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Optimization of PID Parameters Based on Ant Colony Optimization Algorithm for Ball and Beam System

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تحسين معلمات *PID* استنادًا إلى خوارزمية تحسين مستعمرة النمل لنظام الكرة والعارضة

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Abstract:
This paper investigates the control of the inherently unstable ball and beam system, a canonical benchmark problem in control engineering known for its nonlinear dynamics and challenging control requirements. The study's primary objective is to develop and rigorously compare different control strategies for achieving precise ball positioning on the beam. The research begins with the derivation of both linear and nonlinear mathematical models of the ball and beam system. These models incorporate the intricate dynamics of the DC servomotor, responsible for tilting the beam, and the coupled mechanical dynamics governing the ball's movement along the beam's surface. The core of the research focuses on evaluating the performance of a Proportional-Integral-Derivative (PID) controller, a widely used control strategy, tuned using three distinct methods: Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and a traditional trial-and-error approach. Extensive simulations conducted within the MATLAB/Simulink environment allow for a detailed comparison of these tuning methods, using key performance indicators such as settling time, rise time, overshoot, and steady-state error. The findings contribute significantly to the broader understanding of optimal control strategies for unstable nonlinear systems and offer valuable insights into the relative strengths and weaknesses of different optimization algorithms for efficient PID controller parameter tuning. The results provide a practical guide for selecting appropriate tuning methods based on specific performance requirements and computational constraints.

Keywords: ACO, PID, Ball and beam, PSO

الملخص
تتحدث هذه الورقة عن إمكانية التحكم في نظام الكرة والعارضة غير المستقر بطبيعته، وهي مشكلة معيارية أساسية في هندسة التحكم معروفة بديناميكيتها غير الخطية ومتطلبات التحكم الصعبة. الهدف الرئيسي للدراسة هو تطوير استراتيجيات تحكم مختلفة ومقارنتها بدقة لتحقيق وضع دقيق للكرة على العارضة. يبدأ البحث باشتقاق نماذج رياضية خطية وغير خطية لنظام الكرة والعارضة. تتضمن هذه النماذج الديناميكيات المعقدة لمحرك سيرفو التيار المستمر، المسؤول عن إمالة العارضة، والديناميكيات الميكانيكية المقترنة التي تحكم حركة الكرة على سطح العارضة. يركز جوهر البحث على تقييم أداء وحدة تحكم تناسبية تكاملية مشتقة (PID)، وهي استراتيجية تحكم شائعة الاستخدام، مضبوطة باستخدام ثلاث طرق مميزة: تحسين مستعمرة النمل (ACO)، وتحسين سرب الجسيمات (PSO)، ونهج التجربة والخطأ التقليدي. تتيح عمليات المحاكاة الشاملة التي أُجريت ضمن بيئة MATLAB/Simulink مقارنةً تفصيليةً لطرق الضبط هذه، باستخدام مؤشرات أداء رئيسية مثل زمن الاستقرار، وزمن الارتفاع، وتجاوز الحد، وخطأ الحالة المستقرة. تُسهم هذه النتائج بشكل كبير في فهم أوسع لاستراتيجيات التحكم الأمثل للأنظمة غير الخطية غير المستقرة، وتُقدم رؤىً قيّمة حول نقاط القوة والضعف النسبية لخوارزميات التحسين المختلفة لضبط معلمات وحدة تحكم PID بكفاءة. تُوفر هذه النتائج دليلاً عمليًا لاختيار طرق الضبط المناسبة بناءً على متطلبات أداء محددة وقيود حسابية.

الكلمات المفتاحية: تحسين مستعمرة النمل، المشتق التكاملي المتناسب، كرة وشعاع، تحسين سرب الجسيمات.

