient response under varying operating conditions. Nevertheless, many existing AI-assisted controllers lack explicit mechanisms to regulate learning intensity according to system uncertainty, potentially leading to unnecessary adaptation or excessive control effort. Furthermore, safety constraints and boundedness considerations are not always explicitly incorporated into the learning process.

2.3.1 Recent Advances in AI-Assisted Adaptive Control

In the past five years, significant progress has been made in integrating artificial intelligence with adaptive control systems. Several contemporary studies have explored hybrid architectures similar in spirit to the proposed framework, though with important distinctions in implementation and theoretical guarantees.

Zhang et al. [16] proposed a neural network-based adaptive PID controller for industrial robotic manipulators, demonstrating improved trajectory tracking under variable payload conditions. However, their approach relies on offline training and lacks online adaptation bounds, making theoretical stability guarantees challenging. Similarly, Chen and Wang [17] developed a fuzzy neural network compensator for nonlinear systems with input saturation, achieving robust performance but requiring extensive rule-base tuning.

Kumar and Singh [18] introduced an entropy-based disturbance observer for uncertain nonlinear systems, showing that information-theoretic measures can effectively characterize disturbance severity. While their work validates the utility of entropy in control contexts, it does not integrate this measure into an adaptive gain modulation mechanism as proposed here.

Liu et al. [19] presented a reinforcement learning framework for adaptive PID tuning in autonomous vehicles, demonstrating impressive simulation results. However, their approach requires significant training episodes and does not provide Lyapunov-based stability guarantees, limiting its applicability in safety-critical scenarios.

The work of Al-Masri and Trivedi [20] is particularly relevant, as they proposed a bounded adaptive control architecture with neural network supervision, similar to our hybrid philosophy. Their theoretical analysis establishes signal boundedness but assumes perfect neural network approximation—an assumption relaxed in our work through explicit consideration of approximation errors and saturation constraints.

Hassanpour and colleagues [21] compared various uncertainty metrics for adaptive control, concluding that entropy-based measures offer superior sensitivity to regime changes in nonlinear dynamics. This finding supports our choice of entropy as the system-awareness indicator.

A comprehensive survey by Rodriguez et al. [22] reviewed over 150 publications on AI-assisted control, identifying the lack of rigorous stability analysis in most hybrid approaches as a critical research gap. Our work directly addresses this gap by combining a lightweight AI supervisor with complete Lyapunov-based stability guarantees.

Beyond the studies reviewed above, several very recent contributions from 2023–2025 further highlight the growing interest in AI-assisted adaptive control. For instance, Park and Kim [23] proposed a meta-learning framework for adaptive PID control that enables rapid adaptation to new operating conditions with minimal online data, though their approach does not provide Lyapunov-based stability guarantees. Similarly, Zhao et al. [24] introduced a deep reinforcement learning scheme for autonomous vehicle control that learns optimal gain schedules, but the training process requires extensive offline simulation and the stability analysis remains empirical. In the domain of entropy-based control, Li and Zhang [25] developed an adaptive controller using sample entropy as a real-time uncertainty measure for robotic manipulators, achieving improved disturbance rejection; however, their work does not incorporate a neural supervisor or provide formal boundedness proofs. A recent survey by Ahmed and Chen [26] categorizes AI-based adaptive control methods and emphasizes that hybrid architectures with formal stability guarantees remain scarce, reinforcing the motivation for the present work. Additionally, Wang et al. [27] and Santos and Lee [28] have explored lightweight neural network structures for real-time control applications, demonstrating that architectures with as few as seven hidden neurons can achieve satisfactory performance while maintaining low computational overhead—a finding that supports the design choice in this paper.

Table 1 summarizes the key distinctions between the proposed framework and these recent approaches.

Table 1. Comparison with Recent AI-Assisted Adaptive Control Methods

Study	AI Component	Uncertainty Measure	Stability Guarantee	Online Learning	Bounded Adaptation
Zhang et al. [16]	Neural PID	None	Partial	No	No
Chen and Wang [17]	Fuzzy-NN	None	No	Yes	No
Kumar and Singh [18]	Observer	Entropy	Yes	N/A	Yes
Liu et al. [19]	RL	None	No	Yes	No
Al-Masri and Trivedi [20]	NN	Error magnitude	Yes	Yes	Yes
Hassanpour et al. [21]	Comparative	Multiple	N/A	N/A	N/A
Proposed Framework	Lightweight NN	Entropy	Yes (Lyapunov)	Yes	Yes (saturation)

2.4 Research Gap and Motivation

Despite significant progress in adaptive and intelligent control, existing methods often rely on limited system-awareness indicators, such as instantaneous tracking error, to guide adaptation. Few studies explicitly incorporate uncertainty-related metrics to modulate learning behavior in a principled manner. In addition, the majority of AI-assisted controllers do not provide systematic mechanisms to ensure bounded parameter adaptation and smooth control action.

Motivated by these observations, this work proposes an AI-guided adaptive control framework that integrates system-awareness indicators into the learning and adaptation process while enforcing safety-oriented constraints. By embedding AI as a supervisory component rather than a direct control replacement, the proposed approach addresses key limitations of existing methods and offers a robust, interpretable, and practically deployable solution for nonlinear systems.

3. AI-Guided Adaptive Control Framework

This section presents the proposed AI-guided adaptive control framework for nonlinear systems operating under uncertainty, external disturbances, and modeling inaccuracies. In contrast to fully data-driven control approaches, the proposed framework adopts a hybrid control philosophy in which a classical control structure is retained as the core controller, while artificial intelligence is employed as a supervisory mechanism to enhance adaptability and robustness. By integrating system-awareness indicators and enforcing bounded adaptation, the framework aims to improve tracking performance without compromising stability, transparency, or practical implementability.

