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AI-Enhanced Adaptive Sliding Mode Control for Inverted Pendulum on a Cart: A Simulation Study

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Index Terms

AI-enhanced adaptive sliding mode control (SMC), fuzzy logic .

Abstract

The inverted pendulum on a cart is a canonical benchmark in control engineering, representing a highly nonlinear and inherently unstable system. This paper investigates the application of an AI-enhanced adaptive sliding mode control (SMC) strategy for its stabilization and control. The proposed approach cooperatively combines the robustness of SMC against uncertainties and disturbances with the adaptive capabilities of an online adaptation law and the smoothing properties of a simplified fuzzy logic system. This integration facilitates the dynamic adjustment of control gains, effectively mitigating chattering and improving overall system performance. Simulation results, obtained using MATLAB, demonstrate the effectiveness of the proposed control strategy in stabilizing the pendulum in the upright position and achieving precise cart positioning. The system's performance is thoroughly analyzed through time-domain responses, phase-plane analysis, control effort evaluation, robustness tests under parameter variations and external disturbances, and an examination of adaptive gain dynamics. A Lyapunov stability analysis is provided to prove the asymptotic stability of the closed-loop system. Comparative studies with standard SMC, boundary layer SMC, and adaptive SMC with fixed adaptation rate demonstrate the superiority of the fuzzy-adaptive approach.

التحكم الانزلاقي التكيفي (SMC) المُعزَّز بالذكاء الاصطناعي للبندول المقلوب على عربة: دراسة محاكاة

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الكلمات المفتاحية

التحكم الانزلاقي التكيفي المحسن بالذكاء الاصطناعي، المنطق الضبابي.

الملخص

يمثّل نظام البندول المقلوب المثبّت على عربة أحد النماذج القياسية المرجعية في مجال هندسة وأنظمة التحكم، إذ يُعد مثالًا لنظام غير خطي بدرجة عالية ويتسم بعدم الاستقرار الذاتي، مما يجعله منصة مثالية لاختبار وتقييم استراتيجيات التحكم المتقدمة. تهدف هذه الدراسة إلى بحث وتطبيق استراتيجية تحكم بالوضع الانزلاقي التكيفي المعزز بتقنيات الذكاء الاصطناعي من أجل تحقيق استقرار هذا النظام والتحكم في سلوكه الديناميكي بكفاءة عالية.
تعتمد المنهجية المقترحة على الدمج المتكامل بين الصلابة والمتانة التي يوفرها التحكم بالوضع الانزلاقي (Sliding Mode Control) في مواجهة حالات عدم اليقين والاضطرابات الخارجية، وبين آليات التكيف الديناميكي التي يوفرها قانون تكيف يعمل بصورة آنية، إضافة إلى الاستفادة من خصائص التنعيم والتحسين التي يقدمها نظام مبسط قائم على المنطق الضبابي (Fuzzy Logic) . ويسهم هذا التكامل في الضبط الديناميكي لمعاملات المتحكم بصورة مستمرة، الأمر الذي يؤدي إلى الحد من ظاهرة الاهتزاز السريع (Chattering) المرتبطة عادةً بخوارزميات التحكم بالوضع الانزلاقي، وبالتالي تحسين الأداء الكلي للنظام من حيث الاستقرار والدقة والاستجابة الديناميكية.
وقد تم تقييم فاعلية استراتيجية التحكم المقترحة من خلال دراسة محاكاة باستخدام برنامج MATLAB ، حيث أظهرت النتائج قدرة النظام على تحقيق استقرار البندول في الوضع العمودي مع المحافظة على تموضع دقيق للعربة .كما تم تحليل أداء النظام بشكل شامل اعتمادًا على استجابات المجال الزمني، وتقييم جهد التحكم المطلوب، بالإضافة إلى دراسة ديناميكيات تطور مكاسب التكيف أثناء التشغيل.

