

Article

$PI-D^{\mathcal{A}}$: An Adaptive PID Controller Utilizing a New Adaptive Exponent ($\mathcal{A}$) Algorithm to Solve Derivative Term Issues

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Abstract

This study proposes an enhanced derivative control strategy, named $PI-D^{\mathcal{A}}$, designed to overcome key limitations of the derivative (D) term, such as noise amplification, derivative kick ($D-k$), and tuning difficulties. These issues often arise in high-frequency or rapidly changing systems, in which traditional PID controllers struggle. The proposed solution introduces a novel adaptive exponent algorithm ($\mathcal{A}$) that dynamically modulates the D term based on the evolving relationship between system output and setpoint. This yields the $PI-D^{\mathcal{A}}$ controller, which adapts in real time to changing conditions. The results show significant performance improvements. Simulation results on two systems demonstrate that $PI-D^{\mathcal{A}}$ achieves a 90% faster response time, a 35% reduction in peak time, and a 100% improvement in settling time compared with conventional PID controllers, all while maintaining a near-zero steady-state error even under external disturbances. Unlike more-complex alternatives such as fuzzy logic, neural networks, or sliding mode control, $PI-D^{\mathcal{A}}$ retains the simplicity and robustness of PID, avoiding high computational costs or intricate setups. This adaptive exponent strategy offers a practical and scalable enhancement to classical PID, improving performance and robustness without added complexity, and thus provides a promising control solution for real-world applications in which simplicity, adaptability, and reliability are essential.

Keywords: adaptive PID control; nonlinear control; robust control; PID tuning algorithms



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1. Introduction

PID control is widely used in industry to regulate variables such as temperature, speed, and position. Its name derives from its three terms, proportional, integral, and derivative, each with a specific function and a specific gain, k_P , k_I , and k_D . The P term produces an output proportional to the current error. The I term eliminates steady-state error, and the D term anticipates future errors using the D of error.

D is considered valuable as it enhances response time and transient behavior and is particularly effective in shortening response time and accelerating recovery from system disturbances [1–3]. This improves response speed and reduces overshoot, quickly stabilizing the system. However, D also has drawbacks, such as noise amplification and difficulty in proper tuning. Its sensitivity to noise in measurement signals can lead to unstable responses, and it requires deep knowledge of the system to properly adjust k_D .

Additionally, there are phenomena such as the (*Ltd-D*) bandwidth-limited derivative control and the “(*D-kick*) derivative kick”. The *Ltd-D* occurs when a process-variable measurement contains excessive noise due to high-frequency components in the system. *D* amplifies this noise because it has a high-frequency gain, making it unable to respond effectively to rapid changes and limiting its performance. In practical scenarios, a highly noisy control signal can cause actuator damage, leading to poor actuator performance [4].

D-kick occurs with abrupt changes in SP, resulting in a sharp peak in the control signal. This undesired behavior makes *D* excessively large, potentially causing overshoot or actuator saturation, complicating control and stability.

In summary, *D* enhances a control system’s performance but must be carefully implemented to avoid undesired effects.

Various strategies have been proposed to mitigate the adverse effects of *D* [3,4]. Among these, the pure differentiator enhances high-frequency gain and prevents impulses in control signals, often combined with filtering techniques to minimize undesired effects, as demonstrated by Rojas et al. [5]. Another widely adopted method is the linear low-pass filter, proposed by Jin et al. [6], in which a first-order low-pass filter is cascaded with the differentiator. This approach is particularly effective in data acquisition processes, although it tends to slow down transient responses. The speed feedback technique [7], which employs PV instead of the $e(t)$ signal, offers another alternative for refining *D*. Similarly, setpoint filters, as implemented by Arun et al. [8], reduce sensitivity to SP changes and mitigate overshoot. However, tuning these filters for stability and robustness remains a complex task. Pre-filters, analyzed by Singh et al. [9], are often used to achieve smooth control during step changes in SP but fail to address disturbances effectively as they are not integrated into a feedback loop. Finally, nonlinear mean filters, evaluated by Abdel-Razak et al. [10], provide another solution by averaging data points to eliminate noise and disturbances. While these filters effectively smooth control signals and suppress noise, they often increase response times and excessively dampen underdamped processes, limiting their utility in dynamic systems.

These remedies only provide partial solutions. They primarily involve calculating filters to attenuate the controller signal, which cancels *D* under certain operating conditions.

Besides these approaches, advanced control strategies, such as FL and NN, have been proposed as alternatives to improve the controller’s performance. Fazlollahtabar et al. [11], for instance, demonstrated improved system behavior using FL in a specific plant. While these methods enhance performance, they rely on expert knowledge, demand significant computational resources, and require intricate rule definitions. Similarly, NNs [11] and other adaptive techniques [8]—such as GA, SMCs [11], and fractional-order controllers [12]—offer robustness and adaptability for nonlinear systems but suffer from drawbacks like high computational complexity, convergence issues, chattering effects, and challenging parameter tuning.

The main goal of this paper is to retain the functionality and effectiveness of *D* without compromising the simplicity of the controller. This study also aims to develop a simple control strategy that avoids the complexity of advanced methods while preserving the *D* term, unlike filtering approaches that often suppress it.

Furthermore, *D* continues to present challenges (including *Ltd-D* and *D-kick*) that must be overcome. Current solutions primarily focus on attenuating the control signal or applying tuning techniques that fail to address these issues holistically, as previously mentioned. To bridge this gap, this study proposes a novel controller, the $PI-D^{\mathcal{A}}$ controller, which leverages adaptive control theories and self-calculation of the exponential term *D*.

Unlike traditional approaches, this controller will not rely on training, rule-based systems, complex computations, or filters. Instead, it will employ adaptive control theories

to dynamically adjust D through self-tuning mechanisms, including self-calculation of its exponential, effectively enhancing performance without significantly increasing complexity.

The proposed $PI-D^{\mathcal{A}}$ controller aims to enhance the performance of D by effectively reducing noise sensitivity and managing abrupt SP changes. It seeks to prevent system destabilization and output signal saturation, providing a robust and efficient alternative to conventional PID tuning methods. In addition, it is hoped that this controller will become a tool that can be implemented in a wide variety of control systems. Furthermore, this work focuses on the development of an algorithm validated through the simulation and analysis of transient and steady-state responses.

The letter “ $\mathcal{A}$ ” is used in this article as a symbolic notation to represent the dynamic combination of proportional and derivative effects in the proposed controller. This choice is inspired by its origin as a ligature of the vowels “a” and “e,” which conceptually parallels the adaptive fusion of two classical control components. Thus, its use not only provides a compact representation of the algorithm but also conveys the integrated nature of these control actions.

The rest of this article is organized as follows. Section 2 presents the $PI-D^{\mathcal{A}}$ controller. Section 3 evaluates its performance on a first-order and inverted pendulum–cart system. Section 4 describes the application of $PI-D^{\mathcal{A}}$ with a detailed analysis of its response in time and under disturbances. Section 5 concludes the study with discussions. Finally, Section 6 proposes the conclusions and opportunities for future improvements.

2. Controller Presentation

PID contains three parts, as follows:

$$C_P(s) = P + I + D \quad (1)$$

The parallel structure of PID is selected as shown in Equation (2).

$$C_P(s) = k_P + \frac{k_I}{s} + k_D(s) \quad (2)$$

Now, a new concept of $\mathcal{A}$ is presented:

$$C_P(t) = \frac{U(s)}{Y(s)} = k_P e(t) + \frac{k_I}{I} e(t) + \left[k_D \frac{de(t)}{dt} \right]^{\mathcal{A}} \quad (3)$$

$$C_P(s) = k_P + \frac{k_I}{s} + [k_D(s)]^{\mathcal{A}} \quad (4)$$

$\mathcal{A}$ dynamically adjusts the D system’s behavior by accelerating or mitigating the response, depending on the desired control effect, as shown in Figure 1.

For example, if the exponent is $\mathcal{A} = 1$, we obtain classic PID , and if $\mathcal{A} = 0$, we obtain PI . Extending this concept, $\mathcal{A}$ is assumed to take values within the range $(-\infty, \infty)$, including infinitesimally small values approaching zero, offering a continuum of control strategies between PI and PID .

This simple and robust idea considers an adaptive exponent ($\mathcal{A}$) for D , proposing that D be enhanced as a dynamic, adaptive parameter instead of a fixed constant.

Based on the classical PID response (the Output signal amplitude system depicted in Figure 2), the proposed concept introduces an analysis of D across its full range of values $(-\infty, \infty)$. This analysis redefines D as a new, independent parameter with a $D^{\mathcal{A}}$ function, enabling the transformation of the system’s response. By employing the proposed exponential function, $D^{\mathcal{A}}$, the system’s future behavior can be effectively modified, as illustrated in Figures 2 and 3.

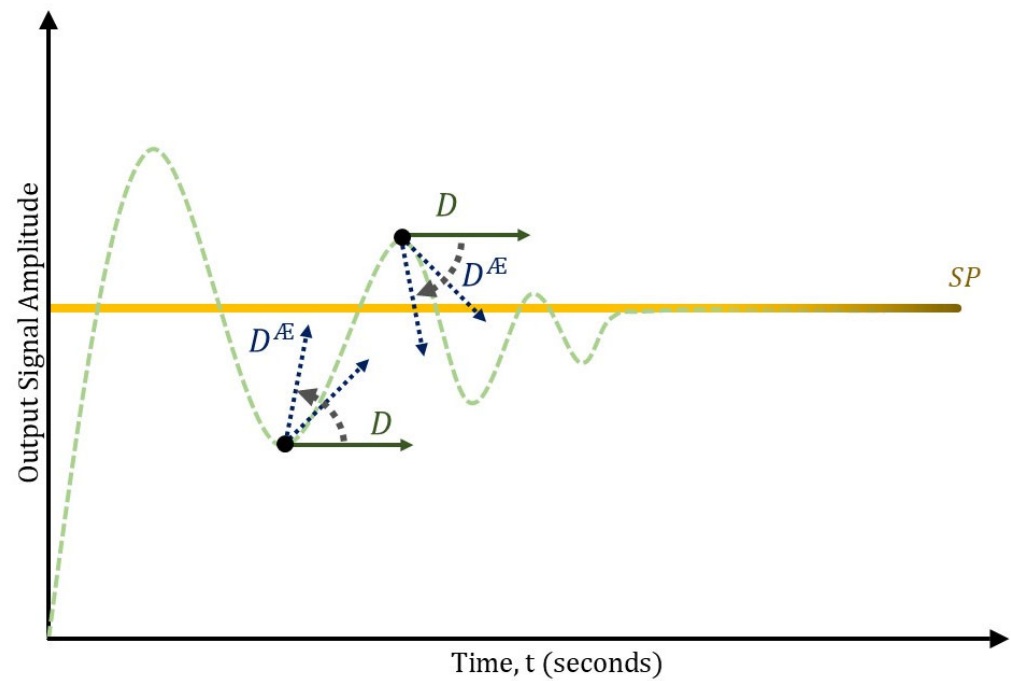


Figure 1. $D^{\mathcal{A}}$ modification of behavior response. This figure illustrates how the proposed $D^{\mathcal{A}}$ term dynamically adjusts the influence of the derivative component. Depending on the value of the exponent $\mathcal{A}$, the controller's behavior can range from PI control ($\mathcal{A} = 0$) to classical PID control ($\mathcal{A} = 1$) or to even more aggressive responses. This adaptability enhances the system's transient performance without relying on external filters.