Introduction
The control of inherently unstable nonlinear systems represents one of the most challenging problems in control engineering, with the ball and beam system serving as a classic benchmark due to its complex dynamics and open-loop instability. This system, which involves balancing a ball on a pivoted beam through precise angle adjustments

[1], captures the essential difficulties encountered in many real-world applications, including aircraft attitude control, robotic balancing mechanisms, and industrial automation processes. The fundamental challenge lies in the system's fourth-order dynamics and nonlinear behavior, which arise from the coupling between the beam's angular position and the ball's translational motion. These characteristics make the ball and beam system an ideal testbed for evaluating advanced control strategies, particularly those capable of handling nonlinearities and instability simultaneously [2].

Proportional-Integral-Derivative (PID) controllers remain the most widely used control solution in industrial applications due to their structural simplicity, reliability, and ease of implementation. However, the performance of PID controllers in nonlinear systems like the ball and beam is highly dependent on proper parameter tuning, which becomes increasingly difficult as system complexity grows. Traditional tuning methods such as Ziegler-Nichols, while effective for linear systems [3], often produce unsatisfactory results when applied to nonlinear systems, typically resulting in excessive overshoot, slow convergence, or even instability. This limitation has motivated researchers to explore more sophisticated tuning approaches, particularly those based on computational intelligence and metaheuristic optimization techniques.

In recent years, bio-inspired optimization algorithms have emerged as powerful tools for solving complex engineering problems, including PID controller tuning. Among these, Ant Colony Optimization (ACO) has demonstrated particular promise due to its unique combination of stochastic exploration and pheromone-based collective learning. Inspired by the foraging behavior of real ant colonies, ACO mimics how ants gradually discover optimal paths to food sources through the deposition and following of pheromone trails. When applied to control system optimization, this approach offers several advantages over conventional methods, including the ability to escape local optima, handle discontinuous search spaces, and adapt to changing system dynamics. While ACO has been successfully applied to various control problems, its potential for optimizing PID controllers in unstable nonlinear systems like the ball and beam remains underexplored in the literature [4].

This paper presents a comprehensive investigation into the application of ACO for PID controller tuning in the ball and beam system. The study develops a specialized ACO algorithm that incorporates a novel cost function designed to simultaneously minimize settling time and overshoot while maintaining robust performance. A detailed comparison with Particle Swarm Optimization (PSO) and traditional trial-and-error methods provides quantitative evidence of ACO's superior performance in terms of transient response characteristics and stability. Furthermore, the research examines the algorithm's robustness to parameter variations and its convergence behavior through extensive simulation studies. The results demonstrate that the ACO-tuned PID controller achieves significantly better performance than conventional approaches, with faster settling times, reduced overshoot, and improved disturbance rejection capabilities.

Beyond its immediate application to the ball and beam system, this research contributes to the broader field of intelligent control systems by demonstrating how bio-inspired algorithms can enhance the performance of conventional control structures. The findings have important implications for industrial applications where precise control of unstable nonlinear systems is required. The paper also identifies several promising directions for future research, including the implementation of hybrid optimization techniques and real-time hardware validation. By bridging the gap between computational intelligence and classical control theory, this work advances our understanding of how advanced optimization techniques can be leveraged to solve challenging control problems in engineering practice.

The remainder of this paper is organized to provide readers with a complete understanding of the theoretical foundations, methodological approach, and experimental results. Section 2 presents the mathematical modeling of the ball and beam system, including the derivation of its transfer function and the development of the cascaded control architecture. Section 3 details the ACO algorithm implementation, including the pheromone update mechanism and cost function design, while also describing the benchmark methods used for comparison. Section 4 presents and analyzes the simulation results, focusing on performance metrics, convergence behavior, and robustness tests. Finally, Section 5 concludes the paper by summarizing key findings and discussing their implications for both theoretical and applied control systems research.