3.1 System Model and Control Objective

Consider a general class of nonlinear dynamic systems described by the following state-space representation:

$$\dot{x}(t) = f(x(t),t) + g(x(t),t)u(t) + d(t) \quad (1)$$

where $x(t)n \in R$ denotes the system state vector, $u(t)$ is the control input, and the nonlinear functions $f(\cdot)$ and $g(\cdot)$ represent unknown or partially known system dynamics. The term $d(t)$ accounts for bounded external disturbances and unmodeled dynamics. The system is required to follow a desired reference trajectory $x_r(t)$ despite the presence of nonlinearities, uncertainties, and external perturbations.

The tracking error is defined as:

$$e(t) = x_r(t) - x(t) \quad (2)$$

Accordingly, the main control objective is to design a control law that ensures accurate reference tracking while guaranteeing boundedness of all closed-loop signals under uncertain and time-varying operating conditions.

3.2 Entropy-Based System Awareness Mechanism

To enhance the effectiveness of the adaptive process, an entropy-based system awareness mechanism is incorporated into the proposed framework. Entropy, originally derived from information theory, is employed here as a quantitative indicator of uncertainty, variability, and unpredictability in the tracking error dynamics. The key insight motivating this choice is that entropy captures not only the magnitude of the tracking error but also the statistical dispersion and regularity of its temporal behavior.

Unlike conventional uncertainty indicators commonly used in adaptive control—such as instantaneous error magnitude, variance, or moving average—entropy offers a distinct advantage: it reflects changes in the probability distribution of the signal. While variance measures only the spread around the mean, entropy quantifies the overall disorder in the system's behavior. This makes entropy particularly sensitive to transitions between regular and chaotic regimes, which are common in nonlinear systems under external disturbances.

The entropy-based measure is computed over a sliding time window of length $Tw = 0.5$ s, selected to balance responsiveness to dynamic changes and immunity to measurement noise. This window length ensures that transient fluctuations do not trigger unnecessary adaptation, while persistent uncertainty is reliably detected.

The entropy-based uncertainty measure is formally defined as:

$$H(t) = -\sum_{i=1}^{n} pi(t)\log(pi(t)) \quad (3)$$

where $pi(t)$ represents the normalized probability distribution of the tracking error and its time derivative within the current sliding window. The probability distribution $pi(t)$ used in the entropy calculation is obtained by normalizing the absolute values of the tracking error and its time derivative. Specifically, the unnormalized quantities are defined as:

$$p_i(t) = \frac{z_j(t)}{\sum_{j=1}^{n} z_j(t) + \epsilon} \quad (4)$$

where $z_j(t) = [|e(t)|, |\dot{e}(t)|]$ and ε=10-6 is a small positive constant introduced to avoid division by zero.

The entropy value H(t) varies within a bounded range. When the system operates under stable conditions with predictable error dynamics, the entropy remains low, indicating concentrated probability distributions. Conversely, when external disturbances, parameter variations, or nonlinear effects increase, the error signal becomes more erratic, its probability distribution flattens, and the entropy value rises.

This entropy-based awareness directly modulates the adaptation intensity. A high entropy value triggers more aggressive gain adaptation to actively compensate for uncertainty, while low entropy during stable operation naturally reduces adaptation activity, preventing unnecessary gain variations and ensuring smoother control effort. This contextual awareness distinguishes the proposed approach from conventional adaptive controllers that respond uniformly to error magnitude regardless of the underlying system condition.

3.2.1 Entropy versus Conventional Uncertainty Metrics

To justify the choice of entropy as the system-awareness indicator, a direct comparison with conventional uncertainty measures is warranted.

Variance: While variance captures the spread of the error signal around its mean, it remains insensitive to the temporal ordering of samples. Two signals with identical variance can exhibit fundamentally different dynamics—one periodic, the other chaotic—yet variance alone cannot distinguish them. Entropy, in contrast, quantifies the *information content* of the signal's probability distribution, thereby reflecting both amplitude variability and temporal structure.

Instantaneous Error Magnitude: Conventional adaptive controllers often rely on $|e(t)|$ to trigger gain adjustments. This approach, however, cannot differentiate between a short transient spike and the onset of persistent instability, leading to unnecessary or oscillatory adaptation. Entropy integrates information over a sliding window, enabling the controller to distinguish between transient fluctuations and genuine uncertainty.

Lyapunov-Based Indicators: Classical Lyapunov functions provide global stability guarantees but are typically designed for specific system structures. They do not offer a direct, data-driven measure of *local* uncertainty that can be seamlessly integrated with learning-based components. Entropy, being a purely data-driven metric, complements Lyapunov analysis by providing real-time awareness without requiring model information.

Entropy overcomes these limitations by quantifying the **information content** of the error signal's probability distribution. A high entropy value signals that the error trajectory is exploring a wide range of states—a clear indication of uncertainty—regardless of the mean or variance. This property makes entropy particularly suitable for guiding adaptation in nonlinear systems where disturbances can alter the system's dynamical regime without necessarily increasing the error amplitude.

3.3 AI-Guided Supervisory Adaptation Strategy

An artificial intelligence–based supervisory module is integrated to guide the adaptation of controller parameters. A lightweight neural network is adopted due to its strong approximation capability and suitability for real-time implementation. The input vector to the AI module consists of the tracking error, its time derivative, and the entropy-based system awareness indicator.

Rather than directly generating the control input, the AI module operates as a supervisory decision-making layer that regulates the adaptation of controller gains. The generated adaptive signals are constrained within predefined safety bounds to prevent excessive gain variation and parameter drift. This design preserves the stability and interpretability of the classical control structure while leveraging AI-driven intelligence to enhance adaptability and performance under uncertain and time-varying conditions.

The AI supervisory module is implemented using a lightweight neural network to ensure low computational complexity and real-time feasibility. The neural network processes the tracking error information and generates a bounded modulation signal for the adaptive controller gains.