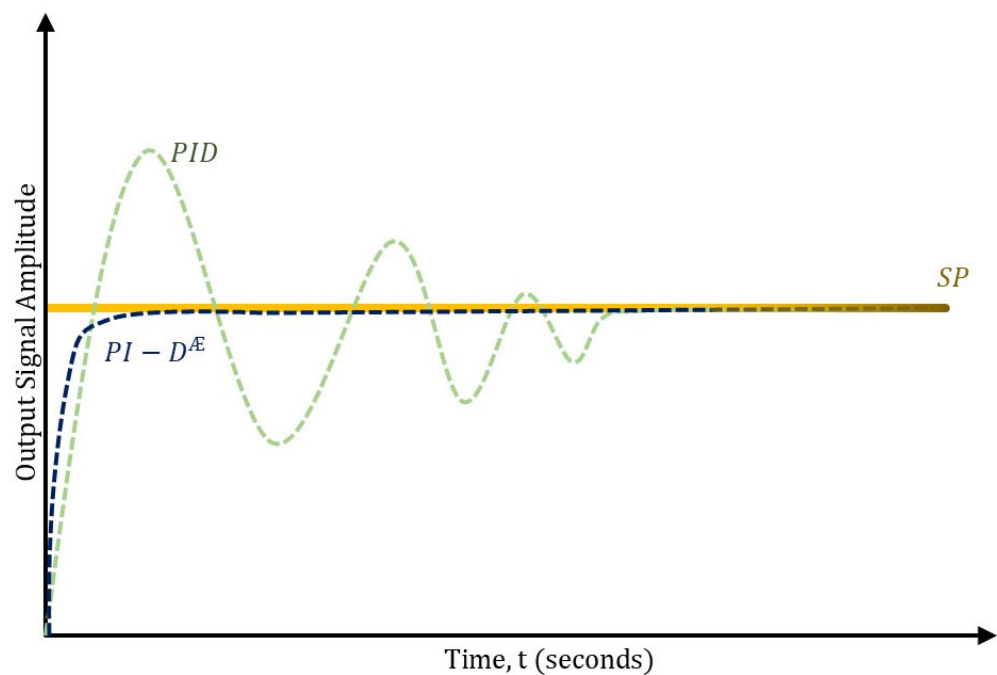


Figure 2. PID vs. $PI-D^{\mathcal{A}}$ responses. The figure highlights how the $PI-D$ controller modifies the output dynamics compared with a traditional PID . The use of the adaptive exponent $\mathcal{A}$ results in faster rise times, reduced overshoot, and shorter settling times, demonstrating improved robustness to setpoint changes.

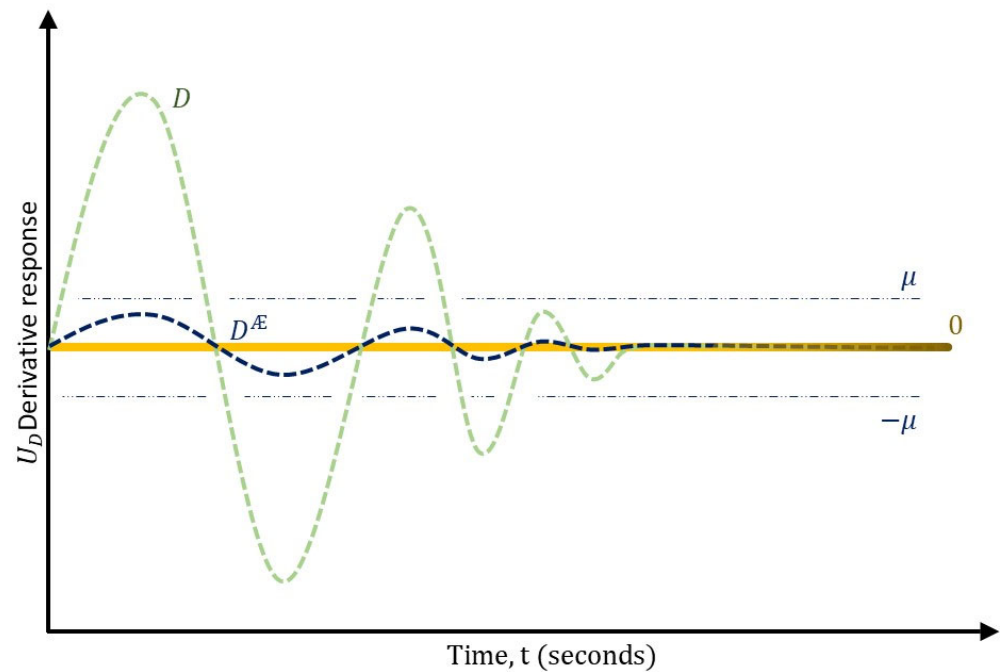


Figure 3. D vs. D^E responses. This plot shows how D either attenuates or intensifies the derivative action based on the system state. This adaptiveness prevents noise amplification and contributes to improved controller stability under disturbances or time-varying conditions.

According to Liuping Wang [4], maintaining the robustness of a PID design is essential; a positive D ($D > 0$) can destabilize the system and provide excessive disturbance, while a negative signal ($D < 0$) is negligible. To prevent instability, D can be deactivated. In the $PI-D$ controller, D^E remains continuously active, ready to respond to any disturbance or SP change. It dynamically adjusts the behavior of D in real time at any $Y(s)$, as illustrated in Figures 4 and 5.

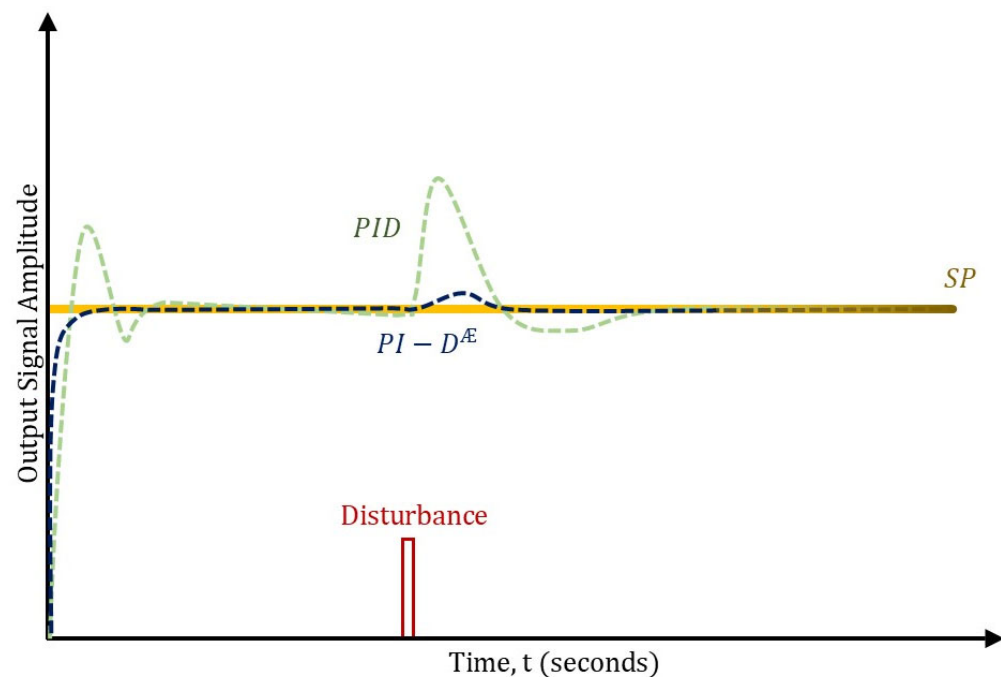


Figure 4. PID and $PI - D^E$ responses with disturbance. The figure demonstrates the superior disturbance rejection capability of the $PI - D^E$ controller. Compared with the conventional PID , the $PI - D^E$ recovers equilibrium faster and exhibits reduced oscillatory behavior, ensuring improved robustness in non-ideal environments.

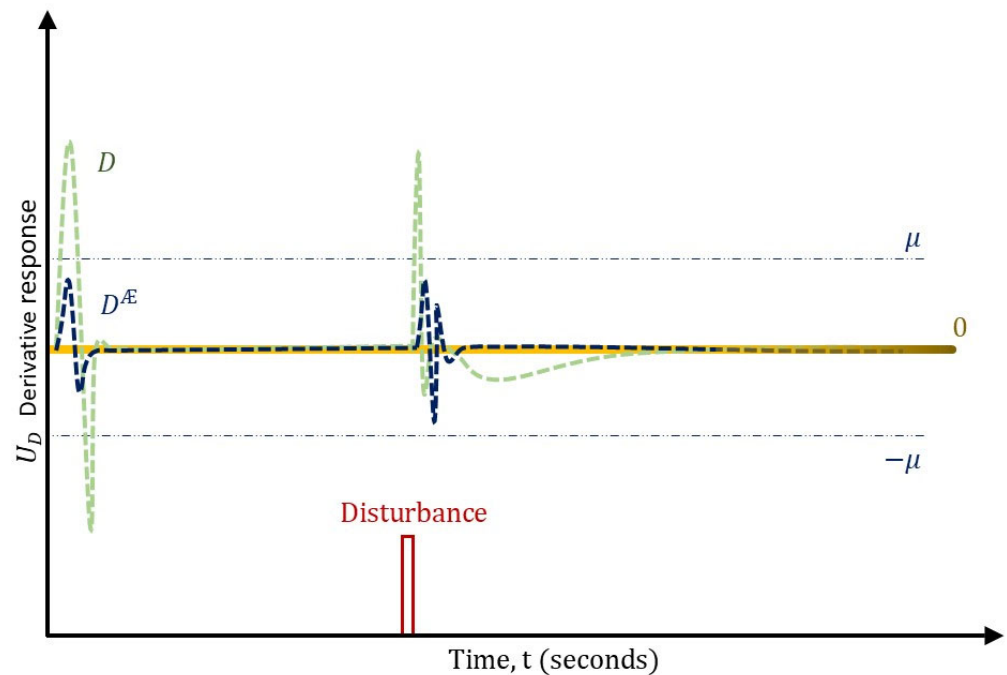


Figure 5. D and $D^{\mathcal{A}E}$ responses with disturbance. This figure presents the response of the derivative terms under perturbations. While the classical D term amplifies noise and generates abrupt control actions, the $D^{\mathcal{A}E}$ term adaptively regulates its magnitude via the $\mathcal{A}E$ exponent, resulting in smoother and safer control signals.

$PI-D$ employs an ($\mathcal{A}E$) adaptive exponent within its structure. Unlike other PID -based controllers, this approach uses an adaptive exponent with an open-loop adaptive control mechanism, shown in Figure 6, allowing the behavior of D to be modified instantly using only the input-to-output relationship of C_P .

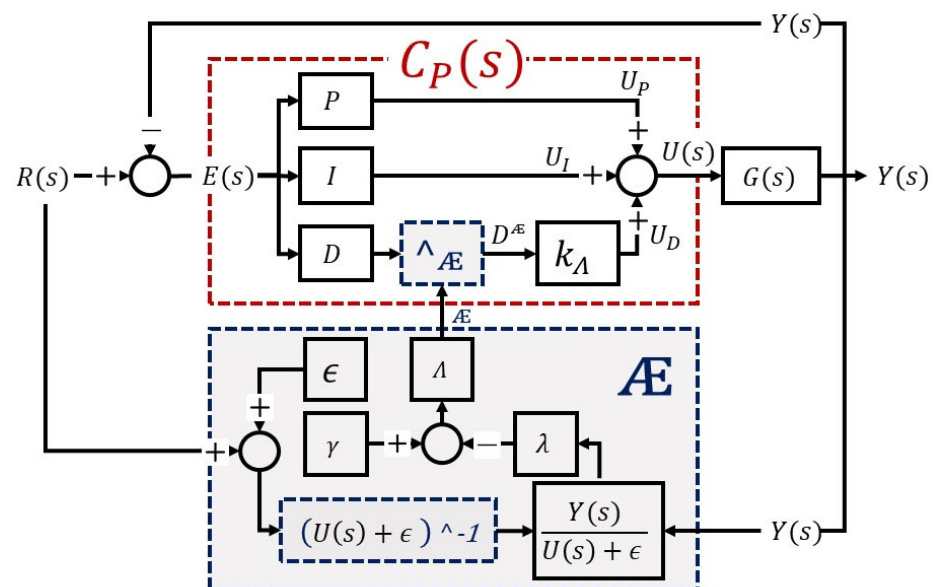


Figure 6. Proposed adaptive $PI-D^{\mathcal{A}E}$ controller structure. This block diagram presents the architecture of the $PI-D^{\mathcal{A}E}$ controller, in which the adaptive exponent $\mathcal{A}E$ modulates the derivative action. The total control signal is composed of independent proportional, integral, and adaptive derivative components. A switching gain is included to enable or disable the derivative term as needed, providing flexibility in controller deployment.

Equation (5) defines $\mathcal{AE}$ as follows:

$$\mathcal{AE} = \Lambda \left(\mu - \frac{\sigma \cdot R(s)}{U(s) + \epsilon} \right) \quad (5)$$

where μ is the maximum limit predefined for $\mathcal{AE}$; σ is a sensitivity factor (100 is the recommended value), which determines how reactive the algorithm will be to changes in $Y(s)$; ϵ is an indeterminate avoidance value ($\epsilon \simeq 0$); and Λ is an auxiliary gain (recommended values of 1 or 2) that can be added and is helpful in situations in which the gain must be modified indirectly from without altering the initial tuning.