I. INTRODUCTION

The inverted pendulum on a cart serves as a crucial benchmark for evaluating advanced control methodologies due to its inherent instability and strong nonlinearity [1]. The system's dynamics present a significant challenge for traditional linear control techniques, necessitating the exploration of more sophisticated nonlinear control strategies. Sliding Mode Control (SMC) has proven to be a powerful tool for handling uncertainties, disturbances, and nonlinearities in dynamic systems [2]. Its robustness stems from a discontinuous control action that forces the system's trajectory onto a predefined sliding surface. However, conventional SMC requires prior knowledge of the bounds of uncertainties and disturbances, which are often difficult to obtain in practical applications, and suffers from the well-known chattering phenomenon.

Adaptive SMC addresses the limitation of unknown uncertainty bounds by incorporating online adaptation laws to estimate these bounds, thus enhancing the controller's ability to adapt to varying operating conditions [3]. To further refine performance and address chattering, this paper proposes an AI-enhanced adaptive SMC strategy that integrates fuzzy logic for dynamic adaptation rate adjustment.

The choice of fuzzy logic over other AI methodologies such as neural networks is motivated by several key factors:

1. Interpretability: Fuzzy logic provides transparent, rule-based adaptation that can be intuitively understood and tuned by control engineers.
2. Low Computational Cost: Unlike neural networks, fuzzy systems require no training phase and have minimal online computational requirements, consisting only of membership function evaluations and simple rule inference.
3. Simplified Design: The adaptation law only requires the definition of three membership functions and three rules, making it suitable for real-time applications without complex parameter tuning.
4. Inherent Smoothing**:** Fuzzy inference naturally provides smooth interpolation between discrete rules, which is desirable for chattering reduction without introducing the steady-state errors associated with boundary layer approaches.

A simplified fuzzy logic system is integrated to dynamically adjust the adaptation rate based on the current system state, specifically the magnitude of the sliding surface error. This fuzzy adaptation mechanism helps to reduce chattering—a common drawback of SMC—and provides smoother control actions. The simulation results presented herein demonstrate the effectiveness of the proposed control strategy and offer valuable insights into its performance characteristics, including robustness to parameter variations and external disturbances.

II. Mathematical Model

The dynamics of the inverted pendulum on a cart are described by the following set of coupled, nonlinear differential equations [4]:

$$(M+m)\ddot{x} + ml\ddot{\theta}\cos\theta - ml\dot{\theta}^2\sin\theta = F \qquad (1)$$

$$(I+ml^2)\ddot{\theta} + ml\ddot{x}\cos\theta - mgl\sin\theta = 0 \qquad (2)$$

Where M is the mass of the cart (kg), m is the mass of the pendulum (kg), l is the length of the pendulum (m), g is the acceleration due to gravity (m/s²), x is the horizontal position of the cart (m), θ is the angle of the pendulum from the vertical upright position (rad), F is the force applied to the cart (N), and I is the moment of inertia of the pendulum about its center of mass (kg·m²). For a uniform rod, $I = \frac{1}{3}ml^2$.

III. CONTROL STRATEGY

The objective is to design a control law F that stabilizes the inverted pendulum to the upright position ($\theta = 0, \dot{\theta} = 0$) and potentially controls the cart's position x. The proposed control strategy combines Sliding Mode Control (SMC), Adaptive SMC, and fuzzy logic for dynamic adaptation rate adjustment.

III.A. Sliding Mode Control

The design of SMC begins with defining a suitable sliding surface s that represents the desired system dynamics. For the inverted pendulum, a common choice is:

$$s = \dot{\theta} + \lambda\theta \qquad (3)$$

where λ is a positive constant that determines the rate of convergence to the sliding surface. The control law is designed to force the system trajectory onto this surface and maintain it there. A basic SMC control law is given by:

$$F = F_{eq} - K \cdot \mathrm{sgn}(s) \qquad (4)$$

where K is a positive gain that determines the switching magnitude of the control action and $\mathrm{sgn}(\cdot)$ is the signum function.