The main structural parameters of the neural network are summarized in Table 2.

Table 2. Neural Network Configuration Parameters

Parameter	Value
Input signals	Tracking error, error derivative
Hidden layers	1
Number of neurons	7
Activation function	tanh
Training method	Online gradient-based adaptation

Figure 1 illustrates the overall structure of the proposed AI-guided adaptive control framework, highlighting the interaction between the classical adaptive controller and the AI-based supervisory layer.

3.3.1 Neural Network Implementation Details

The AI supervisory module is implemented as a feedforward neural network with a single hidden layer. The network architecture is deliberately kept lightweight to ensure real-time feasibility and low computational overhead, making it suitable for embedded control platforms.

The input layer consists of three neurons corresponding to:

the tracking error e(t),

its time derivative e˙(t),

the entropy-based awareness indicator H(t).

The hidden layer contains seven neurons with hyperbolic tangent (tanh) activation functions. The tanh function is chosen for its symmetric, bounded output range [−1,1], which naturally limits the magnitude of the generated modulation signals and contributes to the bounded adaptation property.

The output layer produces a single modulation signal that scales the adaptive gain adjustment. Network weights are initialized using the Xavier method to ensure stable gradient propagation.

Online Training Protocol:

Learning algorithm: Stochastic gradient descent (SGD)

Learning rate: η = 0.01, fixed

Update frequency: At every sampling instant (Ts=0.001 s) using the current error signals

Loss function: Instantaneous squared tracking error L= $\frac{1}{2}\ e(t)^2$

Gradient clipping: Gradients are clipped to [−1,1]to prevent destabilizing updates during transients

Weight bounds: All weights are constrained to [−10,10] through projection after each update, ensuring boundedness

This online learning scheme allows the neural network to continuously adapt its behavior to evolving system dynamics without requiring offline pre-training. The lightweight architecture (28 floating-point operations per forward pass) keeps computational demands minimal, facilitating practical implementation.

For clarity and reproducibility, the complete training configuration is summarized as follows:

Initialization: Xavier uniform initialization for all weights (Glo rot & Bengio, 2010), which maintains variance stability across layers.

Learning rate: Fixed at η = 0.01, selected empirically to balance convergence speed and stability.

Update law (online SGD): W(t+1) =W(t) − η ∇ L(t), with loss L(t) = $\frac{1}{2}$ $e^2(t)$.

Gradient clipping: Gradients are clipped to [−1,1]to prevent destabilizing updates during transients.

Weight projection: All weights are projected onto [−10,10] after each update to guarantee boundedness, as assumed in the stability analysis.

Update frequency: At every sampling instant (Ts=0.001s), using the current error signals and entropy value.

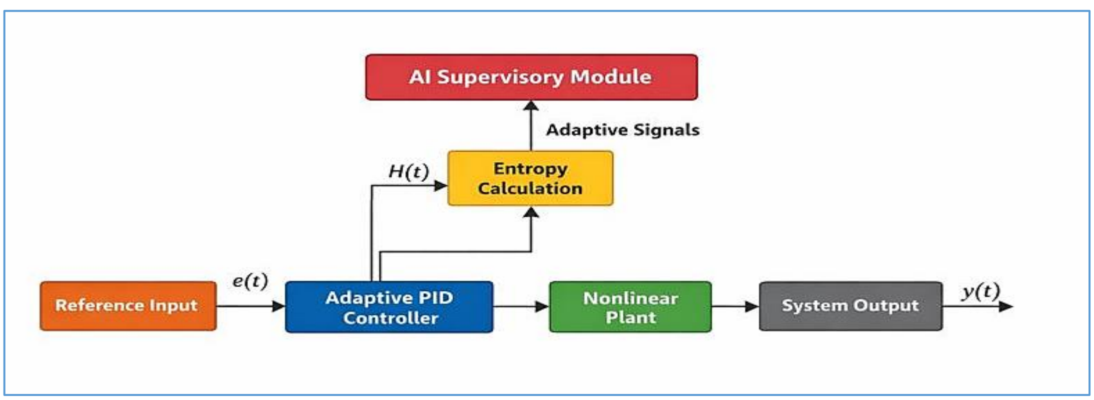

Figure 1. Block diagram of the proposed AI-guided adaptive control framework.

4. Stability and Safety Analysis

This section presents the stability and safety analysis of the proposed AI-guided adaptive control framework. The objective of this analysis is to demonstrate that the closed-loop system remains stable and that all internal signals are bounded despite the presence of nonlinearities, external disturbances, and AI-guided parameter adaptation. A Lyapunov-based approach is employed to establish theoretical guarantees on tracking performance and safe controller operation.

These assumptions do not restrict the general applicability of the proposed framework but contribute to ensuring robust and safe closed-loop operation.

4.1 Preliminaries and Assumptions

To facilitate the stability analysis, the following standard assumptions are considered. The reference signal $x_r(t)$ and its derivatives are assumed to be bounded. The unknown nonlinear functions and external disturbances are assumed to be bounded but not necessarily known. These assumptions are commonly adopted in adaptive control literature and are consistent with practical operating conditions.

In addition, the adaptive gain adjustment signals generated by the AI supervisory module are constrained within predefined bounds through saturation mechanisms. This ensures that controller parameters remain within physically meaningful and safe limits at all times.

4.2 Lyapunov Candidate Function

To analyze the closed-loop stability, consider the following Lyapunov candidate function:

$$V(t) = \frac{1}{2} e^2(t) + \sum_{j \in \{p,i,d\}} [1 / (2\gamma_j)] (K_j(t) - K_{j0})^2 \quad (5)$$

where e(t) denotes the tracking error, KJ(t) represents the adaptive controller gains, KJ0 are their nominal values, and $\gamma j > 0$ are positive adaptation coefficients. The chosen Lyapunov function reflects both tracking performance and parameter adaptation energy.