There are two possible scenarios:

- (1) If the input is greater than the output, $U(s) > Y(s)$, so the response of exponent $\mathcal{AE}$ is increasing and positive.

For example, if $Y(s) = 0$, $R(s) = 1$, and $\mu = \sigma = 100$, this represents the condition $Y(s) < R(s)$, where $e(s)$ is positive and at its maximum. In this case, $\mathcal{AE} = 100$, leading to a rapid response in $D^{\mathcal{AE}}$ as its exponential increases.

- (2) If the output is greater than the input, $Y(s) > U(s)$, so the response of $\mathcal{AE}$ is decreasing and negative.

And, if $Y(s) = 2$, $R(s) = 1$, and $\mu = \sigma = 100$, this represents condition $Y(s) > R(s)$, where $e(s)$ is negative and at its maximum. In this case, $\mathcal{AE}$ is negative, leading to a rapid response in $D^{\mathcal{AE}}$ as its exponential decreases. And results in a maximum negative decrease $\mathcal{AE} = -100$.

μ and σ can be adjusted based on the system's requirements, such as speed and noise rejection, as suggested by Dastjerdi et al. [13] for P . These parameters are associated with a high crossover frequency of D , which plays a critical role in achieving stability and optimal control system performance.

The parameters μ , σ , and ϵ directly influence the adaptive response of the exponent $\mathcal{AE}$ and, therefore, the behavior of the $D^{\mathcal{AE}}$ term. Increasing μ allows a wider dynamic range for $\mathcal{AE}$, making the controller more aggressive and responsive but potentially increasing overshoot. A higher σ makes the controller more sensitive to small changes in output, improving reactivity but also amplifying noise—excessively high σ can destabilize the system in noisy environments. Conversely, a lower σ smooths the response but reduces adaptability. The parameter ϵ ensures numerical stability when the reference $R(s)$ approaches zero. If ϵ is too small, the system may become unstable; if too large, it weakens the effect of $\mathcal{AE}$. Proper tuning of these parameters enables the controller to balance fast adaptation, robustness, and noise immunity effectively. The values presented in this article were carefully selected as ideal defaults for the initial presentation of the algorithm, providing a robust and balanced behavior across typical operating conditions.

In an additional case, if $Y(s) \simeq U(s)$, $\mathcal{AE}$ modifies its response, resulting in a null $D^{\mathcal{AE}}$ response, even if noise variations in D occur.

So, replacing $\mathcal{AE}$ in Equation (4) is achieved as follows:

$$C_P(s) = k_P + \frac{k_I}{s} + [k_D(s)]^{\Lambda(\mu - \frac{\sigma \cdot Y(s)}{R(s) + \epsilon})} \quad (6)$$

The proposed adaptive $PI-D^{\mathcal{AE}}$ controller is presented in Figure 6. The gain k_{switch} serves as a practical switch that activates or deactivates D in the control system. By assigning a value of 1 to the gain, D is enabled, while a value of 0 disables it.

$$C_P(s) = k_P + \frac{k_I}{s} + k_{switch} \cdot [k_D(s)]^{\Lambda(\mu - \frac{\sigma \cdot Y(s)}{R(s) + \epsilon})} \quad (7)$$

$$C_P(s) = k_P + \frac{k_I}{s} + k_{switch} \cdot [k_D(s)] \quad (8)$$

$$C_P(s) = P + I + D \quad (9)$$

k_Λ serves as a practical switch that activates or deactivates D in the control system. By assigning a value of 1 to the switch, D is enabled, while a value of 0 effectively disables it, providing a straightforward mechanism for managing its influence on the system's response.

The total control signal is given as follows:

$$U(s) = U_P(s) + U_I(s) + U_D(s) \quad (10)$$

3. Materials and Methods

In this section, two proposed control systems are presented. Simulations and graphs were obtained using MATLAB 2024a and Simulink software.

3.1. Test Plants

3.1.1. First-Order System

A first-order plant as in Equation (11) is considered for testing the controller.

$$G(s) = \frac{K}{1 + Ts} e^{-Ls} \quad (11)$$

3.1.2. Inverted Pendulum on a Cart IPC

And a second plant [14–16] is presented to test the proposed algorithm, an inverted pendulum on a cart, as shown in Figure 7.

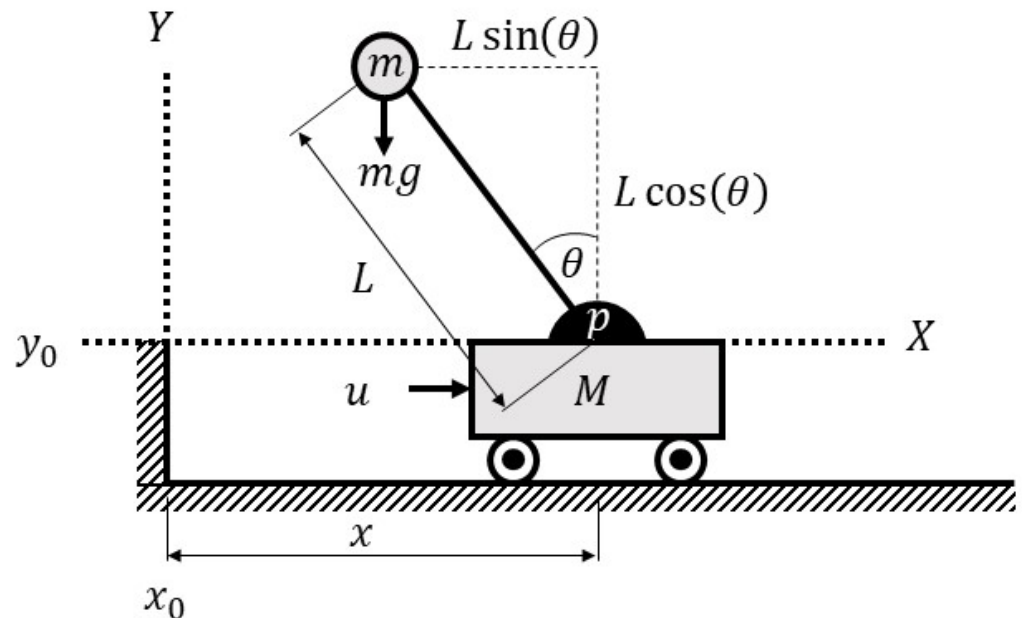


Figure 7. System of IPC.

Here, M is the mass of the car; p is the pivot point; L is the pendulum; the horizontal direction is x ; u is the force; and θ is the angle.

The relevant state-space equations are as follows:

$$\dot{x}_1 = x_2 \quad (12)$$

$$\dot{x}_2 = \frac{(M+m)g\sin x_1 - mLx_2^2(\sin x_1 \cos x_1) - u \cos x_1}{ML + mL(\sin x_1)^2} \quad (13)$$

$$\dot{x}_3 = x_4 \quad (14)$$

$$\dot{x}_4 = \frac{u + mLx_2^2(\sin x_1) - mg \cos x_1 \sin x_1}{M + m(\sin x_1)^2} \quad (15)$$

where

$x_1 = \theta$; the angle of the inverted pendulum.

$x_2 = \dot{\theta}$; the angular velocity of the inverted pendulum.

$x_3 = x$; the position of the cart.

$x_4 = \dot{x}$; the velocity of the cart.

4. Simulation Results

4.1. First-Order System

The controller was first tested in a first-order plant, where $K = 10$, $T = 1$ s, and $L = 0.1$ were proposed as in reference [17].

$$G(s) = \frac{10}{s+1} e^{-0.1s} \quad (16)$$

Figure 8 presents the PID response to emphasize the destabilizing effect of D when different values of τ_D are assigned. These τ_D values are proposed according to the analysis conducted by Ang et al. [17], with an additional value ($\tau_D = 0.4$). The PID and $PI-D^{\mathcal{E}}$ parameters can be found in Table 1.

Table 1. Controller parameters.

	$\tau_D=0$	$\tau_D=0.03$		$\tau_D=0.1$		$\tau_D=0.2$		$\tau_D=0.4$	
	$PI(D)$	PID	$PI-D^{\mathcal{E}}$	PID	$PI-D^{\mathcal{E}}$	PID	$PI-D^{\mathcal{E}}$	PID	$PI-D^{\mathcal{E}}$
k_P					0.644				
k_I					0.625				
τ_I					1.03				
k_D	0	0.019		0.064		0.128		0.257	
τ_D	0	0.0303		0.1		0.2		0.4	
Λ			2		2		2		2
μ			100		100		100		100
ϵ			0.01		0.01		0.01		0.01
k_{Λ}			1		1		1		1

Figures 9–11 represent a comparison between PID and $PI-D^{\mathcal{E}}$ when $\tau_D = 0.03$ and $\tau_D = 0.1$, which shows its property acceleration response by implementing $PI-D^{\mathcal{E}}$. Additionally, Figure 10 includes the system's behavior under a disturbance at $t = 1$.

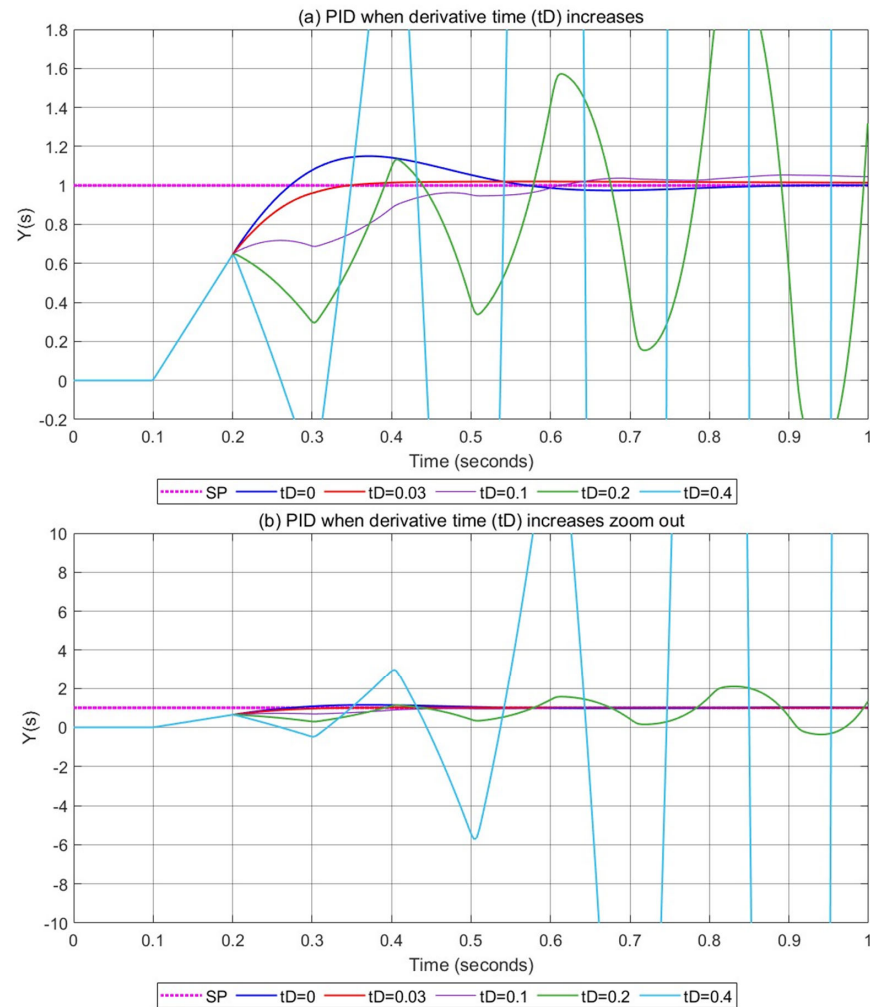


Figure 8. PID controller with different τ_D values. (a) This figure presents the response of a classical PID controller using various values of the derivative time constant τ_D . (b) The simulation highlights the destabilizing effects of the derivative term as τ_D increases, including excessive overshoot and longer settling times. These results underscore the limitations of fixed-gain derivative action in conventional PID tuning, particularly under dynamic or noisy conditions.

