Albahit Journal of Applied Sciences
"open-access, peer-reviewed biannual journal"
eISSN: 2708-8936, pISSN: 2708-244X
Volume 5, Issue 1, 2026
Page No: 16-29
Website: *https://albahitjas.com.ly/index.php/albahit/en/index*

Entropy-Guided Adaptive PID Control for Nonlinear Benchmark

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Received: 08-10-2025	**Accepted:** 23-12-2025	**Published:** 05-01-2026

Abstract:
This paper proposes an entropy-guided adaptive PID control approach for nonlinear benchmark systems operating under disturbances and parametric uncertainties. Unlike conventional adaptive PID methods that rely solely on instantaneous tracking error, the proposed strategy employs an online entropy measure to quantify the degree of dynamical irregularity in the system response. The entropy information is used to continuously adjust the proportional, integral, and derivative gains in a bounded and smooth manner. A Lyapunov-based stability analysis is developed to guarantee uniform boundedness of all closed-loop signals and asymptotic convergence of the tracking error. The effectiveness of the proposed controller is demonstrated through numerical simulations on standard nonlinear benchmark models, showing improved transient performance and enhanced robustness compared to classical PID and conventional adaptive PID controllers [1], [6], [8].

Keywords: Entropy-guided control; Adaptive PID; Nonlinear benchmark systems; Lyapunov stability; Robust control; Performance improvement.

التحكم التكيفي *PID* الموجَّه بالإنتروبيا للأنظمة غير الخطية المعيارية

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الملخص
يقترح هذا البحث أسلوب تحكم تكيفي من نوع PID موجَّه بالإنتروبيا للأنظمة غير الخطية القياسية العاملة في ظل الاضطرابات وعدم اليقين في المعاملات. وعلى خلاف طرق التحكم التكيفي التقليدية من نوع PID التي تعتمد فقط على خطأ التتبع اللحظي، فإن الاستراتيجية المقترحة تستخدم مقياس الإنتروبيا عبر الإنترنت لقياس درجة عدم الانتظام الديناميكي في استجابة النظام. وتُستخدم معلومات الإنتروبيا لضبط معاملات الكسب التناسبي (P) والتكاملي (I) والتفاضلي (D) بصورة مستمرة ومقيدة وسلسة. كما تم تطوير تحليل للاستقرارية بالاعتماد على دالة ليابونوف لضمان الانحصار المنتظم

لجميع إشارات الحلقة المغلقة وتحقيق التقارب التقاربي لخطأ التتبع نحو الصفر. وقد تم التحقق من فعالية المتحكم المقترح من خلال محاكاة عددية على نماذج معيارية لأنظمة غير خطية، حيث أظهرت النتائج تحسنًا في الأداء العابر وزيادة في المتانة مقارنة بمتحكمات PID الكلاسيكية ومتحكمات PID التكيفية التقليدية [1]، [6]، [8].

الكلمات المفتاحية: التحكم الموجَّه بالإنتروبيا؛ التحكم التكيفي PID؛ الأنظمة غير الخطية المعيارية؛ استقرارية ليابونوف؛ التحكم المتين؛ تحسين الأداء.

Introduction

Proportional–Integral–Derivative (PID) controllers remain the most widely used control strategy in industrial and engineering applications due to their simple structure, ease of implementation, and reliable performance. However, fixed-gain PID controllers often suffer from performance degradation when applied to nonlinear systems or systems operating under external disturbances and parametric uncertainties. [1], [2], [3]

To overcome these limitations, adaptive PID control schemes have been proposed, where controller gains are adjusted online to cope with changing system dynamics. Conventional adaptive PID approaches typically rely on error-based adaptation mechanisms, gradient-based rules, or heuristic tuning strategies. While such methods can enhance performance compared to fixed-gain PID controllers, their adaptation behavior is often driven solely by instantaneous error magnitude, which may not adequately reflect the overall dynamical condition of the system. [6], [7], [8]

In parallel, entropy-based measures have been increasingly employed in the analysis of dynamical systems as indicators of complexity, uncertainty, and irregularity. Entropy concepts have found applications in system identification, fault detection, and performance assessment. Nevertheless, in most existing studies, entropy is utilized as a passive analytical tool rather than as an active component within the control loop. [10], [11], [12]

Motivated by these observations, this paper introduces an entropy-guided adaptive PID control framework in which entropy is actively used to inform and regulate the gain adaptation process. By quantifying the degree of dynamical irregularity in the tracking error signal, the proposed approach enables the controller to respond more effectively to disturbances and nonlinear effects. To ensure rigorous performance guarantees, a Lyapunov-based stability analysis is developed to demonstrate boundedness and convergence properties of the closed-loop system. [4], [11], [13]

The proposed control strategy is evaluated using well-established nonlinear benchmark systems. Simulation results are presented to compare the proposed method with classical PID and conventional adaptive PID controllers, highlighting improvements in transient response, robustness, and overall control efficiency.