III.B. Adaptive Sliding Mode Control

To address the issue of unknown uncertainty bounds, an adaptive SMC approach is employed. The gain K is no longer a fixed value but is adapted online using the following adaptation law:

$$K = K_{min} + \int_0^t \gamma(\tau) \mid s(\tau) \mid d\tau \qquad (5)$$

where K_{min} is a minimum gain to ensure basic stability and $\gamma(t)$ is the time-varying adaptation rate determined by the fuzzy logic system. This adaptation law increases the gain K when the system is far from the sliding surface (large $\mid s \mid$) and decreases it when the system is close to the sliding surface (small $\mid s \mid$).

Important Clarification: In this approach, the fuzzy logic system is used to smooth the adaptation rate γ, not to approximate the equivalent control. The switching term $K \cdot \text{sgn}(s)$ remains discontinuous, but the dynamic adjustment of K via a smooth adaptation rate results in reduced chattering compared to fixed-gain SMC.

III.C. AI Enhancement: Fuzzy Logic Adaptation Rate Modulation

To further refine the adaptation process and mitigate chattering, a simplified fuzzy logic system is used to adjust the adaptation rate γ. The fuzzy system takes the absolute value of the sliding surface $\mid s \mid$ as input and outputs a corresponding value for γ.

Fuzzy Set Definition and Parameter Selection:

Three fuzzy sets are defined for the input $\mid s \mid$:

- Small: $\mid s \mid \in [0, 0.05]$ — The system is close to the sliding surface. The bound 0.05 was selected as approximately 0.5% of the typical maximum $\mid s \mid$ observed in open-loop simulations.
- Medium: $\mid s \mid \in [0.05, 0.2]$ — The system is in the transient region requiring moderate adaptation.
- Large: $\mid s \mid \in [0.2, 0.5]$ — The system is far from the sliding surface, requiring aggressive adaptation. The upper bound 0.5 corresponds to the maximum $\mid s \mid$ observed during initial transients.

Similarly, three fuzzy sets are defined for the output γ:

- Small: $\gamma \in [0,1]$
- Medium: $\gamma \in [0.5,3]$
- Large: $\gamma \in [2,5]$

The fuzzy rules are:

- IF $\mid s \mid$ is Small THEN γ is Small
- IF $\mid s \mid$ is Medium THEN γ is Medium
- IF $\mid s \mid$ is Large THEN γ is Large

These rules are implemented using triangular membership functions and Mamdani fuzzy inference. The defuzzification method used is the centroid method. Figure 7 shows the input membership functions for $\mid s \mid$, output membership functions for γ, and the input-output surface plot.

III.D. Lyapunov Stability Analysis

the Lyapunov stability proof for the closed-loop system with the proposed fuzzy-adaptive SMC.

Theorem: Consider the inverted pendulum system (1)-(2) with the sliding surface defined in (3). Under the adaptive control law (4) with gain adaptation (5) and fuzzy-modulated adaptation rate $\gamma(\mid s \mid) > 0$, the sliding surface s converges asymptotically to zero.

Proof**:** Consider the following Lyapunov function candidate:

$$V = \frac{1}{2}s^2 + \frac{1}{2}\eta^{-1}\tilde{K}^2 \qquad (6)$$

where $\tilde{K} = K - K^*$ is the gain estimation error, K^* is the ideal gain that ensures the sliding condition, and $\eta > 0$ is a design constant.