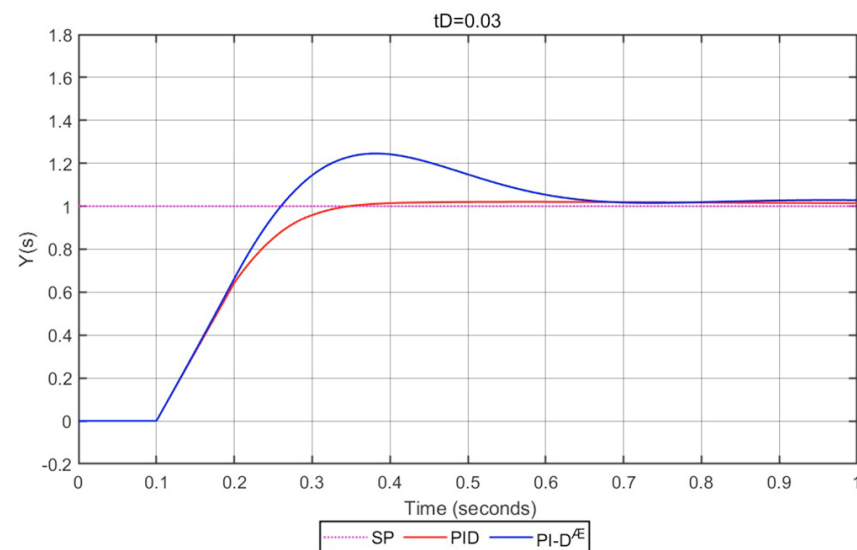


Figure 9. PID and PI-D^E. $\tau_D = 0.03$.

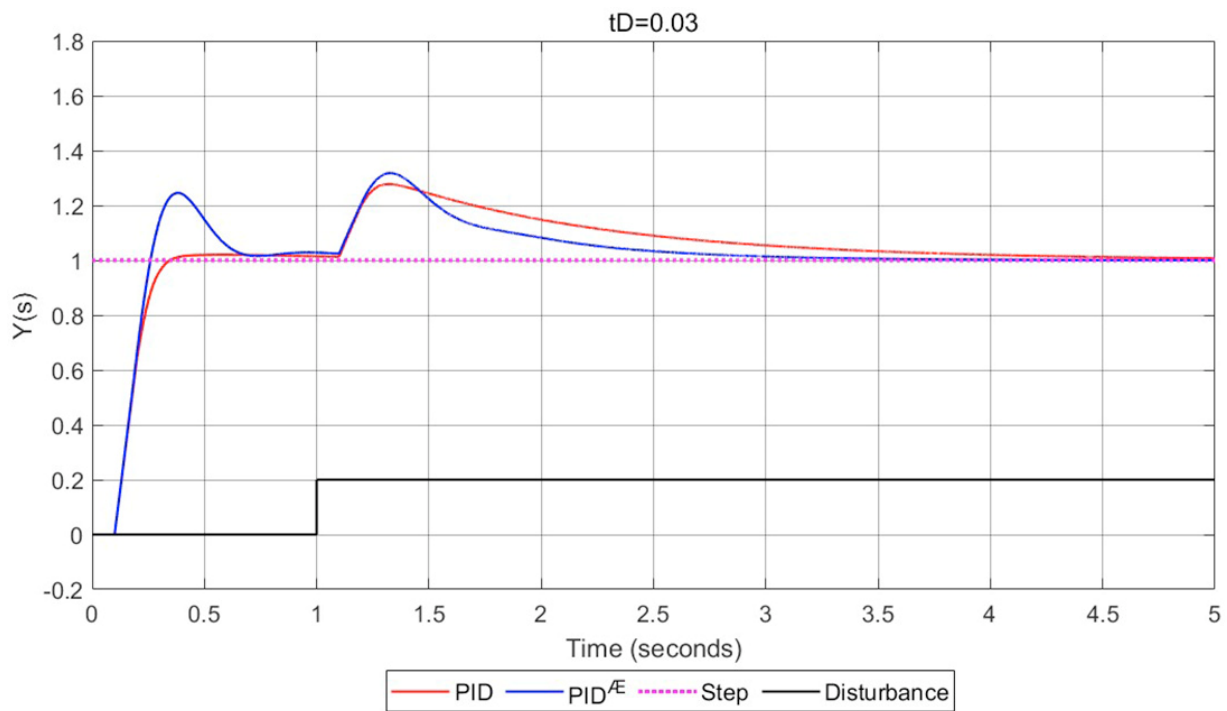


Figure 10. PID and $PI-D^{AE}$. $\tau_D = 0.03$ with disturbance.

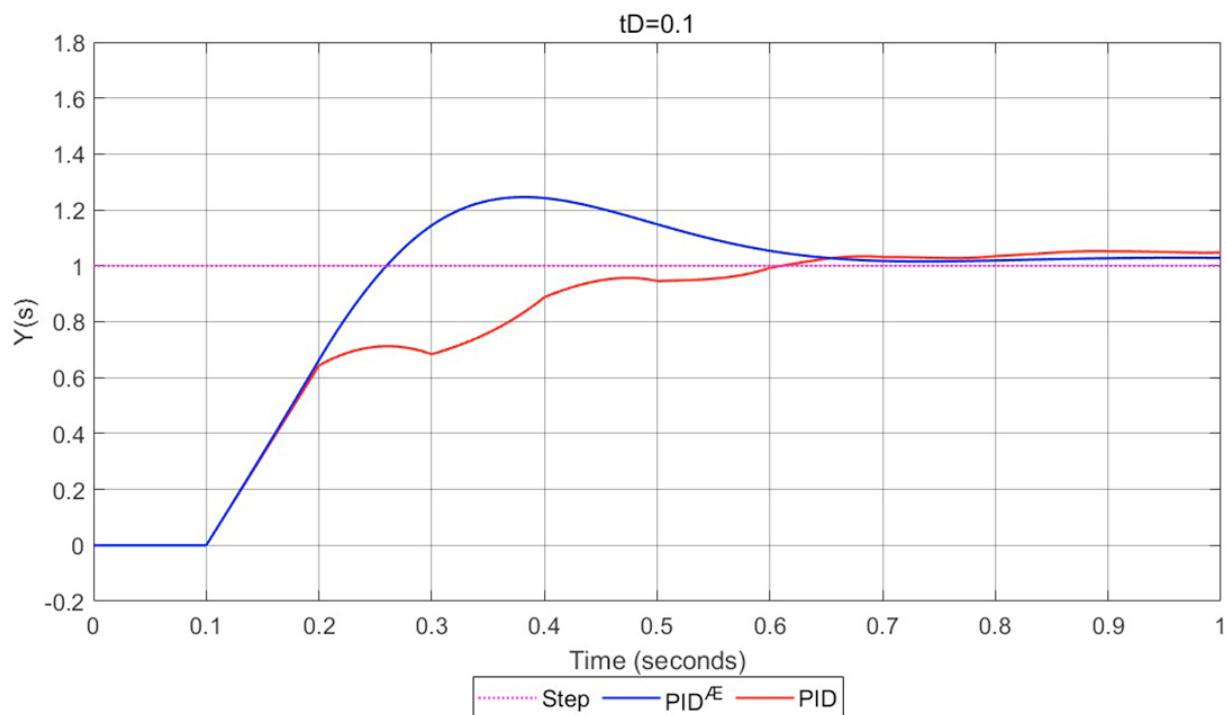


Figure 11. PID and $PI-D^{AE}$. $\tau_D = 0.1$.

Furthermore, Figures 12 and 13 present a comparison between PID and $PI-D^{AE}$ when $\tau_D = 0.2$ and $\tau_D = 0.4$, respectively. Figures 14 and 15 present a comparison between PID and $PI-D^{AE}$ derivatives when $\tau_D = 0.2$ and $\tau_D = 0.4$, respectively. Table 2 provides a quantitative demonstration of the effectiveness of the AE algorithm.

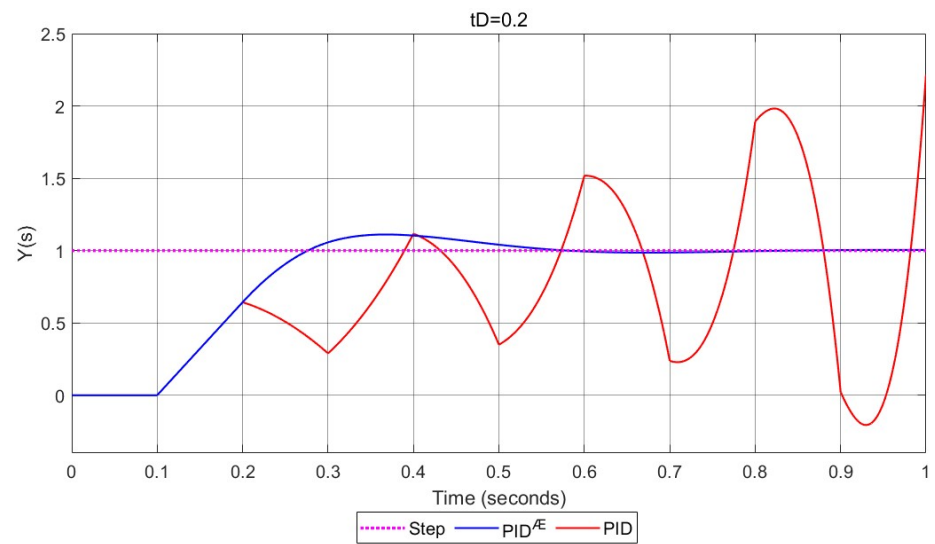


Figure 12. PID and $PI-D^E$. $\tau_D = 0.2$.

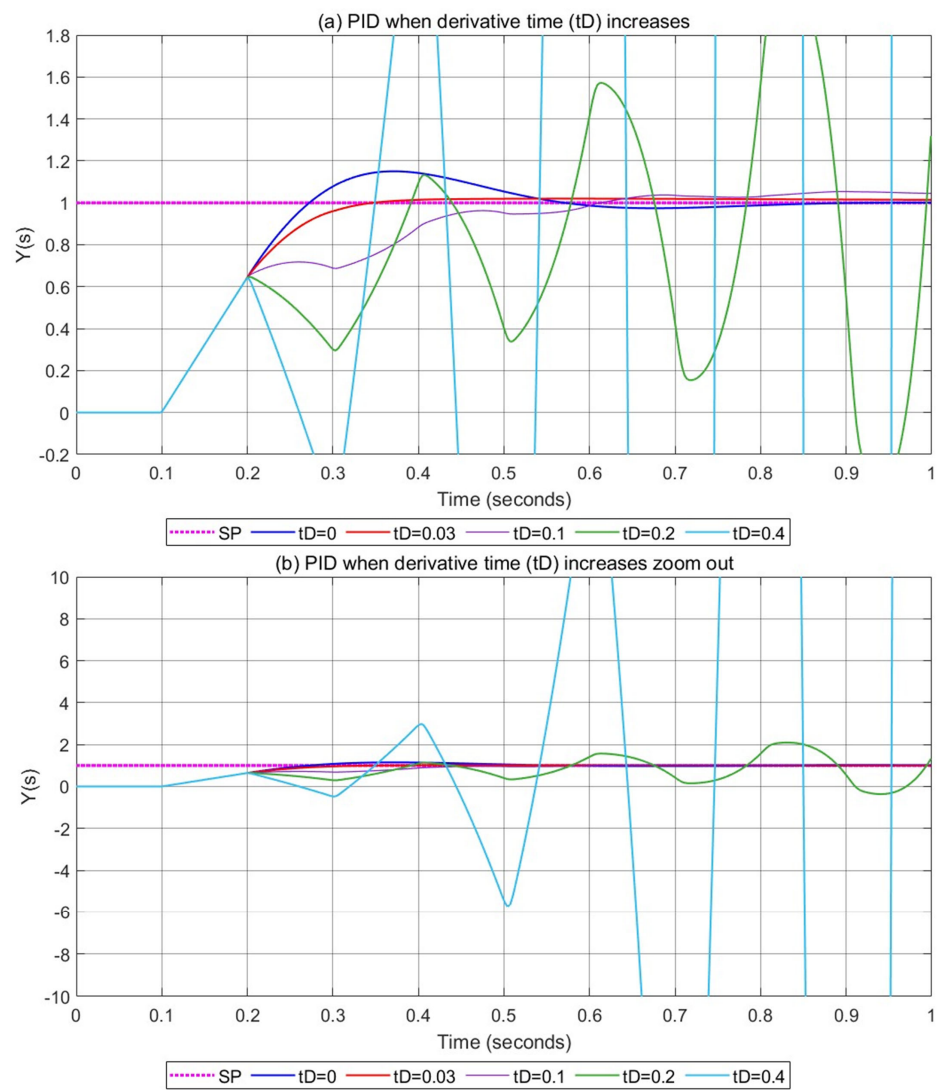


Figure 13. PID and $PI-D^E$. $\tau_D = 0.4$.