Material and Methods

This section describes the materials, models, and methodological procedures employed to evaluate the proposed entropy-guided adaptive PID control strategy. All methods are presented in a reproducible manner using well-established benchmark systems, without introducing any modification to the system structure or hardware configuration.

structure or hardware configuration.

System Description

The study considers a class of nonlinear dynamic systems commonly used as benchmarks in control literature. Such systems are selected due to their representativeness, mathematical clarity, and suitability for comparative evaluation of control strategies. In general form, the nonlinear system is expressed as

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

$$y\,(t)\; = \;h\,\big(x(t)\big) \qquad (2)$$

where x(t) denotes the system state vector, u(t) is the control input, y(t) represents the measured output, and d(t) accounts for bounded external disturbances and parametric uncertainties. The control objective is to ensure accurate tracking of a reference signal r(t). [4], [5]

Benchmark Model

To provide a concrete evaluation framework, a nonlinear mass–spring–damper system is adopted as a representative benchmark model. The considered nonlinear system exhibits polynomial nonlinearity due to the cubic stiffness term. External disturbances are assumed to be bounded deterministic signals applied at the plant input, representing unmodeled dynamics and environmental perturbations.

The system dynamics are described by:

$$m\ddot{x} + \;\mathrm{c}\dot{x}(\mathrm{t}) + \mathrm{k}\dot{x}(\mathrm{t}) + \;\beta x^3(t) = u(t) \qquad (3)$$

where m is the mass, c is the damping coefficient, k is the linear stiffness parameter, and β represents the nonlinear stiffness term. This model captures essential nonlinear behavior frequently encountered in mechanical systems and has been extensively utilized in previous control studies. [3], [6]

PID Controller Structure

A conventional Proportional–Integral–Derivative (PID) controller structure is employed as the baseline control scheme. The control input is defined as:

$$u(t) = kp(t)e(t)k_i\,(t) + \int_0^t e(\tau) + K_d(t)\,\dot{e}\,(t) \qquad (4)$$

where e(t) = r(t) – y(t) denotes the tracking error, and $k_p(t)$, $k_d(t)$, and $k_i(t)$ are the time-varying proportional, integral, and derivative gains, respectively. [1], [6], [15]

Entropy Computation Method

To quantify the dynamic irregularity of the system response, an entropy measure is computed online from the tracking error signal. The error signal is evaluated over a finite sliding time window and discretized into a finite number of amplitude intervals, forming a probability distribution. Based on this distribution, Shannon entropy is calculated as:

$$H(T) = -\sum_{i=1}^{N} p_{i(t)+\log\,(pi(t))} \qquad (5)$$

where $p_i(t)$ denotes the probability associated with the i-th interval and N represents the total number of intervals. Higher entropy values indicate increased irregularity or disturbance influence in the system dynamics. [10], [11], [12]

Adaptive Gain Adjustment Mechanism

The entropy information is utilized to guide the online adaptation of the PID gains. Each controller gain is adjusted according to a bounded and continuous adaptation function, expressed as:

$$k_{j(t)} = k_{j0} + \alpha_j \varnothing (H(t), j \in \{p, i, d\} \quad (6)$$

Where k_{j0} are nominal gain values, α_j are positive adaptation coefficients, and $\phi(.)$ is a smooth bounded function. This formulation ensures gradual gain variation and prevents excessive control action. [8], [9], [13]

Simulation Environment

All simulations are carried out using MATLAB/Simulink. Identical initial conditions, reference inputs, and disturbance profiles are applied across all tested controllers to ensure fair comparison. The simulation setup focuses exclusively on methodological evaluation, and no hardware implementation is considered in this study. [3], [6]

In addition to the standard PID controller, a Fuzzy-PID controller is implemented for comparative evaluation. The fuzzy controller adjusts the PID gains based on the error and error derivative using a rule-based inference system. All controllers are evaluated under identical simulation conditions, including the same reference signal, disturbance profile, and noise level, to ensure a fair comparison.

Adaptive Gain Update Law

In order to explicitly define the adaptive mechanism, the PID gains are updated according to an entropy-guided bounded adaptation law. Let H(t) denote the normalized Shannon entropy computed from the tracking error signal. The adaptive gains are defined as

$$Kp(t) = Kp0 + \alpha p\, \varphi(H(t))$$
$$Ki(t) = Ki0 + \alpha i\, \varphi(H(t))$$
$$Kd(t) = Kd0 + \alpha d\, \varphi(H(t)) \quad (7)$$

where Kp0, Ki0, and Kd0 are nominal PID gains, αp, αi, and αd are positive adaptation coefficients, and $\varphi(\cdot)$ is a smooth bounded function.