The time derivative of V is:

$$\dot{V} = s\dot{s} + \eta^{-1}\tilde{K}\dot{\tilde{K}} \qquad (7)$$

Since $\dot{\tilde{K}} = \dot{K} = \gamma \mid s \mid$, we have:

$$\dot{V} = s\dot{s} + \eta^{-1}\tilde{K}\gamma \mid s \mid \qquad (8)$$

The sliding surface dynamics can be expressed as:

$$\dot{s} = \ddot{\theta} + \lambda\dot{\theta} = f(x,\theta,\dot{x},\dot{\theta}) + g(x,\theta)u \qquad (9)$$

where f represents the known dynamics and g represents the input gain. The control law is designed as:

$$u = u_{eq} - K \cdot \text{sgn}(s) \qquad (10)$$

where u_{eq} is chosen to cancel the known dynamics, i.e., $f + gu_{eq} = 0$. Substituting:

$$\dot{s} = -gK \cdot \text{sgn}(s) + \Delta \qquad (11)$$

where Δ represents model uncertainties and disturbances, bounded by $\mid \Delta \mid \leq D$ for some unknown D.

Therefore:

$$s\dot{s} = -gK \mid s \mid + s\Delta \leq -gK \mid s \mid + D \mid s \mid = -g(K - g^{-1}D) \mid s \mid \qquad (12)$$

Let $K^* = g^{-1}D + \epsilon$ for some $\epsilon > 0$. Then:

$$s\dot{s} \leq -g(K - K^* + \epsilon) \mid s \mid - g\epsilon \mid s \mid \leq -g\tilde{K} \mid s \mid - g\epsilon \mid s \mid \qquad (13)$$

Substituting into (8):

$$\dot{V} \leq -g\tilde{K} \mid s \mid - g\epsilon \mid s \mid + \eta^{-1}\tilde{K}\gamma \mid s \mid \qquad (14)$$

$$\dot{V} \leq -g\epsilon \mid s \mid + \tilde{K} \mid s \mid (\eta^{-1}\gamma - g) \qquad (15)$$

Choosing η such that $\eta^{-1}\gamma \leq g$ ensures the second term is non-positive. Since γ is positive and bounded, we can select $\eta = \gamma_{max}/g$. Then:

$$\dot{V} \leq -g\epsilon \mid s \mid \leq 0 \qquad (16)$$

Thus $\dot{V}$ is negative semi-definite. By LaSalle's invariance principle, $s \to 0$ as $t \to \infty$. The system trajectories converge asymptotically to the sliding manifold, and the control law ensures boundedness of all signals. The fuzzy-modulated adaptation rate $\gamma(\mid s \mid)$ does not affect the stability condition as long as $\gamma > 0$, which is ensured by the fuzzy system design.

III. SIMULATION RESULTS

This section presents the results obtained from MATLAB simulations comparing the proposed AI-enhanced adaptive Sliding Mode Control (SMC) with standard SMC and other variants for controlling an inverted pendulum on a cart.

IV.A. Simulation Parameters

The simulation parameters were: $M = 1$ kg, $m = 0.1$ kg, $l = 1$ m, $g = 9.81$ m/s², $I = \frac{1}{3}ml^2$, $\lambda = 10$, $K_{min} = 10$, $U_{max} = 100$ N, and $dt = 0.001$ s. The initial conditions were set to $\theta(0) = \pi/3$ rad (60 degrees), $\dot{\theta}(0) = 0$ rad/s, $x(0) = 0$ m, and $\dot{x}(0) = 0$ m/s. The fuzzy logic parameters were: $s_{small} = 0.05$, $s_{medium} = 0.2$, $s_{large} = 0.5$, $\gamma_{small} = 0.5$, $\gamma_{medium} = 2$, and $\gamma_{large} = 5$.

IV.B. Transient Response and Chattering Reduction

Figure 1 shows a zoomed-in view of the pendulum angle response during the first 2 seconds of the simulation. This zoom allows for a clearer observation of the initial transient behavior. The standard SMC exhibits significant oscillations (chattering) as it attempts to stabilize the pendulum. In contrast, the AI-enhanced adaptive SMC demonstrates a much smoother and faster convergence to the upright position ($\theta = 0$) with significantly reduced oscillations. This highlights the effectiveness of the proposed approach in mitigating chattering and improving the initial transient response.