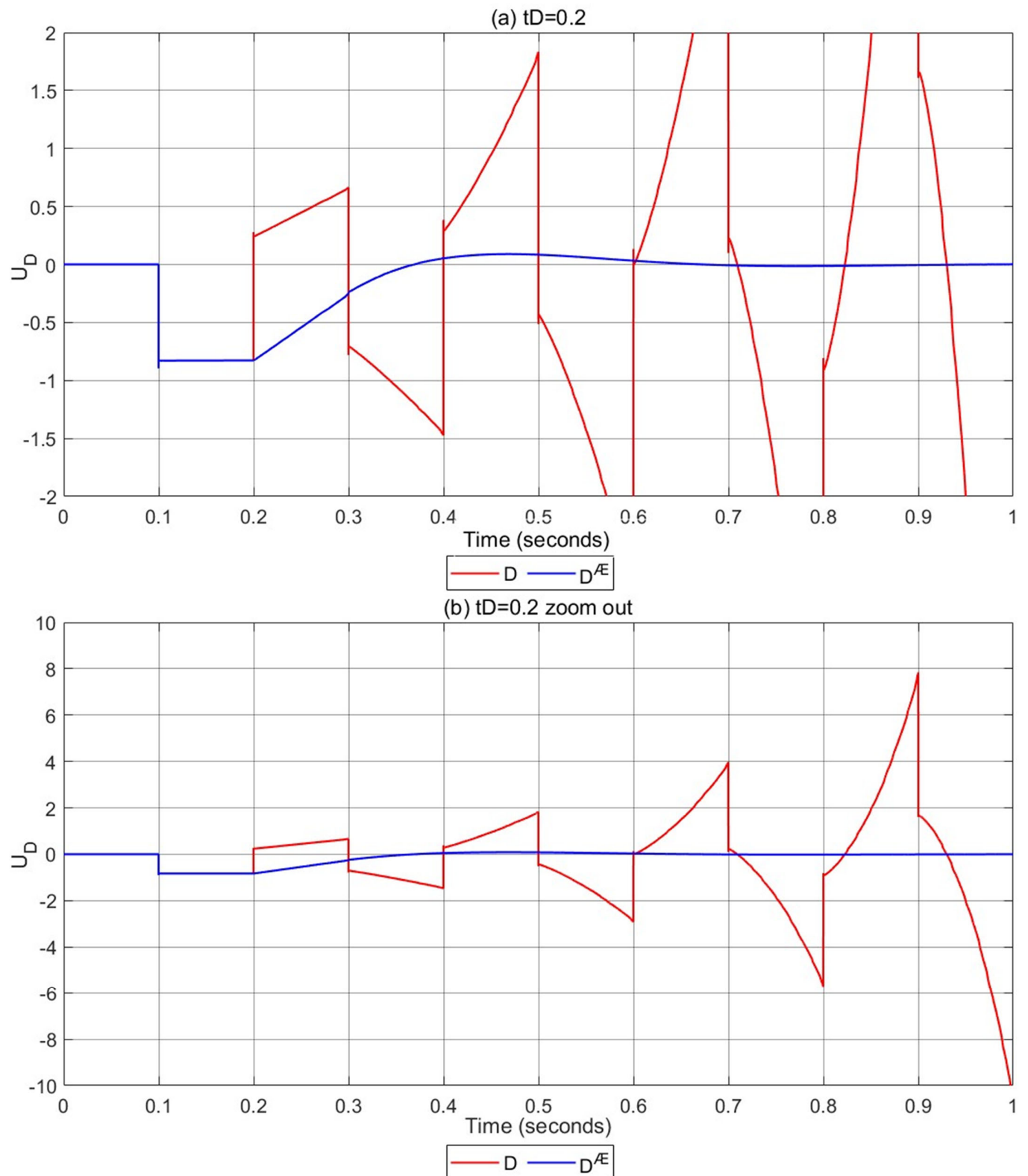


Figure 14. PID and PI-D^E derivatives. $\tau_D = 0.2$.

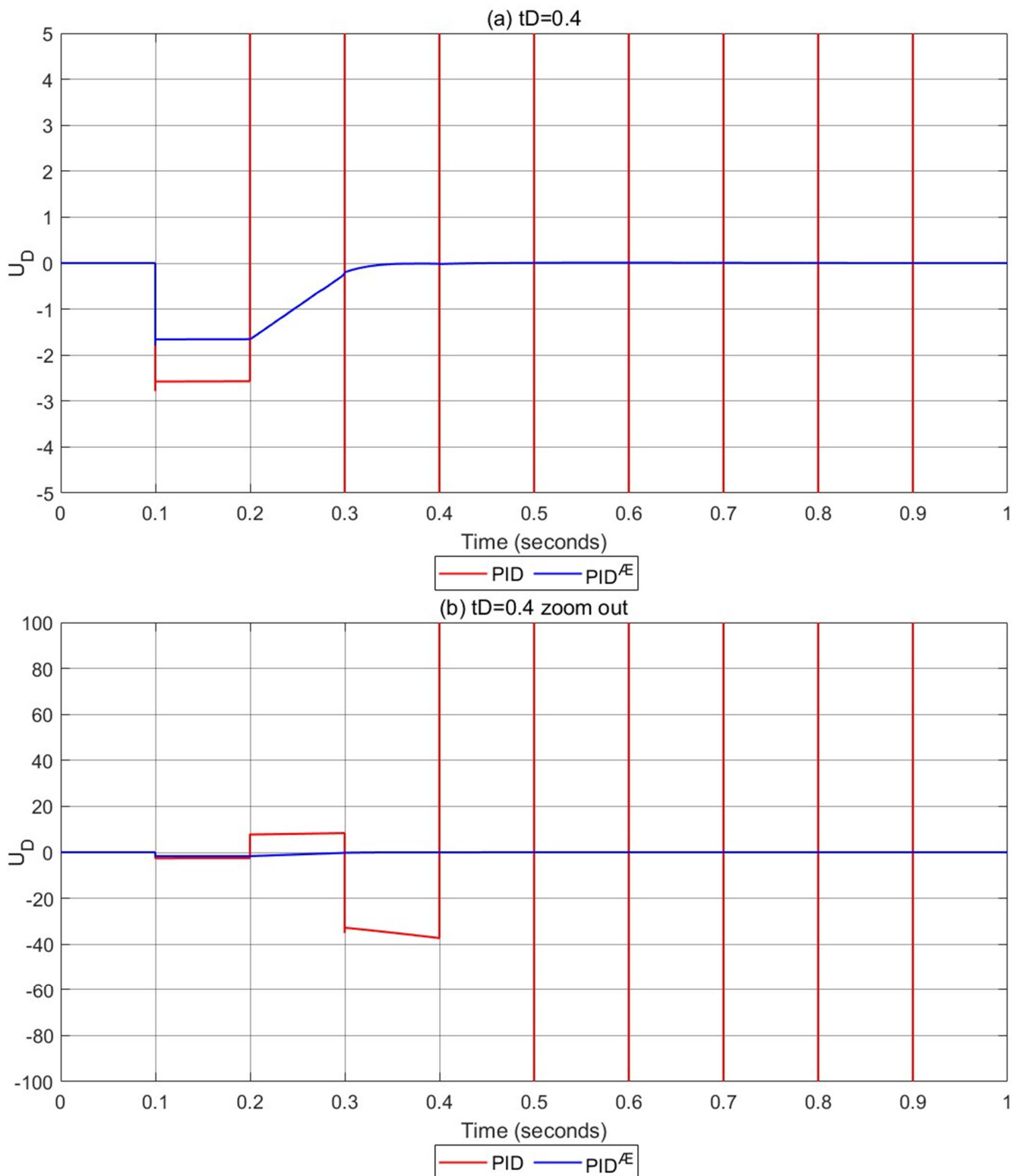


Figure 15. PID and $PI-D^E$ derivatives. $\tau_D = 0.4$.

Figure 16 shows a comparison between PID at $\tau_D = 0.03$ and $PI-D^E$ at $\tau_D = 0.4$, the values at which better responses are observed for each controller. And Figure 17 shows the system's behavior under a disturbance at $t = 1$, demonstrating how its signal is recovered faster using $PI-D^E$ than with PID .

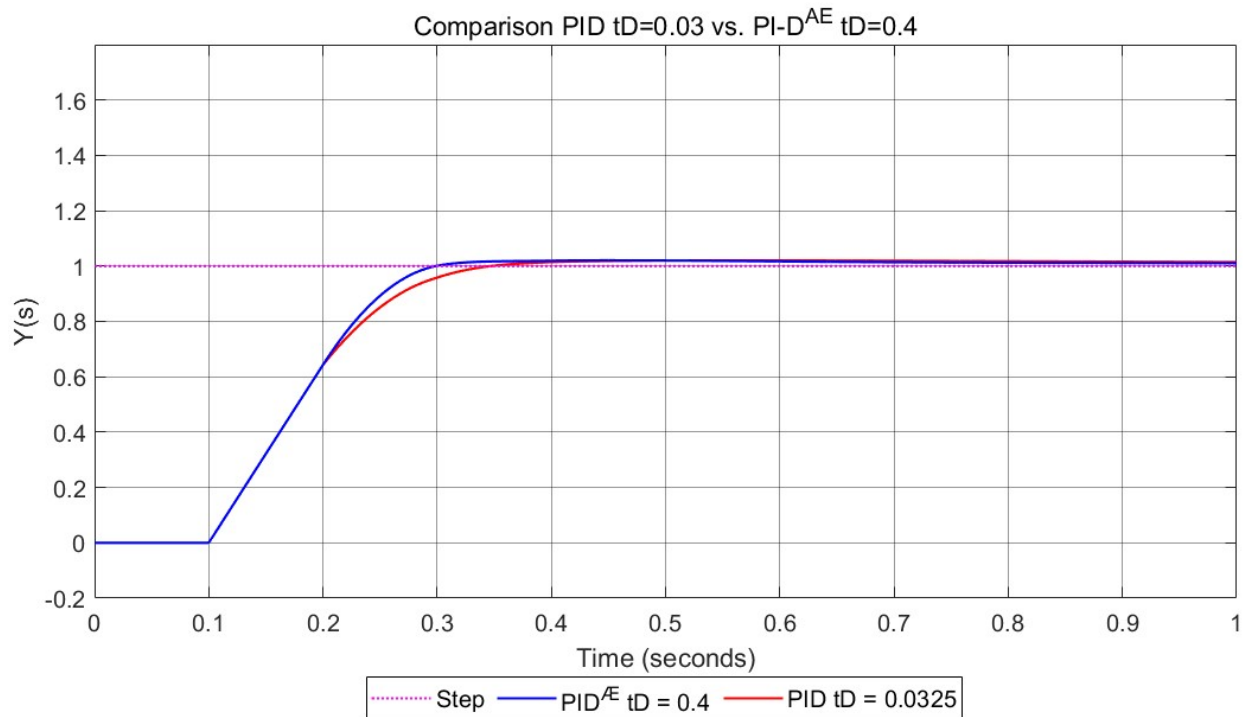


Figure 16. PID at $\tau_D = 0.03$ and $PI-D^{AE}$ at $\tau_D = 0.4$.