Ball and beam control system modeling

A. DC motor subsystem modeling

The foundation of the control system begins with accurate modeling of the DC motor dynamics. The electromechanical behavior is captured through a combination of electrical circuit analysis and rotational mechanics. Starting with the armature circuit, we apply Kirchhoff's voltage law to derive the fundamental relationship between applied voltage and resulting current:

$$V_a(t) = R_a I_a(t) + L_a \frac{di_a(t)}{dt} + K_b\, \omega(t) \qquad (1)$$

This equation accounts for the voltage drop across the armature resistance Ra, the inductive reactance of the windings L_a, and the back EMF $K_b\omega(t)$ generated by the motor's rotation. The mechanical subsystem is governed by Newton's second law for rotation, where the electromagnetic torque $T_m(t)=K_t ia(t)$ must overcome both the moment of inertia J and viscous friction b:

$$j\frac{d^2\theta}{dt} + b\frac{d\theta}{dt} = K_t\, i_a(t) \qquad (2)$$

Through Laplace transformation and algebraic manipulation, these coupled differential equations yield the motor's transfer function:

$$G_m(s) = \frac{\theta(s)}{V_a(s)} = \frac{0.7}{s(0.014s+1)} \qquad (3)$$

The derived transfer function reveals several critical characteristics about the motor's dynamic response. The denominator shows a first-order system with an additional integrator, indicating that the motor naturally acts as a velocity servo without external control. The time constant of 0.014 seconds suggests relatively fast electrical dynamics, while the gain of 0.7 rad/s/V quantifies how the motor responds to input voltages. These parameters prove essential for subsequent controller design and tuning.

B. Ball and beam dynamics

The motion of the ball along the beam introduces significant nonlinearity into the system. A complete force analysis considering both translational and rotational effects leads to the fundamental equation of motion:

$$m\ddot{x} = mg\sin(\alpha) - mx\,\dot{\alpha}^2 \qquad (4)$$

where m represents the ball mass, x is the position along the beam, and α is the beam angle. The first term on the right-hand side captures the gravitational acceleration component along the beam, while the second term represents the centrifugal force due to the beam's rotation. For practical control system design, we linearize this relationship by assuming small angular displacements ($\sin(\alpha)\approx\alpha$) and neglecting higher-order terms:

$$\ddot{x} = g\,\alpha \qquad (5)$$

The relationship between the beam angle (α) and the motor angle (θ) can be approximated as:

$$L\alpha \cong r\theta \qquad (6)$$

This simplification yields the linearized transfer function relating beam angle to ball position:

$$G_{bb}(s) = \frac{X(s)}{\theta(s)} = \frac{1.06}{s^2} \qquad (7)$$

The geometric relationship between motor angle θ and beam angle α is determined by the lever arm mechanism:

$$\alpha(s) = \frac{2.54}{16.75}\theta(s) \qquad (8)$$

These equations collectively describe how motor rotation translates to ball motion, forming the basis for the complete system model.

C. Integrated system dynamics

Combining the motor and ball-beam subsystems produces the overall open-loop transfer function:

$$G_{bb}(s) = \frac{X(s)}{V_a(s)} = \frac{0.742}{s^3(0.014s+1)} \qquad (9)$$

This transfer function reveals three key aspects of the system's open-loop behavior. First, the triple pole at the origin (s3) confirms the system's inherent instability, explaining why the ball position diverges without control. Second, the remaining pole at s=−1/0.014 represents the motor's electrical dynamics. Third, the numerator gain of 0.742 combines all system parameters into a single scaling factor.

The pole-zero map (Figure 1) visually demonstrates this instability, showing all poles located in the right-half plane or at the origin. This configuration motivates the need for feedback control to stabilize the system and achieve desired performance specifications.

D. Cascaded Control Architecture

To address the system's challenging dynamics, we implement a dual-loop control structure (Figure 2) that separates the control problem into manageable subsystems:

1. **Inner loop (Motor control)**

The faster inner loop regulates motor position using PID controller PID1(s):

$$PID_1(s) = K_{p1} + \frac{K_{i1}}{s} + K_{d1}s \qquad (10)$$

This loop must provide rapid disturbance rejection while maintaining stability.