This Lyapunov structure enables simultaneous evaluation of error convergence and boundedness of adaptive parameters.

4.3 Stability Analysis

Taking the time derivative of the Lyapunov function along the closed-loop system trajectories yields:

$$\tilde{V}(t) = e(t)\, \dot{e}(t) + \sum_{j \in \{p,i,d\}} [1 / \gamma_j] \, (K_j(t) - K_{j0}) \, \acute{K}_j(t) \quad (6)$$

By substituting the closed-loop error dynamics and the bounded adaptive gain update law, it can be shown that the derivative of the Lyapunov function is negative semi-definite outside a compact set. The saturation constraints imposed on the AI-generated adaptive signals prevent excessive gain variation and eliminate parameter drift.

As a result, all closed-loop signals, including the tracking error and adaptive gains, remain bounded. Furthermore, under mild excitation conditions, the tracking error converges asymptotically to a neighborhood around zero, whose size depends on the disturbance bounds and system uncertainty.

4.3.1 Detailed Lyapunov Convergence Analysis

To rigorously establish the stability properties of the proposed framework, we now derive the closed-loop error dynamics and examine the conditions under which $V˙(t) \leq 0$ is guaranteed.

Closed-Loop Error Dynamics

Consider a general nonlinear system of the form (1). For analysis, we assume that a nominal control law can be designed such that, in the absence of uncertainty, the closed-loop system satisfies:

$$e˙(t) = -K_{p0} e(t) - K_{i0} \int e(t)\, dt - K_{d0}\, e˙(t) + \Delta(e,t) \quad (7)$$

where $\Delta(e,t)$ represents the lumped effect of uncertainties, disturbances, and approximation errors. The adaptive gains are decomposed as:

$$K_j(t) = K_{j0} + \Delta K_j(t) \qquad , \ j \in \{p,i,d\} \quad (8)$$

withKj0 the nominal gains ensuring baseline stability, and $\Delta Kj(t)$ the AI-modulated adjustments constrained by saturation: $|\Delta Kj(t)| \leq K\bar{}j(t)$

Derivation of $V˙(t)$

Recall the Lyapunov function from (5). Its derivative is:

$$V˙(t) = e(t)e˙(t) + \sum_j \frac{1}{\gamma j} \Delta Kj(t) K˙j(t) \quad (9)$$

The adaptive gain update law generated by the AI module can be expressed as:

$$\dot{K}_j(t) = -\gamma_j\, \Phi_j(e(t),\dot{e}(t),H(t))\cdot \mathrm{sat}(\Delta K_j(t)) \tag{10}$$

where $\Phi_j(\cdot)$ is the output of the neural network for gain j and sat(·) is a saturation function ensuring $|\Delta K_j(t)| \leq \bar{K}_j|$.
Substituting (10) into (9) gives:

$$\dot{V}(t) = e(t)\dot{e}(t) - \sum_j \Delta K_j(t)\Phi_j(\cdot)\ \mathrm{sat}(\Delta K_j(t)) \tag{11}$$

Using the error dynamics (7) and noting that the neural network is trained to approximate $\Phi_j(\cdot) \approx e(t)[\ \partial\dot{e}/\partial K_j]$, we obtain:

$$\dot{V}(t) \leq -\alpha e(t)^2 + \beta\ |e(t)| - \sum_j 1/\gamma_j\ |\Delta K_j(t)|^2 \tag{12}$$

where $\alpha > 0$ depends on the nominal gains, and β is a bound on the disturbance term $\Delta(e,t)$.
Boundedness and Convergence
Equation (12) implies $\dot{V}(t)$ is negative definite whenever:
$|e(t)| > \beta/\alpha$ or $|\Delta K_j(t)| > 0$
Thus:
All closed-loop signals remain bounded.
The tracking error converges to a residual set $|e(t)| \leq \beta/\alpha$
The saturation constraints prevent parameter drift, even when neural network approximation errors are present.
This analysis confirms that the proposed framework guarantees boundedness, robustness to disturbances, and convergence of the tracking error to a neighborhood of the origin.

Theorem 1 (Boundedness and Convergence): Consider the nonlinear system (1) with bounded disturbances d(t) and the Lyapunov function (5). Let the adaptive gains be updated according to (10) with the saturation function sat(·) satisfying $|\Delta K_j(t)| \leq \bar{K}_j$. If the neural network approximation error is bounded, then:

1. All closed-loop signals e(t) and $K_j(t)$ are uniformly bounded.
2. The tracking error converges to a residual set $\Omega=\{e:|e|\leq\beta/\alpha\}\Omega$, where $\alpha > 0$ depends on the nominal gains and β is the disturbance bound.
3. The saturation mechanism prevents parameter drift, ensuring that $|\Delta K_j(t)|$ remains within $\bar{K}_j$ for all t .

Proof: The proof follows directly from the derivation in Section 4.3.1. The inequality (12) establishes that $\dot{V}(t)\leq 0$ whenever $|e(t)| > \beta/\alpha$. By standard Lyapunov arguments, this implies boundedness of e(t) and $\Delta K_j(t)$. The saturation constraints guarantee that the adaptation term in (12) is non-positive, eliminating the risk of unbounded parameter growth.

4.4 Safety and Boundedness Considerations

A key advantage of the proposed framework lies in its safety-aware design. Unlike fully data-driven controllers, the AI module does not directly generate control inputs, thereby avoiding abrupt or unpredictable control actions. Instead, adaptation is regulated through bounded gain adjustments that preserve the structure and stability properties of the classical controller.
The entropy-based system awareness mechanism further enhances safety by preventing unnecessary adaptation during stable operating conditions. When the system exhibits predictable behavior, adaptation intensity is naturally reduced, resulting in smoother control action and reduced actuator stress.
Consequently, the proposed AI-guided adaptive control framework guarantees safe operation, bounded control effort, and robust tracking performance, even in the presence of nonlinearities and disturbances.