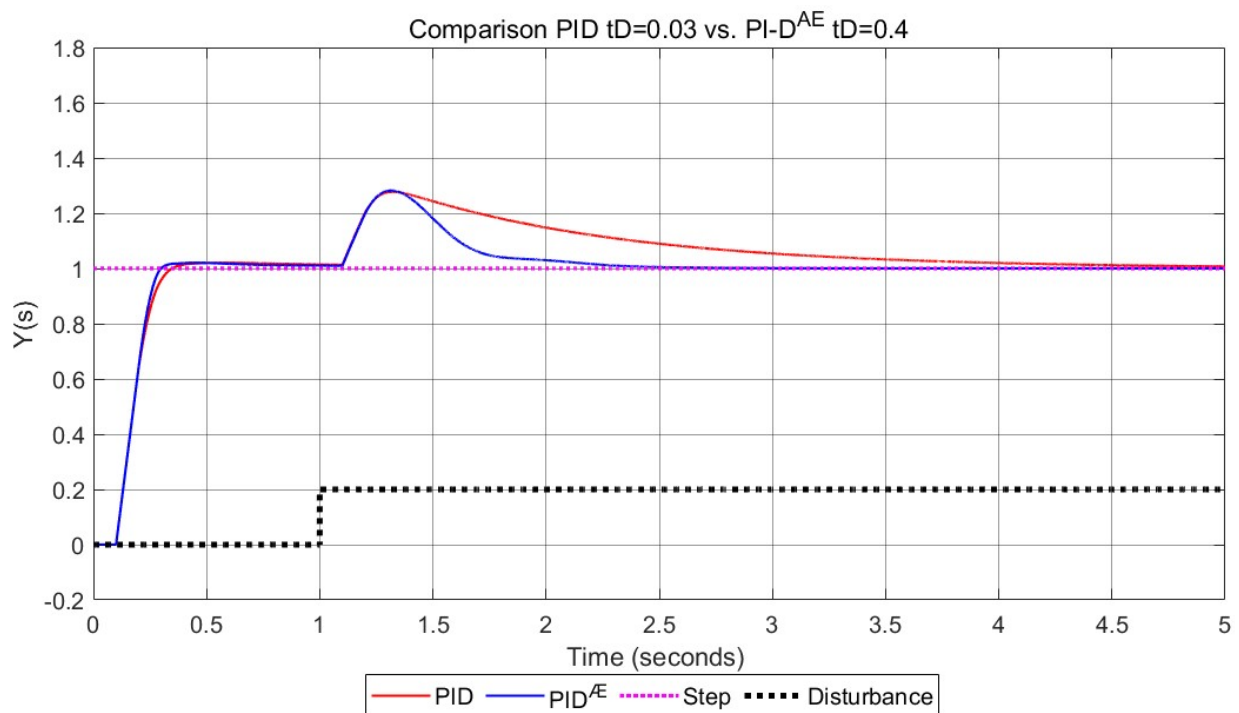


Figure 17. PID at $\tau_D = 0.03$ and $PI-D^{AE}$ at $\tau_D = 0.4$ with disturbance.

Tables 3 and 4 compare $PI-D^{AE}$ vs. PID and the $PI(D)$ vs. the PI controller, named as such because, in this case, D is deactivated (see Table 1). Table 3 provides a response time comparison, and Table 4 provides insight into the activation of D . D can be utilized (using the algorithm) to achieve better results, specifically results that would not be attainable with PID .

Table 2. Controller comparison.

	$\tau_D=0$	$\tau_D=0.03$		$\tau_D=0.1$		$\tau_D=0.2$		$\tau_D=0.4$	
	<i>PI(D)</i>	<i>PID</i>	<i>PI-D^E</i>	<i>PID</i>	<i>PI-D^E</i>	<i>PID</i>	<i>PI-D^E</i>	<i>PID</i>	<i>PI-D^E</i>
t_d (s)					0.177				
t_r (s)	0.273	0.347	0.273	0.613	0.273	0.392	0.276	0.349	0.300
M_p	1.150	1.020	1.149	1.054	1.140		1.111		1.020
t_p (s)	0.372	0.573	0.372	0.897	0.369		0.369		0.570
t_s 2% (s)	0.745	0.318	0.743		0.723		0.534		0.287
t_s 5% (s)	0.504	0.292	0.504		0.500		0.486		0.269
<i>IAE</i>	0.2105	0.1958	0.2103	0.2457	0.2082	0.5791	0.2017	40.30	0.1904
<i>ISE</i>	0.1549	0.1529	0.1549	0.1652	0.1545	0.4547	0.1535	9552	0.1521
<i>ITAE</i>	0.0312	0.0261	0.0310	0.0471	0.0300	0.2906	0.0270	35.75	0.0239
<i>ITSE</i>	0.0134	0.0125	0.0134	0.0166	0.0132	0.2390	0.0128	9030	0.0123

Table 3. Improvement (%) achieved by *PI-D* for each test.

	$\tau_D=0.03$		$\tau_D=0.1$		$\tau_D=0.2$		$\tau_D=0.4$	
	<i>PID</i>	<i>PI-D^E</i>	<i>PID</i>	<i>PI-D^E</i>	<i>PID</i>	<i>PI-D^E</i>	<i>PID</i>	<i>PI-D^E</i>
t_d (s)	0.177		0.177		0.177		0.177	
t_r (s)	0.347	21.32%	0.613	55.46%	0.392	29.59%	0.349	14.04%
M_p	1.020	−12.64%	1.054	−8.15%				
t_p (s)	0.573	35.07%	0.897	58.86%				
t_s 2% (s)	0.318	−133.64%						
t_s 5% (s)	0.292	−72.60%						
<i>IAE</i>	0.1958	−7.40%	0.2457	15.26%	0.5791	65.17%	40.30	99.52%
<i>ISE</i>	0.1529	−1.30%	0.1652	6.47%	0.4547	66.24%	9552	99.99%
<i>ITAE</i>	0.0261	−18.77%	0.0471	36.30%	0.2906	90.70%	35.75	99.93%
<i>ITSE</i>	0.0125	−7.20%	0.0166	20.48%	0.2390	94.64%	9030	99.99%

Table 4. Improvement (%). *PID* vs. *PI-D^E*.

	$\tau_D=0$	$\tau_D=0.03$	$\tau_D=0.1$	$\tau_D=0.2$	$\tau_D=0.4$
	<i>PI(D)</i>	<i>PI-D^E</i>	<i>PI-D^E</i>	<i>PI-D^E</i>	<i>PI-D^E</i>
t_d (s)	0.177				
t_r (s)	0.273			−1.09%	−9.89%
M_p	1.150	0.08%	0.87%	3.39%	11.30%
t_p (s)	0.372		0.80%	0.80%	−53.22%
t_s 2% (s)	0.745	0.26%	2.95%	28.32%	61.47%
t_s 5% (s)	0.504		0.79%	3.57%	46.62%
<i>IAE</i>	0.2105	0.09%	1.09%	4.18%	9.54%
<i>ISE</i>	0.1549		0.25%	0.90%	1.80%
<i>ITAE</i>	0.0312	0.64%	3.84%	13.46%	23.39%
<i>ITSE</i>	0.0134		1.49%	4.47%	8.20%

4.2. Inverted Pendulum on a Cart

The IPC model was obtained according to previous studies [14–16], with $M = 2.4$ kg, $m = 0.23$ kg, $L = 0.36$ m, and $g = 9.81$ m/s². The state space equations are as follows:

$$\dot{x}_1 = x_2 \quad (17)$$

$$\dot{x}_2 = \frac{(2.4 + 0.23)9.81 \sin x_1 - 0.23 \cdot 0.36 x_2^2 (\sin x_1 \cos x_1) - u \cos x_1}{2.4 \cdot 0.36 + 0.23 \cdot 0.36 (\sin x_1)^2} \quad (18)$$

$$\dot{x}_3 = x_4 \quad (19)$$

$$\dot{x}_4 = \frac{u + 0.23 \cdot 0.36 x_2^2 (\sin x_1) - 0.23 \cdot 9.81 \cos x_1 \sin x_1}{2.4 + 0.23 (\sin x_1)^2} \quad (20)$$

Equilibrium and position control are summed into one control signal; therefore, position control is affected by equilibrium control. To gain a better understanding, let us consider a first IPC (Figure 18), where its equilibrium is controlled by the $PI-D^{\mathcal{AE}}$ controller and its position is controlled by the PID controller (affected by the $PI-D^{\mathcal{AE}}$ equilibrium controller).

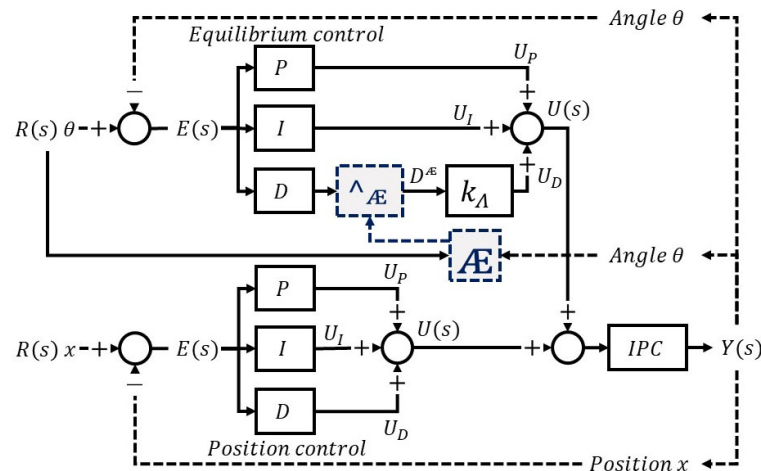


Figure 18. IPC#1 control. $PI-D^{\mathcal{AE}}$ equilibrium control + PID position control.

Considering a second IPC (Figure 19), its equilibrium is controlled by a conventional PID controller, and its position is controlled by another PID controller (affected by the PID equilibrium controller).

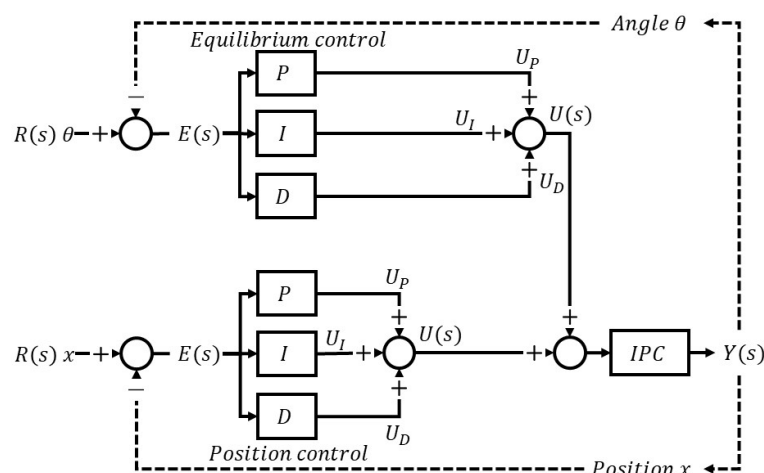


Figure 19. IPC#2 control. PID equilibrium control + PID position control.

Furthermore, the traditional derivative term is defined as Equation (21):

$$D(t) = k_D \frac{de(t)}{dt} \quad (21)$$

where k_D is a fixed gain, and $e(t)$ is the control error.

In contrast, the proposed term modifies the derivative behavior through an adaptive exponent as Equation (22):

$$D^{\mathcal{A}}(t) = \left(k_D \frac{de(t)}{dt} \right)^{\mathcal{A}} \quad (22)$$

where

$$\mathcal{A}(t) = \Lambda \left(\mu - \frac{\sigma Y(s)}{R(s) + \epsilon} \right) \quad (23)$$

This formulation allows the gain applied to the derivative to change dynamically in real time, based on the system's input–output ratio $Y(s)/R(s)$ Equation (23), modulated by the sensitivity σ , a maximum bound μ , and a robustness constant ϵ .

The behavior of $D^{\mathcal{A}}$ becomes nonlinear and adaptive:

If $\mathcal{A} = 1$, the system behaves identically to the classical PID.

If $\mathcal{A} < 1$, the derivative contribution is softened, reducing noise amplification.

If $\mathcal{A} > 1$, the derivative contribution is enhanced, accelerating system response.

If $\mathcal{A} \rightarrow 0$, the derivative term vanishes, effectively converting the controller to a PI type in real-time under certain conditions.

To illustrate this, we have also included Figures 3, 5, 18 and 19 comparing the behavior and structure of $PI-D^{\mathcal{A}}$ and PID , especially under disturbances, to highlight how the adaptive exponent enhances robustness and mitigates derivative kick and noise amplification.

The following comparisons were employed: the equilibrium control comparison is $PI-D^{\mathcal{A}}$ vs. PID , and the position control comparison is the affected PID (indirectly affected by the $PI-D^{\mathcal{A}}$ equilibrium controller) vs. the affected PID (affected by the PID equilibrium controller). Tables 5 and 6 show the parameters of the controllers for balance and position, respectively.

Table 5. Angle control parameters.