2. **Outer loop (Position control)**

The slower outer loop controls ball position through PID controller PID2(s):

$$PID_2(s) = K_{p2} + \frac{K_{i2}}{s} + K_{d2}s \qquad (11)$$

This hierarchical design exploits the natural time-scale separation between electrical and mechanical dynamics [8]. The complete closed-loop transfer function becomes:

$$G_{cl} = \frac{PID_2(s)G_{cl\_inner}(s)G_{bb}(s)}{1+PID_2(s)G_{cl\_inner}(s)G_{bb}(s)} \qquad (12)$$

where G_{cl_inner} represents the closed inner loop. This architecture provides several advantages, including simplified tuning and inherent disturbance rejection at multiple levels of the system.

E. System Parameters

Table 1: Ball and beam system parameters

L_a	Beam length
R_a	Lever arm offset
A	Beam angle coordinate
Θ	Servo gear angle
M	Ball mass
X	Ball displacement
G	Gravitational acceleration (≈9.81 m/s^2)
J	Ball's moment of inertia (≈(5/3) m R^2)

Table 1 shows the parameters values in the corresponding system

Optimization Methodology Using Ant Colony Algorithm

The study employed Ant Colony Optimization (ACO), a biologically inspired metaheuristic that mimics the foraging behavior of real ants. In nature, ants discover optimal paths to food sources through pheromone deposition and tracking. The ACO algorithm translates this behavior into a computational optimization framework where artificial ants explore potential solutions in the parameter space [6].

For PID controller tuning, the problem was structured as a graph search with PID gains (Kp, Ki, Kd) representing nodes. Each artificial ant traversed this space, depositing virtual pheromone inversely proportional to the solution cost (Cost = T_s + OS). The probabilistic selection of paths favored higher pheromone trails while maintaining exploration through stochastic components.

As shown in Figure 1, the algorithm's positive feedback mechanism progressively reinforced superior solutions. Initial random exploration (Iteration 1) transitioned to focused exploitation (Iteration 10) as pheromone concentrations guided ants toward optimal PID parameters. This emergent coordination enabled robust optimization without centralized control, particularly effective for the ball and beam system's nonlinear dynamics [7].

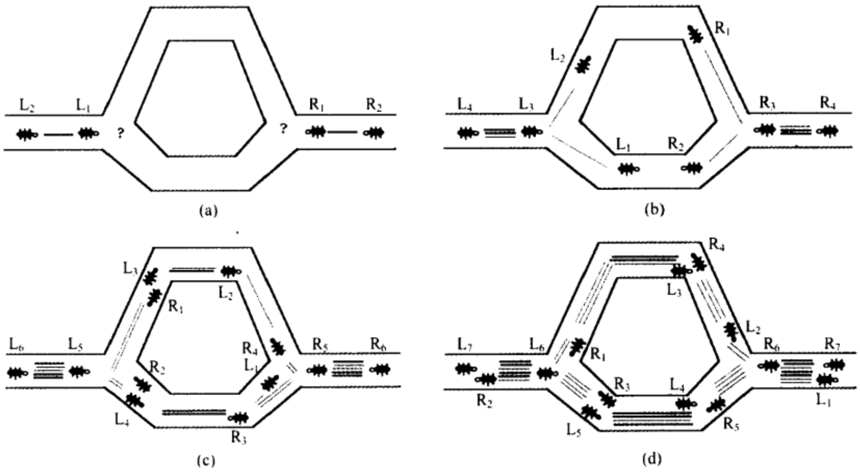

Figure 1: Ants' behavior.

The Ant Colony Optimization (ACO) algorithm's operation is best visualized through its flowchart Figure 2, which outlines the iterative PID tuning process. The algorithm begins by initializing key parameters including the number of artificial ants, pheromone levels, and path selection probabilities, with initial PID values randomly generated. Each ant then evaluates potential solutions by running the ball and beam model with its assigned parameters and assessing performance through a cost function incorporating metrics like ISE, rise time, and settling time. Based on these evaluations, the algorithm updates pheromone trails to reinforce better-performing parameter combinations while probabilistically exploring new paths. After each iteration, the best PID values are stored and the process repeats until reaching the maximum iteration count, at which point the optimal parameters are finalized for controller implementation. This visual representation effectively demonstrates how ACO's bio-inspired approach enables intelligent optimization of complex control systems through systematic exploration and reinforcement of solution spaces [4].