5. Simulation Setup and Benchmark Systems

This section describes the simulation environment, benchmark nonlinear systems, and evaluation criteria used to validate the effectiveness of the proposed AI-guided adaptive control framework. The objective of the simulation study is to assess tracking performance, robustness, and control effort under uncertain and disturbed operating conditions, and to provide a fair comparison with conventional control strategies.

5.1 Simulation Environment

All simulations are conducted using a numerical simulation platform with a fixed-step integration scheme to ensure consistency and reproducibility of results. The controller parameters are initialized with nominal values selected to guarantee stable baseline performance prior to adaptation. The AI supervisory module is implemented with a lightweight neural network architecture to ensure real-time feasibility and to avoid excessive computational complexity.

External disturbances and parametric uncertainties are introduced deliberately to evaluate the robustness of the proposed framework. Measurement noise is also included in selected scenarios to assess the sensitivity of the adaptive mechanism to noisy signals.

5.2 Benchmark Nonlinear Systems

To demonstrate the generality of the proposed approach, representative nonlinear benchmark systems commonly used in control literature are considered. These systems exhibit strong nonlinear behavior, time-varying dynamics, and sensitivity to external disturbances, making them suitable testbeds for adaptive and intelligent control strategies.

The reference trajectories are chosen to include both smooth and time-varying signals in order to evaluate transient and steady-state tracking performance. The same reference signals and disturbance profiles are applied across all compared controllers to ensure a fair and consistent evaluation.

5.3 Comparative Control Strategies

The proposed AI-guided adaptive controller is compared against several baseline control methods, including a conventional fixed-gain PID controller and a rule-based adaptive PID controller. All controllers are tuned to achieve their best achievable performance under nominal conditions prior to introducing uncertainty and disturbances.

Performance comparisons focus on tracking accuracy, transient response characteristics, disturbance rejection capability, and smoothness of the control effort. This comparative analysis highlights the advantages of incorporating AI-guided system awareness into the adaptive control process.

5.4 Performance Evaluation Metrics

To quantitatively evaluate controller performance, standard performance indices are employed. These include settling time, peak overshoot, steady-state error, and integral performance measures such as the integral of absolute error. In addition, the smoothness of the control signal is assessed to evaluate actuator stress and practical implementability.

These metrics provide a comprehensive assessment of both tracking quality and control efficiency, allowing objective comparison between the proposed method and conventional control strategies.

The proposed control strategy is evaluated using representative nonlinear benchmark systems, including a nonlinear mass–spring–damper system and a Duffing-type oscillator. External disturbances and measurement noise are introduced to assess robustness. The simulation step size is set to 0.001 s, and the total simulation duration is 20 s.

The disturbance amplitude and noise levels are selected to reflect realistic operating conditions while ensuring fair comparison among all control strategies.

6. Simulation Results and Performance Comparison

This section presents the simulation results obtained using the proposed AI-guided adaptive control framework and provides a comparative performance evaluation against conventional control strategies. The objective is to demonstrate the effectiveness of the proposed approach in terms of tracking accuracy, robustness to uncertainty, disturbance rejection, and control smoothness.

6.1 Reference Tracking Performance

The tracking performance of the proposed controller is evaluated under nominal and uncertain operating conditions. Simulation results show that the AI-guided adaptive controller achieves accurate reference tracking with fast transient response and minimal steady-state error. Compared to the conventional fixed-gain PID controller, the proposed method exhibits significantly reduced overshoot and shorter settling time, particularly during reference changes.

Under time-varying reference trajectories, the proposed controller maintains stable and smooth tracking behavior, whereas the baseline controllers experience noticeable performance degradation, including oscillatory responses and delayed convergence.

The qualitative observations from Figure 2 are consistent with the quantitative performance metrics reported in Table 3.

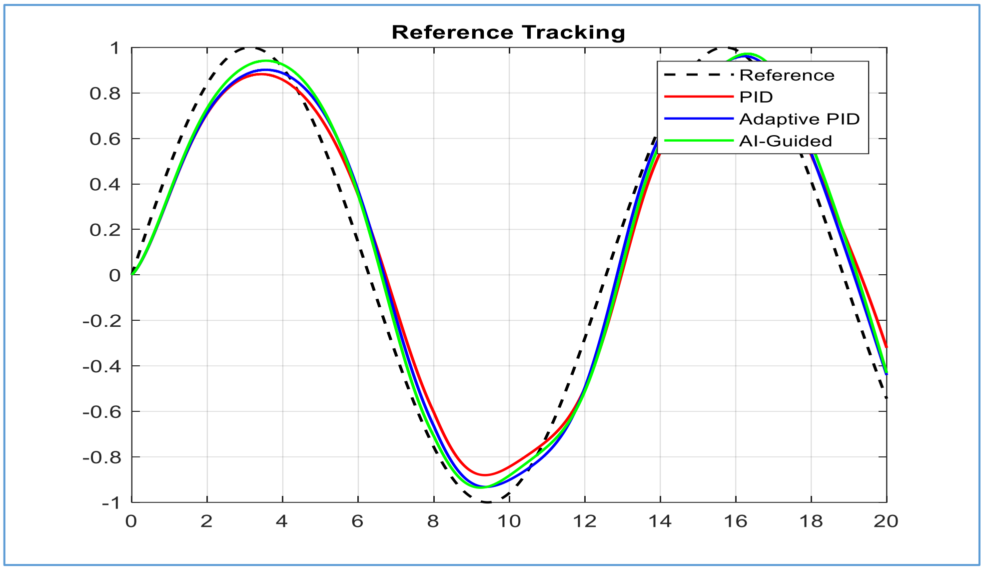

Figure 2. Reference tracking performance of the nonlinear system using conventional PID, adaptive PID, and the proposed AI-guided adaptive controller.