	<i>PID</i>	<i>PI-D^ℳ</i>
k_P	−40	
k_I	0	
τ_I	0	
k_D	−8	
τ_D	0.2	
Λ		2
μ		100
ϵ		0.01
k_Λ		1

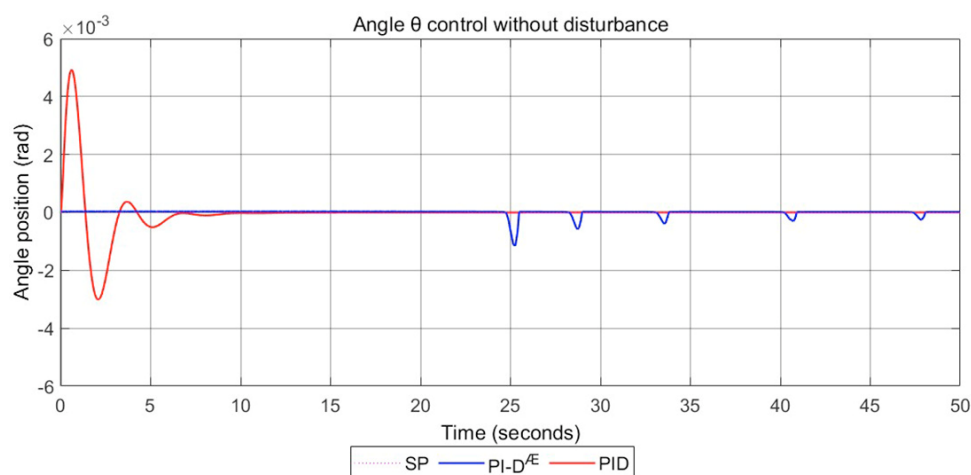
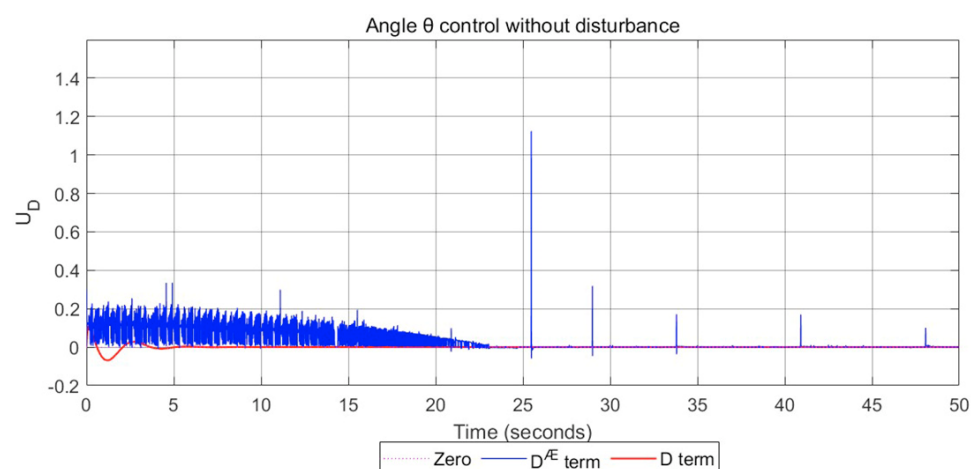
The deactivation of I is due to the fact that the authors of the original test [14–16] conducted their simulations in this way, and we aimed to respect this condition by offering a comparison with the originally proposed PID controller. This does not preclude the fact that the value of the $\mathcal{A}$ algorithm can be further explored by comparing it with PID controllers with all three activated terms (as with the first-order system).

Table 6. Position control parameters.

	<i>PID</i>
k_P	−1.25
k_I	0
τ_I	0
k_D	−3.6
τ_D	2.88

The deactivation of I is due to the fact that the authors of the original test [14–16] conducted their simulations in this way, and we aimed to respect this condition by offering a comparison with the originally proposed PID controller. This does not preclude the fact that the value of the $\mathcal{AE}$ algorithm can be further explored by comparing it with PID controllers with all three activated terms (as with the first-order system).

Figure 20 shows an angle control comparison between PID and $PI-D^{\mathcal{AE}}$. Figures 21–23 compare D and $D^{\mathcal{AE}}$ behavior. Typically, D is equal to $k_D \cdot de(t)$. However, a distinction is made. D and $D^{\mathcal{AE}}$ will be considered D control signals. $k_D \cdot de(t)$ will be considered D behavior; this D behavior will not be the same as D because when $PI-D^{\mathcal{AE}}$ is employed, D becomes more complex than $k_D \cdot de(t)$, so $D \neq D^{\mathcal{AE}}$.

**Figure 20.** PID and $PI-D^{\mathcal{AE}}$ equilibrium control.**Figure 21.** PID and $PI-D^{\mathcal{AE}}$ equilibrium control of D and D control signals.

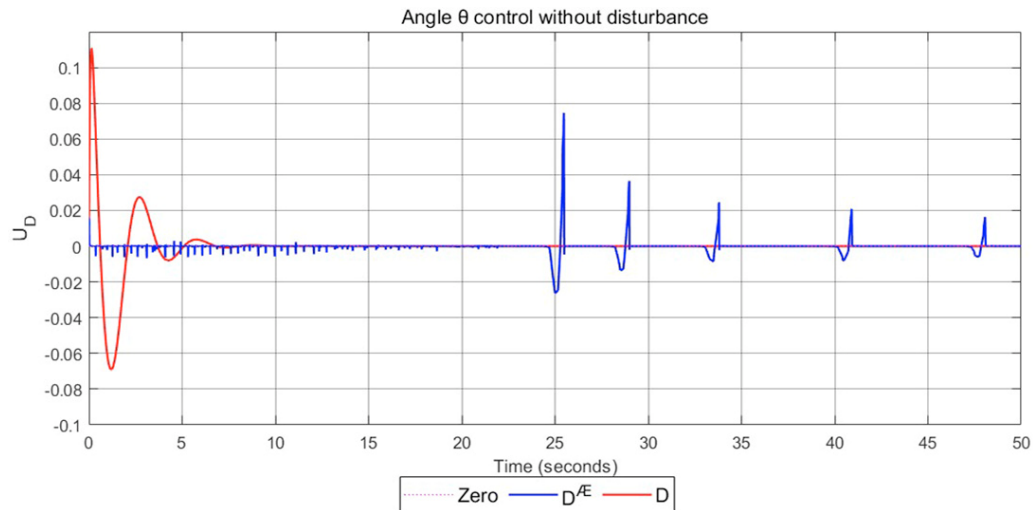


Figure 22. Derivative behaviors of PID and $PI-D^E$ equilibrium control.

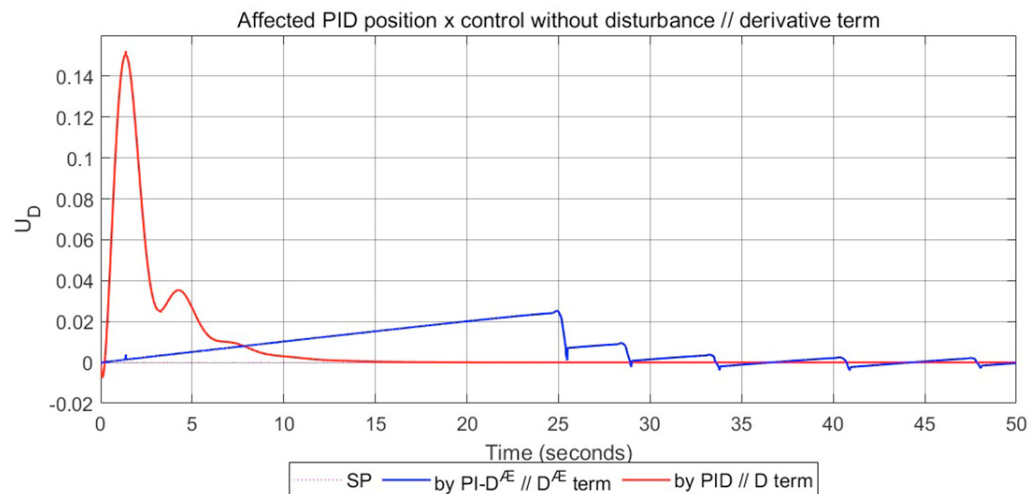


Figure 23. PID position control derivatives affected by equilibrium controllers.

Figure 24 shows a comparison of the position control response between two PID configurations.

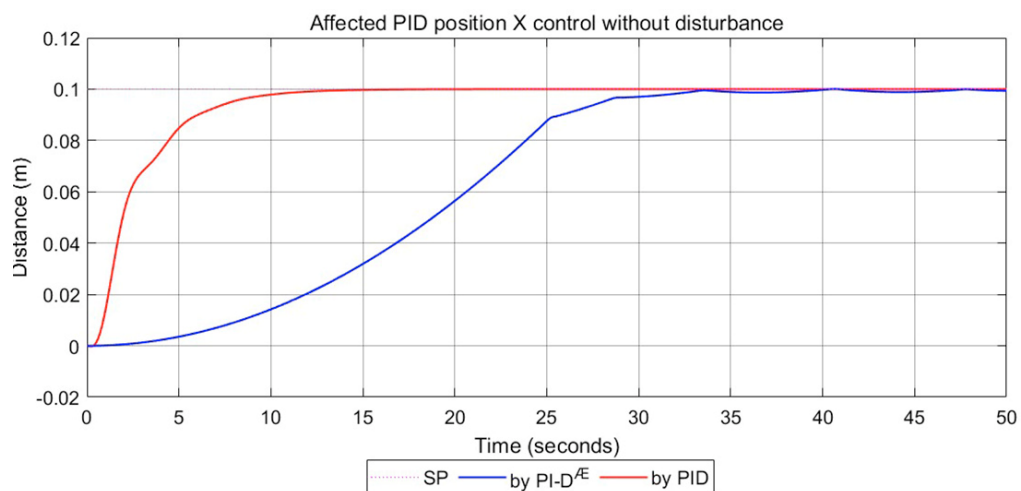


Figure 24. PID position control affected by equilibrium controllers.

Tables 3, 7 and 8 compare the time response improvement of angle and position control, respectively, between $PI-D^E$ and PID .

Table 7. Angle control comparison.

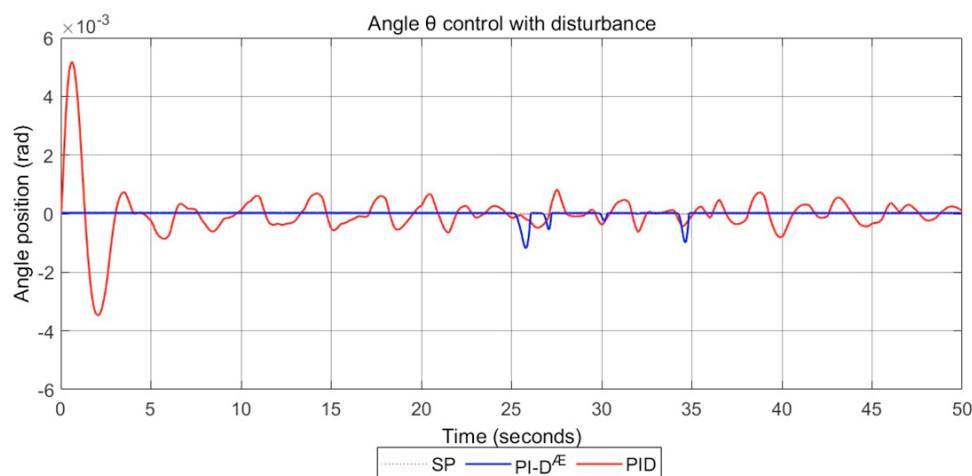
	<i>PID</i>	<i>PI-D^Æ</i>	Improvement
t_d (s)			
t_r (s)	1.375	24.730	−1698.54%
M_p	4.926×10^{-3}	3.052×10^{-5}	99.38%
t_p (s)	0.606	1.901	−213.69%
t_s 2% (s) [0.002, −0.002]	2.586		100.00%
t_s 5% (s) [0.005, −0.005]			
<i>IAE</i>	0.008693	0.00217	75.03%
<i>ISE</i>	2.392×10^{-5}	6.572×10^{-7}	97.25%
<i>ITAE</i>	0.01739	0.0568	−226.62%
<i>ITSE</i>	2.874×10^{-5}	1.802×10^{-5}	37.30%

Table 8. Position control comparison.

	<i>PID</i>	<i>PI-D^Æ</i>	Improvement
t_d (s)	1.938	18.807	−870.43%
t_r (s)	25.269	40.420	−59.95%
M_p		1.001×10^{-1}	
t_p (s)		40.726	
t_s 2% (s)	10.168	31.699	−211.75%
t_s 5% (s)	7.840	28.030	−257.52%
<i>IAE</i>	0.288	1.817	−530.90%
<i>ISE</i>	0.0169	0.142	−740.23%
<i>ITAE</i>	0.7144	19.08	−2570.77%
<i>ITSE</i>	0.02084	1.185	−5586.18%

Inverted Pendulum on a Cart with Disturbances

Input disturbances with a randomly assigned amplitude of 0.01 were introduced and uniformly applied to both control systems *PID* and *PI-D^Æ*. Similar to the previous system, the simulations considering disturbances are shown in Figures 25–28.