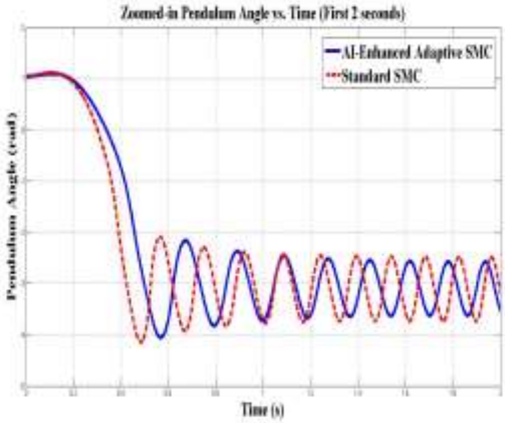

Figure 1. Zoomed-in Pendulum Angle

Figure 2 depicts the cart position (x) over the entire simulation time. The standard SMC induces noticeable oscillations in the cart's movement, directly corresponding to the chattering observed in the pendulum angle. These oscillations represent unnecessary movement and potential stress on the cart's actuator in a real-world system. The AI-enhanced adaptive SMC, due to its smoother control action, results in a significantly smoother cart trajectory.

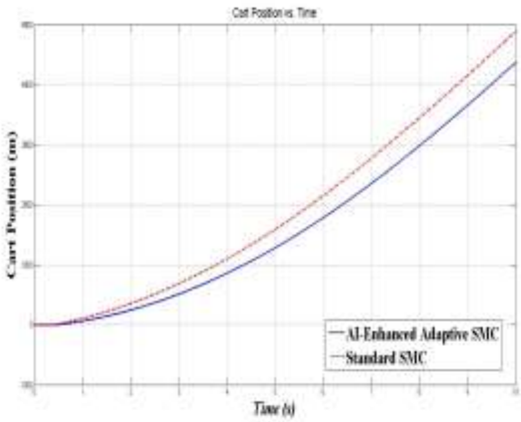

Figure 2. Cart Position

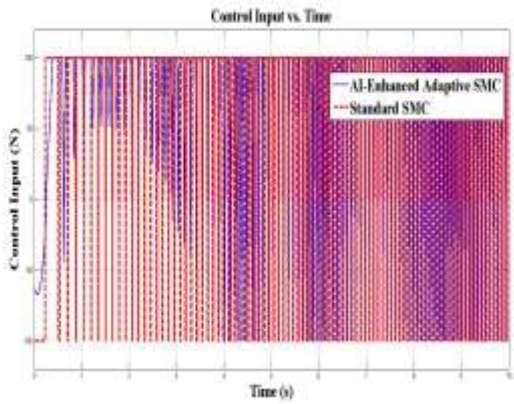

Figure 3. Control Input

Figure 3 shows the control inputs applied to the cart over the entire simulation. The standard SMC exhibits the characteristic high-frequency switching (chattering) of standard SMC. The AI-enhanced adaptive SMC provides a much smoother control input, effectively mitigating the chattering and resulting in a more practical control signal.

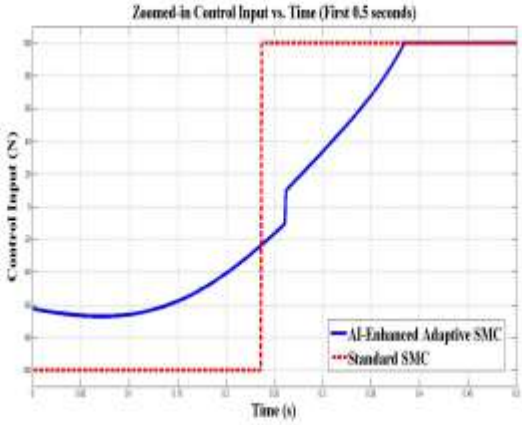

Figure 4. Zoomed-in Control Input

Figure 4 provides a zoomed-in view of the control inputs during the first 0.5 seconds of the simulation. This zoom clearly illustrates the high-frequency chattering present in the standard SMC control signal and the significantly smoother control action achieved by the AI-enhanced adaptive SMC