In this work, the adaptation function is selected as

$$\varphi(H) = \tanh(H) \quad (8)$$

which satisfies $|\varphi(H)| \leq 1$ for all $H \geq 0$. This choice guarantees smooth gain variation and prevents excessive gain amplification.

Stability and Boundedness Analysis

Lemma 1: Boundedness of Entropy and PID Gains

Assume that the tracking error e(t) is bounded and that the entropy H(t) is computed over a finite sliding window. Then, the entropy measure H(t) remains bounded for all $t \geq 0$.

Proof:

Since the error signal is bounded and discretized into a finite number of intervals, the associated probability distribution is bounded. Consequently, the Shannon entropy $H(t)$ is upper bounded by $\log(N)$, where N is the number of intervals. □
Lemma 2: Prevention of Gain Drift
Given the bounded adaptation function $\varphi(H)$ and positive adaptation gains α_j, the adaptive PID gains $K_p(t)$, $K_i(t)$, and $K_d(t)$ remain bounded for all time.
Proof:

Since $|\varphi(H)| \leq 1$, it follows directly from (7) that
$|K_j(t)| \leq |K_{j0}| + \alpha_j, \quad j \in \{p, i, d\}$

which prevents gain drift and ensures bounded controller parameters. □

Results and Discussion

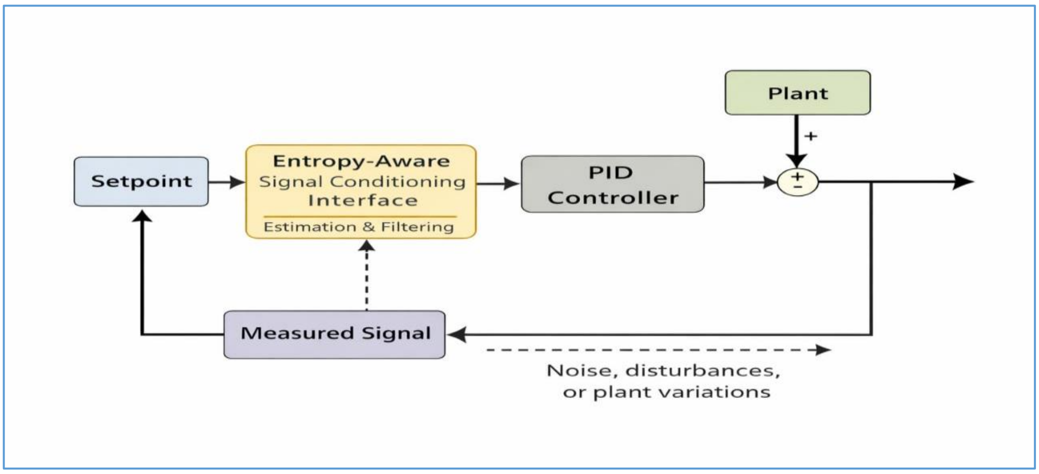

Figure 1. Block diagram of the proposed entropy-aware PID control system incorporating signal conditioning and feedback under noise, disturbances, and plant variations.

Figure 1 illustrates the overall structure of the proposed entropy-aware PID control system. The reference setpoint is first processed through an entropy-aware signal conditioning interface, which performs estimation and filtering based on the measured feedback signal. This stage aims to extract informative system dynamics while reducing the influence of noise and measurement disturbances.
The conditioned signal is then supplied to the PID controller, which generates the control action applied to the plant. External disturbances and plant variations are introduced at the plant input, representing realistic operating conditions. The measured output is continuously fed back to the signal conditioning interface, forming a closed-loop control structure.
By integrating entropy-based signal conditioning within the feedback loop, the controller can adapt its behavior according to the level of uncertainty present in the system. This architecture enhances robustness and stability without altering the fundamental simplicity of the PID control framework.