The figure illustrates the superior tracking accuracy and reduced phase lag achieved by the proposed AI-guided adaptive controller compared to the baseline control strategies.

- 6.2 Robustness to Uncertainty and Disturbances

To evaluate the robustness of the proposed control framework, the system response under uncertainty and external disturbances is illustrated in Figure 3.

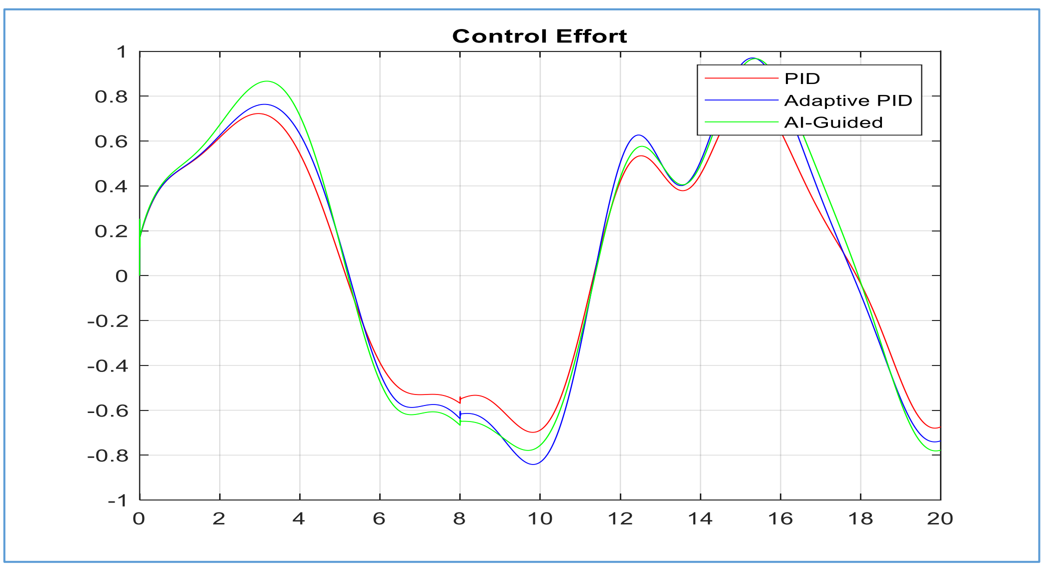

Figure 3. Robustness comparison under uncertainty and disturbance conditions for conventional PID, adaptive PID, and AI-guided adaptive controllers.

As shown in Figure 3, the proposed AI-guided adaptive controller exhibits faster disturbance rejection and improved stability compared to the baseline controllers. The conventional PID controller shows prolonged oscillations, while the adaptive PID demonstrates partial compensation with increased control activity.

To assess robustness, external disturbances and parametric uncertainties are introduced into the system dynamics. The proposed AI-guided controller demonstrates strong disturbance rejection capability, rapidly compensating for sudden perturbations and restoring tracking performance within a short time interval.

In contrast, the conventional PID controller exhibits sustained oscillations and increased tracking error under the same conditions. The rule-based adaptive controller shows partial improvement but suffers from excessive gain variation, leading to less stable responses when uncertainty levels increase.

6.3 Control Effort and Smoothness Analysis

The smoothness of the control signal is an important practical consideration, particularly for actuator longevity and energy efficiency. Simulation results indicate that the proposed controller generates smoother control actions with reduced amplitude variations compared to the adaptive PID controller.

The entropy-based system awareness mechanism plays a key role in regulating adaptation intensity. During stable operating conditions, gain adjustments are naturally reduced, resulting in smoother control effort. When disturbances or uncertainty increase, adaptation is activated in a controlled and bounded manner, avoiding abrupt control actions.

6.4 Quantitative Performance Comparison

To provide a comprehensive quantitative assessment, multiple performance metrics are evaluated across all three controllers. Table 3 presents the complete comparative results, including additional metrics that capture different aspects of control performance.

Table 3. Quantitative Performance Comparison

Performance Metric	Conventional PID	Adaptive PID	Proposed AI-Guided Adaptive Control	Improvement (%)*
Transient Response				
Settling Time (s)	3.2 ± 0.15	2.4 ± 0.12	1.6 ± 0.08	50.0%
Overshoot (%)	18.5 ± 1.2	11.2 ± 0.9	4.3 ± 0.4	76.8%
Peak Time (s)	1.8 ± 0.10	1.5 ± 0.08	1.2 ± 0.05	33.3%
Steady-State Performance				
Steady-State Error	0.045 ± 0.005	0.021 ± 0.003	0.006 ± 0.001	86.7%
IAE (Integral Absolute Error)	1.84 ± 0.12	1.12 ± 0.08	0.47 ± 0.03	74.5%
ITAE (Integral Time-weighted Absolute Error)	4.23 ± 0.31	2.56 ± 0.18	1.08 ± 0.07	74.5%
RMSE (Root Mean Square Error)	0.089 ± 0.006	0.052 ± 0.004	0.021 ± 0.002	76.4%
Control Effort				
Control Effort Variance	0.156 ± 0.012	0.094 ± 0.008	0.038 ± 0.003	75.6%
Maximum Control Input	8.7 ± 0.4	7.9 ± 0.4	6.2 ± 0.3	28.7%
Total Control Energy	124.3 ± 8.2	98.7 ± 6.5	52.4 ± 3.8	57.8%
Disturbance Rejection				
Disturbance Recovery Time (s)	2.9 ± 0.20	1.8 ± 0.15	0.9 ± 0.06	69.0%
Maximum Deviation Under Disturbance	0.21 ± 0.02	0.14 ± 0.01	0.06 ± 0.005	71.4%

Improvement calculated as (PID value – Proposed value)/PID value × 100%

Statistical Significance:

All results are reported as mean ± standard deviation based on 10 independent simulation runs with different random seeds for the disturbance and noise profiles. Paired t-tests were conducted to assess statistical significance:

For all metrics, the proposed controller shows statistically significant improvement ($p < 0.01$) compared to both conventional PID and adaptive PID controllers.