**Figure 25.** System with disturbance under *PID* and *PI-D^Æ* equilibrium control.

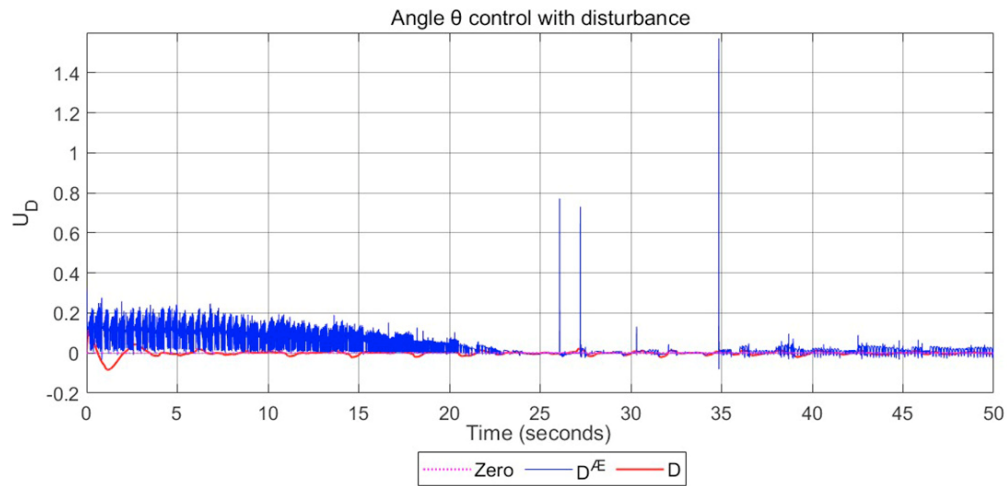


Figure 26. System with disturbance under PID and $PI-D^E$ equilibrium control of D and D^E signals.

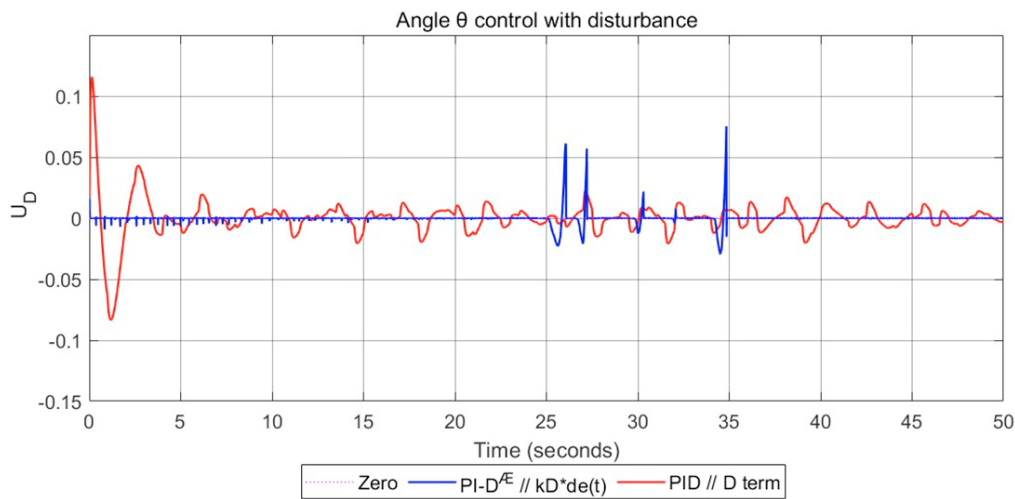


Figure 27. System with disturbance under PID and $PI-D^E$ equilibrium control and derivative behaviors.



Figure 28. System with disturbance and PID position control affected by equilibrium controllers.

Tables 9 and 10 present a comparison of the analysis of transient and steady-state responses, including an optimization percentage.

Table 9. Angle control with disturbance comparison.

	<i>PID</i>	<i>PI-D^{AE}</i>	Improvement
t_d (s)			
t_r (s)	1.343	25.172	−1774.31%
M_p	5.176×10^{-3}	3.093×10^{-5}	99.40%
t_p (s)	0.618	0.835	−35.11%
t_s 2% (s) [0.002, −0.002]	2.617		100.00%
t_s 5% (s) [0.005, −0.005]	0.730		100.00%
<i>IAE</i>	0.02108	0.002263	89.26%
<i>ISE</i>	3.338×10^{-5}	8.439×10^{-7}	97.47%
<i>ITAE</i>	0.3341	0.05867	82.43%
<i>ITSE</i>	0.000161	2.398×10^{-5}	85.10%

Table 10. Position control with disturbance comparison.

	<i>PID</i>	<i>PI-D^{AE}</i>	Improvement
t_d (s)	1.876	18.800	−902.132
t_r (s)	15.089		
M_p	1.019×10^{-1}	9.807×10^{-2}	3.759
t_p (s)	26.193	34.588	−32.051
t_s 2% (s)	43.795		
t_s 5% (s)	7.280		
<i>IAE</i>	0.3216	1.99	−518.781
<i>ISE</i>	0.01672	0.1442	−762.440
<i>ITAE</i>	1.92	26.58	−1284.375
<i>ITSE</i>	0.0225	1.284	−5606.667

5. Discussion

PI-D^{AE} demonstrates significant advantages over the conventional *PID*, particularly in scenarios with varying τ_D values (Tables 3 and 4). For $\tau_D = 0.03$, *PI-D^{AE}* shows marginal improvement; however, its rapid response and steady error reduction are evident. As τ_D increases to 0.1, *PI-D^{AE}* achieves better performance across most criteria, except for an 8% higher overshoot (M_p). Crucially, while *PID* fails to reach a steady state, *PI-D^{AE}* ensures stability and error convergence to zero.

For higher values of τ_D (0.2 and 0.4), the *PID* controllers diverge, whereas *PI-D^{AE}* remains stable and delivers substantial performance improvements. Error accumulation metrics improve by up to 23%, while t_s shows enhancements of up to 61%. Despite a slight increase in t_r , the overall performance indicates faster and more-stable setpoint attainment with *PI-D^{AE}*. Additionally, t_p shows minimal improvement at $\tau_D = 0.2$ but is notably reduced by 53% at $\tau_D = 0.4$. Importantly, M_p decreases by up to 11.3% with *PI-D^{AE}*, ensuring better system stability.

PI-D^{AE} dynamically adapts to D^{AE} , effectively addressing issues such as instability and overshoot while accelerating response times. Figures 3–12 confirm the superior robustness and disturbance rejection of *PI-D^{AE}* compared with *PID*. Optimizing D^{AE} mitigates instability, improves response acceleration, and ensures zero steady-state error, achieving enhanced system performance and reliability.

$PI-D$ demonstrates significant advantages over PID , particularly in equilibrium control. With identical PID tuning, $PI-D^{\mathcal{A}}$ achieves a near-zero steady-state error from the start, while PID requires multiple oscillations before reaching stability. Notably, $PI-D^{\mathcal{A}}$ effectively neutralizes DK observed in PID , as shown in Figure 20, maintaining control over the θ angle with minimal oscillations and a stable signal.

Furthermore, $PI-D^{\mathcal{A}}$'s transient response exhibits unique characteristics. While its t_r is faster, it achieves t_s almost immediately, maintaining control near SP without oscillations. This contrasts with PID , which takes longer to stabilize. $D^{\mathcal{A}}$ actively mitigates instability early on, as indicated by its initial high magnitude, compared with negligible D activity in PID , which leads to pronounced DK .

Regarding t_p and M_p , $PI-D^{\mathcal{A}}$ demonstrates a 99% reduction in M_p , ensuring minimal overshoot and improved stability. Although occasional oscillations are present, their magnitudes are negligible, contributing to overall system robustness. The error accumulation metrics show significant improvements in three of four criteria, with only ITAE showing a slight increase, which remains inconsequential in absolute terms.

In the overlap analysis of equilibrium and position control signals (Figures 18 and 19), $PI-D^{\mathcal{A}}$ introduces slower transient responses and minor steady-state oscillations below SP. While this behavior slightly impacts position control, the primary focus of this study is equilibrium control. $PI-D^{\mathcal{A}}$ demonstrates superior performance in stabilizing equilibrium by neutralizing DK and enhancing robustness under dynamic conditions. These results confirm its effectiveness as a robust alternative to traditional PID controllers, particularly for applications prioritizing stability and precision.

In IPC systems with disturbances, as shown in Tables 9 and 10, the $PI-D^{\mathcal{A}}$ controller significantly improved the control signal compared with PID and maintained low D magnitudes throughout the process. Error accumulation across all the criteria improved by over 82%, reaching up to 97% in the best case.

$PI-D$ achieved steady-state control from the start, while PID failed to reach equilibrium. Although t_p for $PI-D^{\mathcal{A}}$ was longer, the (M_p) overshoot was reduced by 99% relative to PID . Sub-impulses in the $PI-D^{\mathcal{A}}$ response were minimal and acceptable when compared with PID , and the former consistently rejected oscillations and always maintained equilibrium.

The $PI-D^{\mathcal{A}}$ controller stands out for its structural simplicity and computational efficiency, relying on only four parameters (K_p , K_i , K_d , and an adaptive exponent $\mathcal{A}$) for implementation. In contrast to more-complex approaches such as FL PID controllers, which require 10 to 30 inference rules along with associated gain parameters, or NN-based PID controllers, which involve more than 20 parameters related to network architecture and training data, the $PI-D^{\mathcal{A}}$ design does not require any prior training. Furthermore, while fuzzy and NN-based controllers entail medium and high computational costs, respectively, the $PI-D^{\mathcal{A}}$ maintains a significantly low computational burden. Regarding performance, the $PI-D^{\mathcal{A}}$ demonstrates high robustness to noise, comparable with that of NN-based controllers, yet with a considerably simpler and more direct implementation. [18–25]. These features make the $PI-D^{\mathcal{A}}$ a highly effective and practical alternative for control systems in which operational efficiency and noise immunity are of critical importance.

6. Conclusions

The $PI-D^{\mathcal{A}}$ algorithm offers substantial improvements over traditional PID controllers by addressing key challenges such as noise sensitivity and abrupt setpoint changes. Its innovative reformulation of D enhances robustness, reduces oscillations, and ensures system stability under dynamic conditions. Additionally, the algorithm's compatibility with conventional tuning methods broadens its applicability but with considerable advantages over conventional PID , making it a practical solution for modern control systems.

While the initial results demonstrate the $PI-D^{\mathcal{AE}}$ algorithm's superiority in tested systems, further validation across diverse applications and comparison with other advanced control strategies are necessary. The $PI-D^{\mathcal{AE}}$ algorithm's adaptability within the PID structure allows for seamless integration with other control methodologies, presenting a promising avenue for improving performance in a wide range of systems. Future refinements, such as dynamically alternating between D and $D^{\mathcal{AE}}$, could further optimize its effectiveness and expand its potential in control engineering.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

$PI-D^{\mathcal{AE}}$	Adaptive exponent controller
$D^{\mathcal{AE}}$	Adaptive exponent derivative term
$\mathcal{AE}$	Adaptive exponent
θ	Angle
k_{aux}	Auxiliary gain
$Ltd-D$	Bandwidth-limited derivative control
$C_P(s)$	Controller system
t_d	Delay time
k_D	Derivative gain
$D-k$	Derivative kick
D_u	Derivative response
D	Derivative term
τ_D	Derivative time
e or $e(t)$ or $E(s)$	Error
FL	Fuzzy logic
GA	Genetic algorithm
$R(s)$	Input system or reference
IAE	Integral absolute error
k_I	Integral gain
ISE	Integral squared error
I	Integral term
$ITAE$	Integral time absolute error
$ITSE$	Integral time squared error
τ_I	Integral time
IPC	Inverted pendulum on a cart
M_p	Maximum peak
NN	Neural network
$Y(s)$	Output system
t_p	Peak time
x	Position

PV	Process variable
k_p	Proportional gain
P	Proportional term
t_r	Rising time
SP	Setpoint
t_s 2%	Settling time at 2%
t_s 5%	Settling time at 5%
SMC	Sliding mode

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