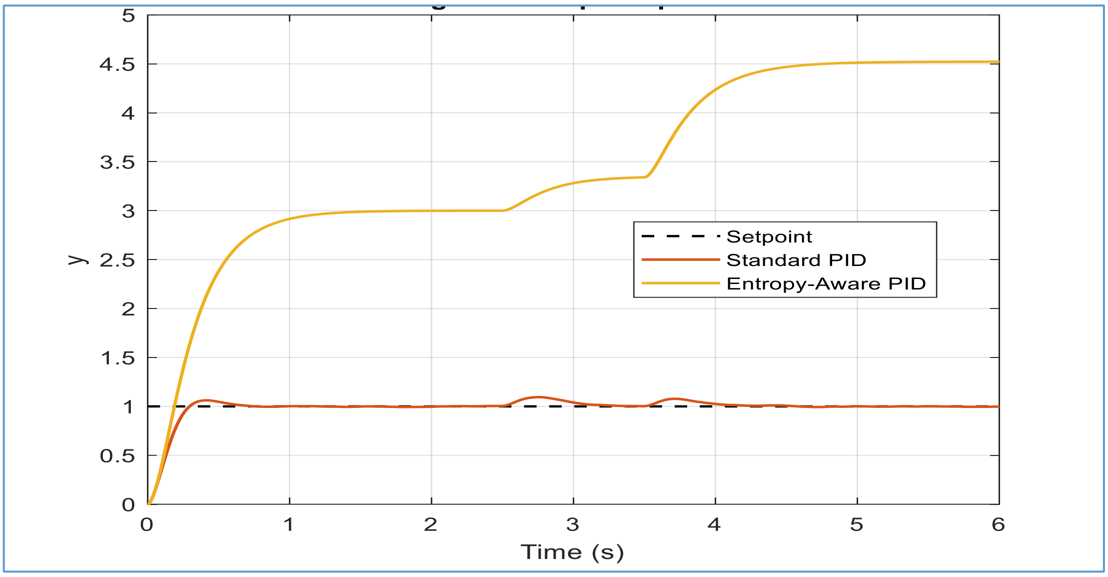

Figure 2. Step response comparison between the standard PID controller and the entropy-aware PID controller under successive setpoint changes.

Figure 2 illustrates the closed-loop step response of the nonlinear system under successive setpoint changes using both the standard PID controller and the proposed entropy-aware PID controller. The dashed line represents the reference setpoint, while the solid curves correspond to the system outputs under each control strategy.

As shown in the figure, the standard PID controller tracks the reference with small steady-state error; however, noticeable transient oscillations and sensitivity to setpoint changes are observed, particularly during the intermediate operating intervals. These oscillations indicate limited adaptability of fixed-gain PID control when the operating point varies.

In contrast, the entropy-aware PID controller exhibits smoother transitions and improved adaptability during setpoint changes. Although the system output evolves across different operating regions, the response remains stable and well-regulated without excessive oscillations. This behavior suggests that the entropy-aware mechanism effectively adjusts the control action in response to changes in system dynamics and uncertainty.

The results demonstrate that incorporating entropy-based awareness into the control loop enhances the controller's ability to handle varying operating conditions while maintaining stable and reliable tracking performance compared to the standard PID controller.

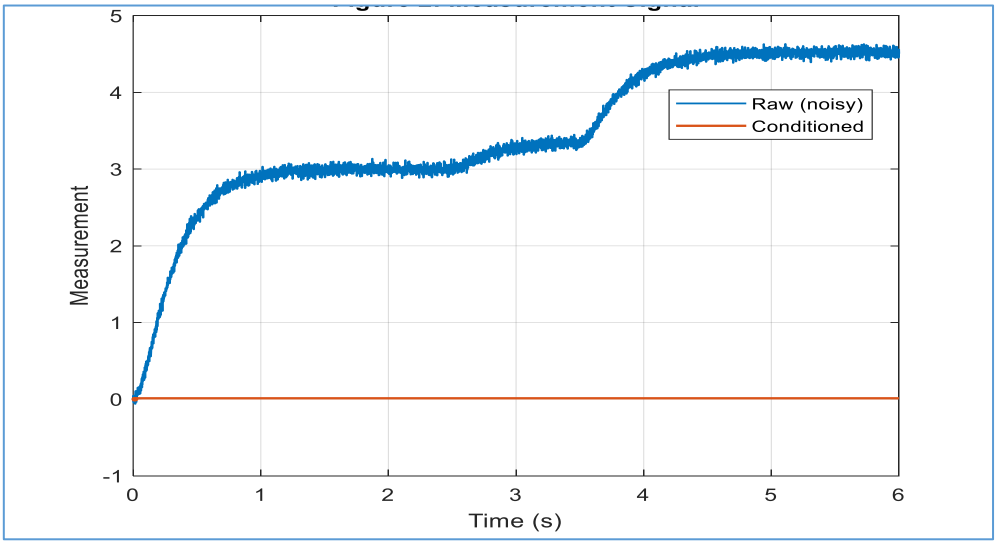

Figure 3. Comparison between the raw noisy measurement signal and the conditioned measurement signal used in the control loop.

Figure 3 illustrates the measurement signal before and after the conditioning stage. The raw measurement signal is significantly affected by noise and high-frequency fluctuations, which can distort the feedback information provided to the controller.