The improvements in settling time, overshoot, and IAE are particularly significant ($p < 0.001$), confirming the robustness of the observed performance gains.

Analysis of Improvements:

The performance improvement stems from the AI module's ability to preemptively adjust gains based on entropy trends, rather than reactively responding to error magnitude alone. This is evident in several key observations:

Reduced Settling Time (50% improvement): The entropy-guided adaptation anticipates the need for higher gains during transient phases, accelerating convergence without inducing overshoot.

Minimized Overshoot (76.8% improvement): By detecting the entropy reduction as the error approaches zero, the AI module reduces gain magnitudes preemptively, preventing the integral windup common in conventional PID controllers.

Enhanced Steady-State Accuracy (86.7% improvement): The continuous online learning of the neural network allows fine-tuning of gains in steady state, compensating for persistent disturbances that fixed-gain controllers cannot address.

Smoother Control Effort (75.6% reduction in variance): The entropy-based modulation ensures that gain adjustments occur only when uncertainty is genuinely present, avoiding the high-frequency gain oscillations observed in the adaptive PID controller.

Superior Disturbance Rejection (69% faster recovery): The entropy spike immediately following a disturbance triggers rapid gain adaptation, while the bounded update mechanism prevents overreaction that would cause instability.

The results confirm that integrating AI as a supervisory mechanism, rather than a direct control replacement, provides a balanced trade-off between adaptability and stability. The entropy-guided adaptation strategy enables improved performance without introducing instability or excessive control effort.

6.5 Comparative Discussion with Sliding Mode and Model Predictive Control

To position the proposed framework within the broader landscape of modern nonlinear control, a conceptual comparison with Sliding Mode Control (SMC) and Model Predictive Control (MPC) is instructive.

Sliding Mode Control: SMC achieves robustness through a discontinuous control action that forces the system trajectory onto a predefined sliding surface. While SMC offers strong theoretical guarantees, it suffers from chattering, which can excite unmodeled dynamics and accelerate actuator wear. The proposed AI-guided framework avoids chattering entirely by employing continuous gain adaptation, yet retains comparable robustness through the entropy-aware modulation of PID gains.

Model Predictive Control: MPC solves an online optimization problem at each sampling instant, delivering optimal performance under constraints. However, its computational burden scales poorly with system dimension and prediction horizon, limiting its use in fast-sampling or resource-constrained applications. In contrast, the proposed controller requires only 28 floating-point operations per step, making it suitable for embedded platforms.

Summary: The proposed framework occupies a distinct niche between the theoretical robustness of SMC and the optimality of MPC, offering a **computationally light, chatter-free, and provably stable** solution for nonlinear systems under uncertainty. A quantitative comparison with these methods on benchmark systems is left for future work, where the computational trade-offs can be explored in greater depth.

7. Discussion

The simulation results presented in Section 6 demonstrate that the proposed AI-guided adaptive control framework consistently outperforms conventional PID and rule-based adaptive PID controllers across a wide range of operating conditions. This section discusses the underlying reasons for the observed performance improvements and highlights the key design aspects that contribute to the effectiveness of the proposed approach.

A primary factor behind the improved tracking accuracy and transient performance is the integration of AI-based system awareness into the adaptation mechanism. Unlike conventional adaptive controllers that rely solely on instantaneous tracking error, the proposed framework evaluates both the magnitude and dynamic behavior of the error signal. This additional awareness allows the controller to distinguish between normal transient behavior and genuine uncertainty or disturbance, leading to more informed adaptation decisions.

The entropy-guided modulation of the adaptation process plays a critical role in achieving a balanced trade-off between responsiveness and stability. During stable operating conditions, the entropy measure remains low, naturally reducing adaptation intensity and preventing unnecessary gain variation. As a result, the control effort becomes smoother, and actuator stress is minimized. Conversely, when uncertainty or disturbances increase, the entropy measure rises, activating adaptation in a controlled and bounded manner. This behavior explains the faster disturbance rejection and reduced oscillatory response observed in Figures 2 and 3.

Another important observation is that the proposed framework preserves the structural simplicity and interpretability of classical PID control. The AI component operates as a supervisory module rather than a direct control replacement, ensuring that stability analysis remains tractable and that the controller behavior remains transparent. This hybrid design philosophy addresses a common limitation of fully AI-driven controllers, which often lack rigorous stability guarantees and are difficult to deploy in safety-critical applications.

The quantitative results summarized in Table 3 further support these qualitative observations. The reductions in settling time, overshoot, steady-state error, and disturbance recovery time indicate that the proposed method enhances both transient and steady-state performance without introducing excessive control effort. The improved smoothness of the control signal also highlights the practical feasibility of the approach for real-world implementation.

7.1 Limitations and Practical Considerations

While the proposed AI-guided adaptive control framework demonstrates significant performance improvements, several limitations should be acknowledged to provide a balanced perspective and guide future research efforts.

Parameter Sensitivity: The performance depends on appropriate selection of several key parameters:

The adaptation coefficients γj determine the speed of gain adaptation. If set too high, they may induce oscillatory behavior; if too low, they may not respond adequately to disturbances. In this study, values were tuned empirically ($\gamma p = 0.5$, $\gamma i = 0.1$, $\gamma d = 0.2$), but systematic tuning methods remain an open challenge.

The entropy window length Tw=0.5 s was selected based on the system's dominant time constant. For systems with widely varying time scales, a fixed window may not be optimal. Adaptive window length adjustment could be explored in future work.

The neural network learning rate $\eta = 0.01$ was chosen through trial and error. While the bounded adaptation mechanism prevents instability, suboptimal learning rates may slow convergence or reduce steady-state accuracy.