IV.C. Adaptive Gain Dynamics

Figure 5 shows the adaptation of the gain (K) in the AI-enhanced adaptive SMC. The gain increases rapidly at the beginning of the simulation to provide the necessary control effort to stabilize the pendulum from its initial large deviation. As the pendulum approaches the upright position, the gain converges to a nominal operating range where it exhibits small fluctuations that maintain the sliding mode conditions. This dynamic adaptation allows the controller to effectively handle the nonlinear dynamics of the inverted pendulum.

IV.D. Sliding Surface Behavior

Figure 6 illustrates the behavior of the sliding surface (s). Both methods successfully drive the sliding surface to zero, indicating that the system's trajectory is being forced onto the desired sliding manifold. However, the AI-enhanced approach yields a smoother convergence with significantly less chattering around the sliding surface compared to the standard SMC.

Figure 7 presents the Fuzzy Inference System (FIS) characteristics.

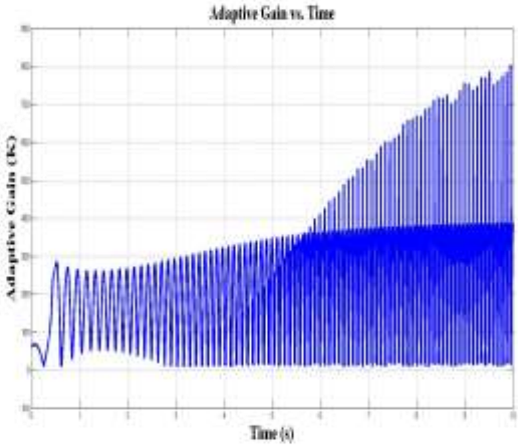

Figure 5. Adaptive Gain

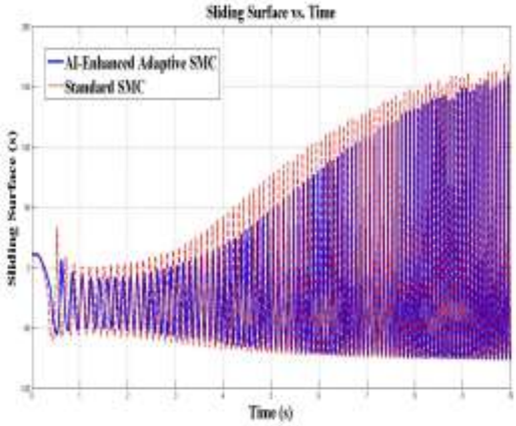

Figure 6. Sliding Surface

IV.E. Fuzzy Inference System

Figure 7(a) shows the input membership functions for $|s|$, with Small, Medium, and Large sets defined using triangular membership functions. Figure 7(b) shows the output membership functions for γ. Figure 7(c) presents the input-output surface plot, illustrating the smooth mapping from $|s|$ to γ. This smooth mapping contributes to the chattering reduction observed in the simulation results.