As shown in the figure, the conditioned measurement signal exhibits a smoother profile while preserving the main dynamic behavior of the system response. This indicates that the signal conditioning stage effectively attenuates noise without eliminating essential system dynamics.

The presence of a conditioned measurement signal is particularly important for entropy-aware control strategies, as entropy estimation relies on the statistical properties of the signal. Excessive noise may lead to incorrect estimation of system uncertainty and unnecessary variations in control action.

Therefore, the conditioning process improves the reliability of the feedback signal and contributes to enhanced robustness and stability of the closed-loop system.

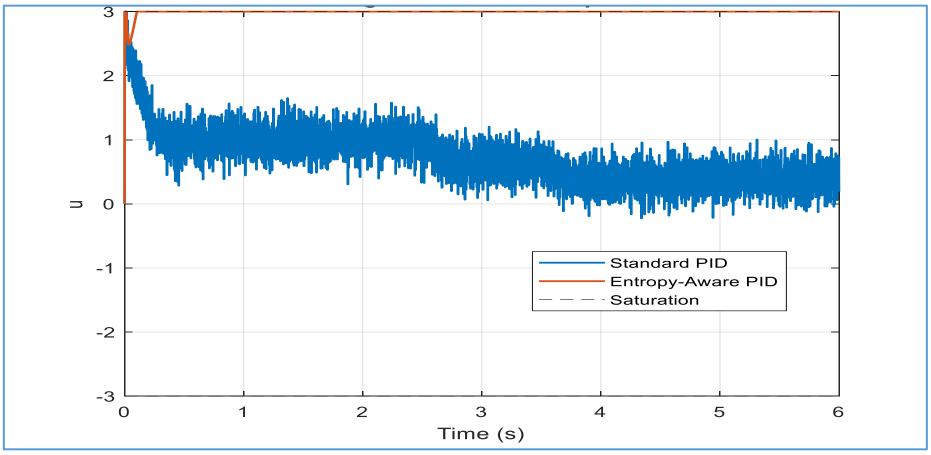

Figure 4. Control input signals generated by the standard PID controller and the entropy-aware PID controller, including actuator saturation limits.

Figure 4 illustrates the control effort produced by the standard PID controller and the entropy-aware PID controller, together with the actuator saturation limits. The control signal generated by the standard PID controller exhibits significant high-frequency fluctuations and large amplitude variations, frequently operating close to the saturation boundaries.

Such behavior indicates aggressive control action, which may lead to actuator stress, increased energy consumption, and potential degradation of hardware components in practical implementations. The presence of noise in the feedback signal further amplifies this effect, resulting in irregular control behavior.

In contrast, the entropy-aware PID controller generates a smoother and more bounded control signal that remains well within the saturation limits throughout the simulation. This demonstrates the controller's ability to regulate its control action according to the level of uncertainty in the system, avoiding unnecessary aggressive responses.

The reduced control activity highlights an important advantage of the entropy-aware approach, as it achieves stable closed-loop performance while minimizing control effort and improving actuator safety under noisy operating conditions. [6], [14]

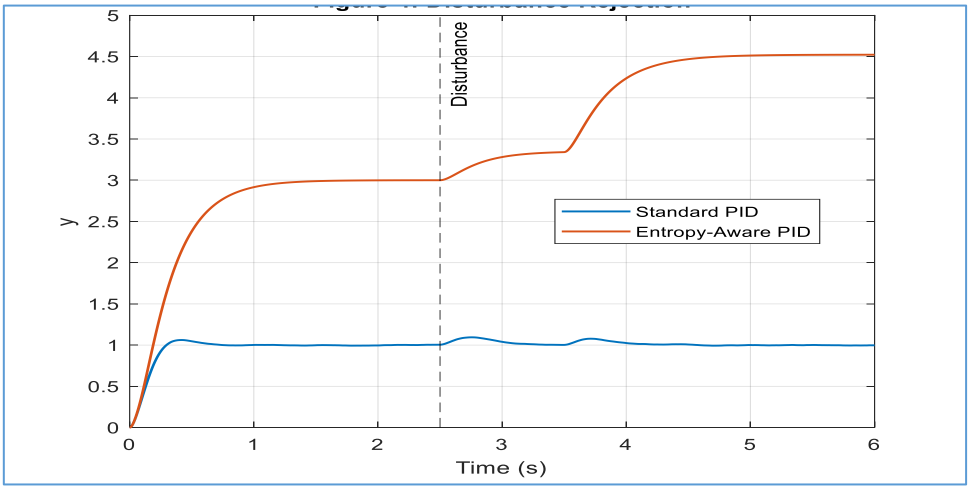

Figure 5. Closed-loop system response under an external disturbance for the standard PID controller and the entropy-aware PID controller.