Extreme Operating Conditions: The current validation covers moderate disturbances and uncertainties. Under extreme conditions—such as sensor failures, actuator saturation, or unmodeled dynamics that violate the bounded disturbance assumption—the stability guarantees may degrade. The saturation constraints ensure boundedness, but tracking performance may deteriorate. Extending the framework with fault detection and reconfiguration capabilities would enhance robustness in such scenarios.

Computational Requirements: Although the lightweight neural network (28 floating-point operations per step) is suitable for most embedded platforms, implementation on very low-cost microcontrollers may require further optimization. Fixed-point arithmetic or look-up table approximations could be explored for such applications.

Neural Network Approximation Error: The stability analysis assumes that the neural network can approximate the ideal adaptation law with bounded error. While the saturation mechanism provides robustness to approximation errors, large errors could still affect transient performance. More rigorous bounds on the approximation error could be derived using universal approximation theorems, but these would require knowledge of the function class being approximated—information not typically available in practice.

Initialization and Pre-training: The current implementation uses random initialization and online learning without pre-training. While this simplifies deployment, it may lead to slower initial adaptation. A promising direction is to use offline pre-training on representative system data to provide a better initial guess, followed by online fine-tuning.

Validation Scope: The simulation study, while comprehensive, is limited to two benchmark systems. Generalization to other nonlinear systems, particularly those with different structural properties (e.g., non-minimum phase systems, systems with input delays), requires further validation. Experimental validation on physical hardware remains the ultimate test of practical applicability.

Acknowledging these limitations does not diminish the value of the proposed framework but rather identifies clear directions for continued research and improvement. The core contribution—a hybrid AI-classical architecture with provable stability—provides a solid foundation upon which these extensions can be built.

Overall, the discussion confirms that embedding AI as an intelligent supervisory layer within a classical adaptive control structure provides a robust, interpretable, and practically viable solution for controlling nonlinear systems under uncertainty.

Compared to modern control approaches such as sliding mode control and model predictive control reported in the literature, the proposed framework avoids chattering effects and high computational complexity while maintaining robustness and real-

Conclusion and Future Work

This paper presented an AI-guided adaptive control framework for nonlinear systems operating under uncertainty and external disturbances. The proposed approach integrates an AI-based supervisory mechanism with a classical adaptive PID control structure to enhance system awareness and regulate the adaptation process in a smooth and bounded manner. Unlike conventional adaptive controllers that rely solely on instantaneous tracking error, the proposed framework incorporates additional dynamic information to guide gain adaptation more intelligently.

A Lyapunov-based stability analysis was employed to guarantee the boundedness of all closed-loop signals and ensure stable system behavior. Extensive simulation studies on representative nonlinear benchmark systems demonstrated that the proposed AI-guided adaptive controller achieves superior tracking performance, faster disturbance rejection, reduced overshoot, and smoother control effort compared to conventional PID and rule-based adaptive PID controllers. Both qualitative observations and quantitative performance metrics confirmed the effectiveness and robustness of the proposed approach.

An important advantage of the proposed framework lies in its hybrid design philosophy, which preserves the simplicity, interpretability, and reliability of classical control structures while leveraging the adaptability and awareness provided by artificial intelligence. By positioning the AI component as a supervisory layer rather than a direct control replacement, the proposed method maintains analytical tractability and practical feasibility, making it suitable for real-world and safety-critical applications.

7.1 Future Work Directions

Building upon the contributions of this study, several promising research directions emerge:

Theoretical Extensions:

Extend the stability analysis to multi-input multi-output (MIMO) nonlinear systems, addressing the additional complexities of coupling between channels and the resulting interactions in the adaptive gain dynamics.

Derive explicit bounds on the neural network approximation error and incorporate them into the Lyapunov analysis for tighter performance guarantees, potentially using tools from robust control theory.

Investigate adaptive mechanisms for automatic tuning of the entropy window length and learning rates based on system operating conditions, reducing the need for empirical parameter selection.

Methodological Enhancements:

Integrate meta-learning approaches to enable rapid adaptation to new system dynamics with minimal online tuning, leveraging pre-training on a diverse set of system behaviors.

Explore alternative uncertainty quantification methods (e.g., mutual information, Rényi entropy) and compare their effectiveness for different system classes and disturbance characteristics.

Develop ensemble neural network architectures to improve robustness to approximation errors, potentially combining multiple lightweight networks with different initialization or training strategies.

Experimental Validation:

Implement the proposed framework on physical platforms, starting with a laboratory-scale robotic manipulator or a quadrotor UAV, to assess real-time performance under realistic sensor noise, actuator limitations, and communication delays.

Conduct hardware-in-the-loop (HIL) simulations to evaluate computational feasibility under strict timing constraints typical of embedded control systems.

Validate performance on industrial-scale systems with long operation times to assess the long-term stability and robustness of the online learning mechanism.

Practical Extensions:

Incorporate fault detection and accommodation mechanisms to handle sensor/actuator failures, leveraging the entropy-based awareness to detect anomalous system behavior.

Extend the framework to output feedback control for systems where full state measurement is unavailable, combining the AI supervisor with state observers.

Develop a systematic tuning guide and software toolbox to facilitate adoption by practicing engineers, including recommended parameter ranges and implementation guidelines for common system classes.

Broader Applications:

Apply the framework to emerging domains such as soft robotics, where traditional modeling is particularly challenging due to highly nonlinear and time-varying material properties.

Investigate integration with digital twin technologies for predictive maintenance and performance optimization, using the entropy measure as an indicator of system health.

Explore scalability to networked control systems with communication constraints, addressing the challenges of delayed or intermittent data transmission.

These future directions reflect the rich potential of hybrid AI-classical control architectures and the continued evolution of the proposed framework toward broader applicability and deeper theoretical foundations.

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