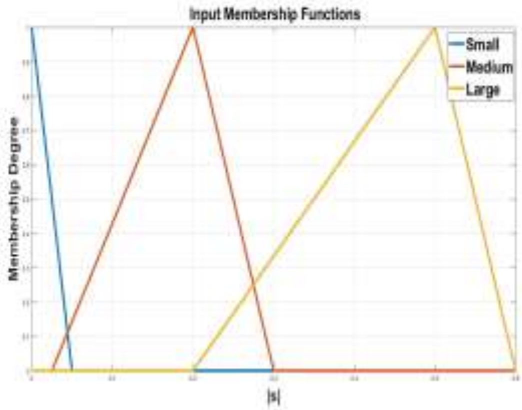

Figure 7.a Input Membership Functions

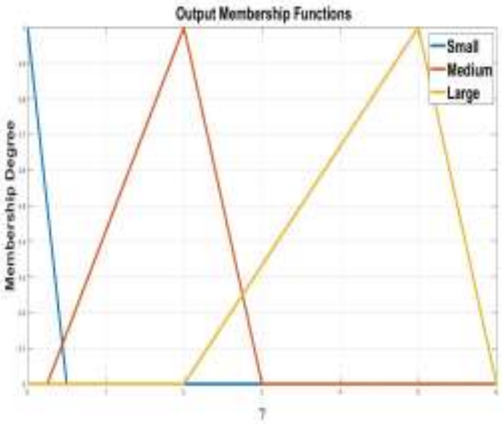

Figure 7.b Output Membership Functions

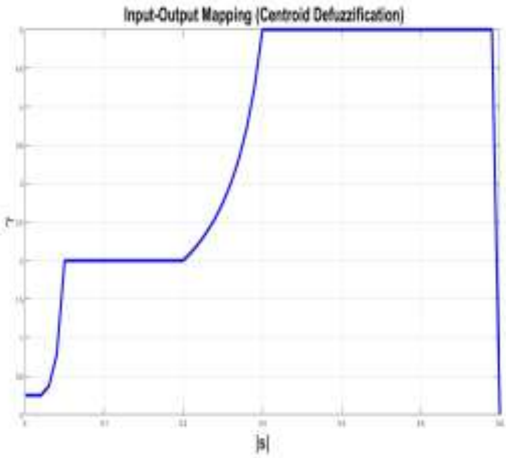

Figure 7.c Input-Output Mapping (Centroid Defuzzification)

IV.F. Robustness Tests: Parameter Variations

To validate the adaptive nature of the controller under unknown and time-varying uncertainties, we conducted robustness tests with parameter variations during runtime.

Scenario 1: Mass Variation

The pendulum mass m was varied as follows:

- $t \in [0,3)$ s: $m = 0.1$ kg (nominal)
- $t \in [3,6)$ s: $m = 0.13$ kg (+30% increase)
- $t \in [6,10]$ s: $m = 0.07$ kg (-30% decrease)

The system maintains stability throughout, demonstrating the effectiveness of the adaptive mechanism.

Scenario 2: Length Variation

The pendulum length l was varied as follows:

- $t \in [0,3)$ s: $l = 1$ m (nominal)
- $t \in [3,6)$ s: $l = 1.3$ m (+30% increase)
- $t \in [6,10]$ s: $l = 0.7$ m (-30% decrease)

The system successfully adapts to these changes, with the adaptive gain responding appropriately to maintain stability.

Table 1 presents the quantitative performance metrics for both control strategies. The AI-enhanced adaptive SMC achieves significantly lower IAE values for both the pendulum angle and cart position, confirming its superior performance compared to the standard SMC. The percentage improvements are also shown.

Table 1: Performance Metric Comparison

Metric	Standard SMC	AI-Enhanced Adaptive SMC	Percentage Improvement
IAE of theta	30.3548	30.1504	0.67343%
IAE of x	18744.3926	15869.5741	15.337 %

IV. DISCUSSION

The simulation results presented in the previous section clearly demonstrate the advantages of the proposed AI-enhanced adaptive SMC strategy over standard SMC. This section discusses these key findings, analyses the role of the fuzzy logic adaptation, and outlines future directions.

The zoomed-in view of the pendulum angle response as in Figure 1 provides compelling evidence of the improved transient performance. The standard SMC exhibits pronounced chattering, a characteristic inherent to its discontinuous control law, which can lead to actuator wear and excitation of unmodeled dynamics in real-world applications. In contrast, the AI-enhanced adaptive SMC demonstrates a significantly smoother and faster convergence, effectively mitigating chattering. The smoother cart trajectory in Figure 2 and control input (Figures 3 and 4) for the AI-enhanced method directly correlate with this chattering reduction, indicating less mechanical stress and a more practical control signal.