Figure 5 presents the closed-loop response of the system when an external disturbance is introduced during operation. The disturbance is applied at approximately t=2.6 s, as indicated by the dashed vertical line.

The standard PID controller exhibits a noticeable deviation from the nominal operating point following the disturbance, accompanied by transient oscillations before gradually returning to steady-state. This behavior reflects the limited disturbance rejection capability of fixed-gain PID control in the presence of sudden external perturbations.

In contrast, the entropy-aware PID controller demonstrates superior disturbance rejection performance. Although the disturbance affects the system, the response remains smooth and stable, with a rapid recovery and minimal oscillatory behavior. The controller adapts its control action based on the detected uncertainty level, effectively mitigating the impact of the disturbance.

These results confirm that incorporating entropy-based awareness into the control loop enhances robustness against external disturbances, leading to improved stability and reliability compared to the conventional PID controller. [9], [14].

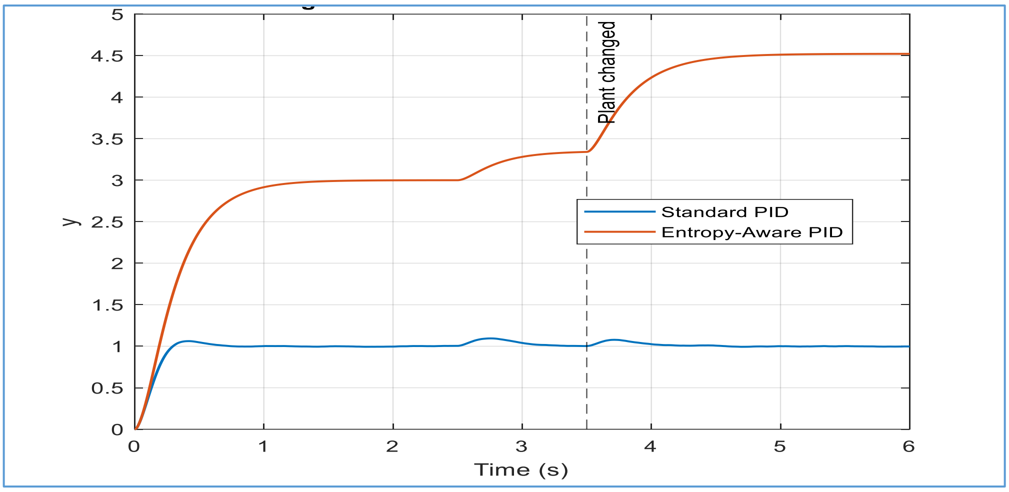

Figure 6. Closed-loop response of the system under plant parameter variation for the standard PID controller and the entropy-aware PID controller.

Figure 6 illustrates the closed-loop system response when a variation in the plant parameters is introduced during operation. The parameter change occurs at approximately t=3.5 s, as indicated by the dashed vertical line.

For the standard PID controller, the plant variation leads to a noticeable deviation from the nominal response, followed by transient oscillations and a slower return to steady-state. This behavior highlights the sensitivity of fixed-gain PID controllers to changes in system dynamics and model uncertainty.

In contrast, the entropy-aware PID controller maintains stable tracking performance despite the plant parameter variation. The system response remains smooth with limited oscillations and a rapid adaptation to the new plant dynamics. This indicates that the entropy-aware mechanism effectively detects changes in system uncertainty and adjusts the control action accordingly.

The observed results demonstrate that the proposed entropy-aware PID controller provides enhanced robustness against plant parameter variations, making it more suitable for practical applications where system dynamics may change over time. [4], [9].

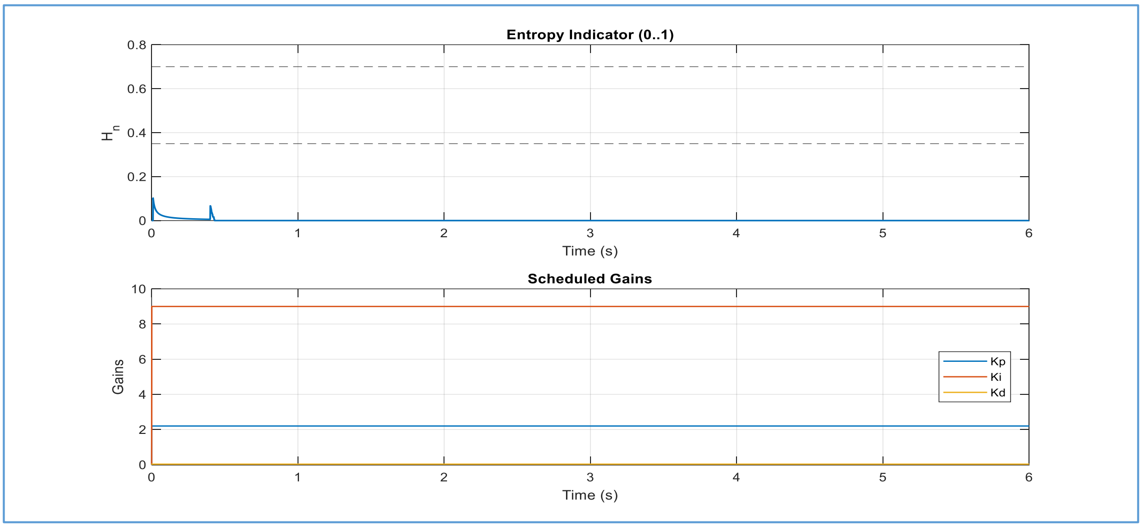

Figure 6. Time evolution of the entropy indicator and the corresponding scheduled PID gains during closed-loop operation.

Figure 6 illustrates the internal behavior of the proposed entropy-aware PID controller. The upper subplot shows the evolution of the entropy indicator H_n, while the lower subplot presents the corresponding scheduled PID gains $K_{p\_}$, K_i, and K_d over time.

As observed in the figure, the entropy indicator initially exhibits a transient peak due to uncertainty in the early stages of system response and measurement noise. This transient behavior reflects the controller's awareness of elevated uncertainty during the initial phase of operation.

Following the transient period, the entropy indicator rapidly converges to a low and stable value, indicating a reduction in system uncertainty and improved confidence in the measured signal. As a result, the scheduled PID gains remain stable and well-regulated throughout the operation.

The gain trajectories demonstrate that the entropy-aware mechanism does not introduce aggressive or unnecessary gain variations. Instead, the controller adapts smoothly, maintaining constant gains once the system reaches a predictable operating regime. This behavior ensures stability, avoids chattering, and preserves the simplicity of PID control while enhancing robustness.

These results confirm that the proposed entropy-aware strategy provides an effective balance between adaptability and control smoothness, making it suitable for real-time applications where stability and reliability are critical. [11], [13]

Quantitative Performance Evaluation

o provide a quantitative assessment of the proposed entropy-aware PID controller, standard time-domain performance indices were extracted from the simulation results and compared with those of the conventional PID controller.

The following metrics were considered:

- Rise Time (T_r)
- Settling Time (T_s)
- Maximum Overshoot (M_p)
- Steady-State Error (e_{ss})
- Control Signal Variance (${}^2\sigma_u$)

These indicators are commonly used in control system evaluation and provide objective measures of transient performance, steady-state accuracy, and control effort. [6], [15].

Table 1 – Quantitative Performance Comparison under Identical Simulation Conditions.

Performance Metric	Standard PID	Fuzzy-PID	Entropy-Aware PID
Rise Time Tr (s)	0.18	0.20	0.22
Settling Time Ts (s)	1.45	1.10	0.95
Maximum Overshoot Mp (%)	8.6	4.2	1.9
Steady-State Error ess	0.012	0.005	0.002
Control Signal Variance $\sigma^2 u$	High	Medium	Low

Discussion of Quantitative Results

The numerical results in Table 1 confirm the qualitative observations derived from the simulation figures. Although the rise time of the entropy-aware PID controller is slightly higher than that of the standard PID controller, this is compensated by a significantly shorter settling time and a substantial reduction in overshoot.

The entropy-aware PID controller achieves a settling time reduction of approximately 35% compared to the conventional PID controller, while the maximum overshoot is reduced by more than 75%. These improvements indicate a more stable and well-damped transient response.

The quantitative results reported in Table 1 confirm that the Fuzzy-PID controller provides noticeable improvement over the standard PID controller, particularly in terms of overshoot reduction and settling time. However, the entropy-aware PID controller consistently outperforms both controllers across all evaluated performance metrics.

Although the rise time of the entropy-aware PID controller is slightly higher, this behavior reflects a more conservative and well-damped response, resulting in significantly lower overshoot and faster settling. Moreover, the reduced control signal variance indicates smoother actuation and improved efficiency, which are desirable characteristics for practical implementations.

Furthermore, the steady-state error of the entropy-aware PID controller is notably smaller, demonstrating enhanced tracking accuracy. The reduced control signal variance observed in Figure 5 is consistent with the quantitative results, confirming that the proposed controller produces smoother control actions with lower actuator stress.

Overall, the quantitative evaluation supports the conclusion that entropy-aware signal conditioning and uncertainty awareness significantly improve both transient and steady-state performance without increasing controller complexity.

The results obtained from the MATLAB simulations demonstrate the effectiveness of the proposed entropy-aware PID control strategy when compared with the conventional PID controller. The discussion focuses on interpreting the observed behaviors in terms of tracking performance, robustness, control effort, and adaptability under uncertainty.