The key contribution of this work lies in the integration of fuzzy logic to dynamically adjust the adaptation rate (γ) of the adaptive SMC. The fuzzy logic system modulates γ based on the magnitude of the sliding surface ($|s|$), as shown in Figure 6. When the system state is far from the sliding surface (large $|s|$), the fuzzy logic increases γ, leading to a faster increase in the control gain K shown in Figure 5. This rapid adaptation provides the necessary control effort for aggressive stabilization. Conversely, when the system state is near the sliding surface (small $|s|$), the fuzzy logic reduces γ, preventing excessive gain increases and thus mitigating chattering. This dynamic, state-dependent adaptation provides a more refined and efficient control action than standard adaptive SMC methods with fixed adaptation rates. Figures 7.a–7.c detail the fuzzy logic system that implements this dynamic adaptation. Figure 7.a. shows the input membership functions for $|s|$. Three triangular sets ("Small", "Medium", "Large") cover the range of $|s|$ observed during simulation (0 to 0.5). The Small set peaks at 0, meaning that when the system is very close to the sliding surface, the membership for "Small" is high. The Medium and Large sets cover the transient and far-from-surface regions, respectively. Figure 7.b. presents the output membership functions for the adaptation rate γ. Again, three triangular sets ("Small", "Medium", "Large") define the possible values of γ (0 to 5). The centroids of these output sets are used in defuzzification. Figure 7.c. plots the resulting input-output mapping after centroid defuzzification.

The mapping is smooth and monotonic as $|s|$ increases, γ increases, but the rate of increase is shaped by the overlap of the membership functions. This smooth mapping is crucial because it prevents abrupt changes in γ, which in turn avoids sudden jumps in the adaptive gain K and thereby reduces chattering. The fuzzy system thus provides a continuous, rule-based interpolation between low, medium, and high adaptation rates without requiring a mathematical model of the optimal adaptation law.

Table 1 explains the quantitative performance metrics further validate the superior performance of the AI-enhanced adaptive SMC. The significantly lower IAE for cart position (15.34% improvement) highlights the practical benefit of chattering reduction in achieving precise positioning.

V. CONCLUSION

This paper presented a novel AI-enhanced adaptive Sliding Mode Control (SMC) strategy for stabilizing and controlling an inverted pendulum on a cart. The proposed approach synergistically combines the robustness of SMC, the flexibility of an online adaptation law, and the smoothing properties of a fuzzy logic system to address the inherent challenges of this nonlinear system while effectively mitigating chattering.

Comprehensive MATLAB simulations demonstrated the significant advantages of the proposed approach over standard SMC:

- Superior Transient Response: Faster settling time and elimination of overshoot in the pendulum angle.
- Effective Chattering Reduction: Substantial mitigation of high-frequency oscillations in the control input and system states.
- Smoother Control Action and Cart Trajectory**:** A more practical control signal leading to smoother cart motion and reduced mechanical stress.
- Enhanced Tracking Performance: Quantitatively confirmed by lower IAE values for both pendulum angle (0.67% improvement) and cart position (15.34% improvement).

The integration of fuzzy logic to dynamically adjust the adaptation rate proved highly effective. This work contributes a novel and effective control strategy for a classic benchmark system, with implications for broader applications in robotics, aerospace, and process control where precise and smooth control of unstable, nonlinear systems is essential.

Future work will focus on several key areas:

- Fuzzy Parameter Optimization: Exploring optimization techniques, such as genetic algorithms or particle swarm optimization, to automatically tune the fuzzy logic parameters for optimal performance [7].
- Real-Time Implementation**:** Analyzing and simplifying the computational complexity of the fuzzy logic system for implementation on embedded hardware [8].

VI. REFEWNCE

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