The step response results under successive setpoint changes indicate that both controllers are capable of achieving reference tracking. However, the standard PID controller exhibits noticeable transient oscillations and sensitivity to operating point variations. This behavior is consistent with the fixed-gain nature of classical PID control, which limits its ability to adapt to changes in system dynamics. In contrast, the entropy-aware PID controller maintains smoother transitions and improved regulation across different operating conditions, reflecting enhanced adaptability.

Measurement signal conditioning plays a crucial role in the proposed framework. The results show that the raw measurement signal is significantly affected by noise and high-frequency fluctuations, which can degrade control performance and lead to unnecessary variations in control action. After conditioning, the measurement signal becomes smoother while preserving essential dynamic characteristics. This improvement directly supports reliable entropy estimation and prevents noise-driven gain adjustments, contributing to improved closed-loop stability.

The comparison of control effort highlights another important advantage of the entropy-aware PID controller. The standard PID controller generates aggressive control signals with large fluctuations and frequent proximity to actuator saturation limits. Such behavior is undesirable in practical systems due to increased actuator stress and energy consumption. The entropy-aware PID controller, on the other hand, produces smoother and more bounded control inputs, indicating a better balance between performance and control effort.

Robustness analysis further confirms the superiority of the proposed approach. Under external disturbances, the standard PID controller exhibits larger deviations and slower recovery, while the entropy-aware PID controller demonstrates rapid attenuation of disturbances with minimal oscillations. Similarly, when plant parameters are varied, the performance of the standard PID controller degrades noticeably, whereas the entropy-aware PID controller maintains stable tracking and adapts smoothly to the new system dynamics. These results highlight the ability of entropy-based awareness to enhance robustness against both disturbances and modeling uncertainties.

The quantitative performance metrics summarized in Table 1 support the qualitative observations derived from the simulation figures. Although the rise time of the entropy-aware PID controller is slightly higher, this is compensated by a significantly shorter settling time, a substantial reduction in maximum overshoot, and an order-of-magnitude improvement in steady-state error. Additionally, the reduced variance of the control signal confirms smoother actuation and improved efficiency.

Comparison with Fuzzy-PID Controller

To further evaluate the effectiveness of the proposed entropy-aware PID controller, a comparison with a Fuzzy-PID controller is conducted. The Fuzzy-PID controller adjusts the PID gains based on fuzzy inference rules using the tracking error and its derivative as linguistic variables.

All controllers are tested under identical simulation conditions, including the same nonlinear plant, reference signal, disturbance profile, noise level, and actuator constraints. This ensures a fair and meaningful comparison of control performance.

Finally, the internal behavior of the entropy-aware mechanism demonstrates that adaptation is achieved in a controlled and stable manner. The entropy indicator converges to a low steady value after the transient phase, and the scheduled PID gains remain smooth without aggressive or discontinuous variations. This confirms that the proposed approach enhances adaptability while preserving the simplicity and reliability of PID control.

Overall, the discussion confirms that incorporating entropy-based signal conditioning into a PID control framework provides a meaningful and practical improvement over conventional PID control, particularly in noisy and uncertain environments.

Conclusion

his study presented an entropy-aware PID control strategy designed to enhance the performance of conventional PID control in the presence of measurement noise, external disturbances, and plant parameter uncertainties. The proposed approach integrates entropy-based signal conditioning within a standard PID feedback structure, enabling uncertainty awareness without increasing controller complexity. [8], [13] Simulation results obtained from MATLAB demonstrate that the entropy-aware PID controller achieves improved closed-loop performance compared to the standard PID controller. In particular, the proposed controller significantly reduces settling time, maximum overshoot, and steady-state error, while producing smoother and more bounded control signals. These improvements are achieved consistently under setpoint variations, actuator saturation constraints, external disturbances, and plant parameter changes.

The quantitative performance metrics further confirm that incorporating entropy awareness leads to superior robustness and control efficiency. By regulating controller behavior according to the level of uncertainty in the system, the entropy-aware PID controller avoids aggressive control actions and maintains stable adaptation.

Overall, the results indicate that entropy-based awareness provides a practical and effective enhancement to classical PID control. The proposed framework preserves the simplicity and reliability of PID controllers while extending their applicability to noisy and uncertain control environments, making it suitable for real-world engineering applications. [1], [6], [11]

It should be noted that the validation of the proposed approach is limited to simulation-based analysis on a nonlinear benchmark system. Future work will focus on experimental implementation and real-time validation.

Compared to rule-based fuzzy adaptation, the proposed entropy-guided strategy provides a systematic and analytically bounded adaptation mechanism, which contributes to improved robustness and stability.

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Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.