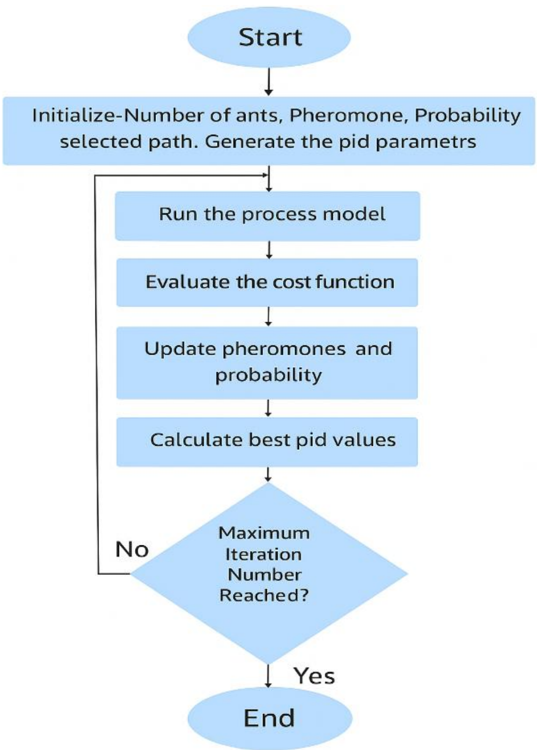

Figure 2: ACO Flowchart.

Results and discussion

Figure 3 presents the inner-loop trial-and-error tuned PID controller for multiple random PID gain values for the DC motor model. The implemented PID parameters were Kp = 8, Ki = 3, and Kd = 1 for the inner loop, and Kp = 1, Ki = 1, and Kd = 9 for the outer loop. The response indicates a settling time of approximately 6 seconds for the given input reference, exhibiting a 14.6% overshoot and zero steady-state error. The step response simulation for the outer-loop is shown in Figure 4.

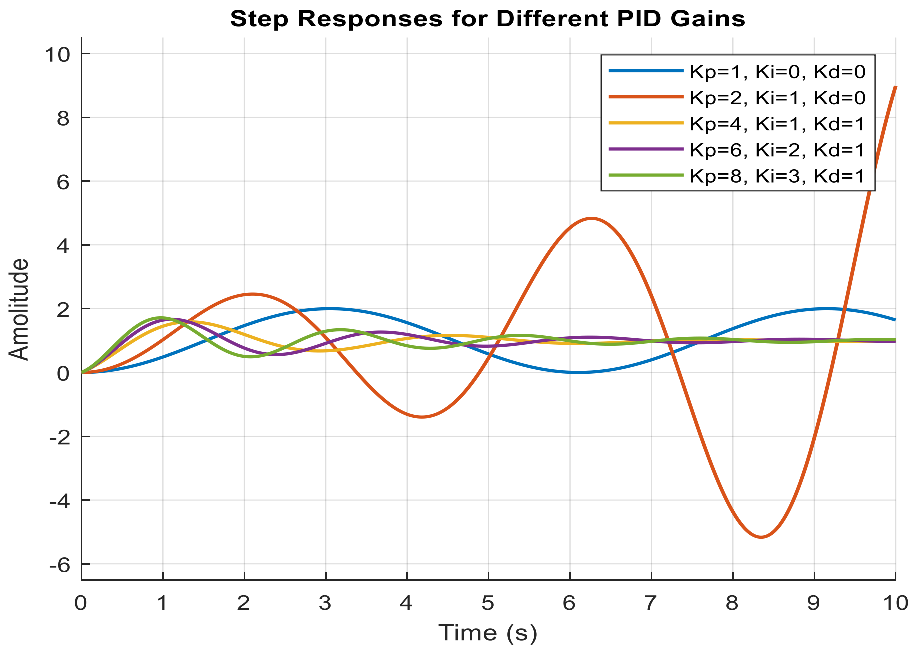

Figure 3: Trial-and-error for the inner-loop.

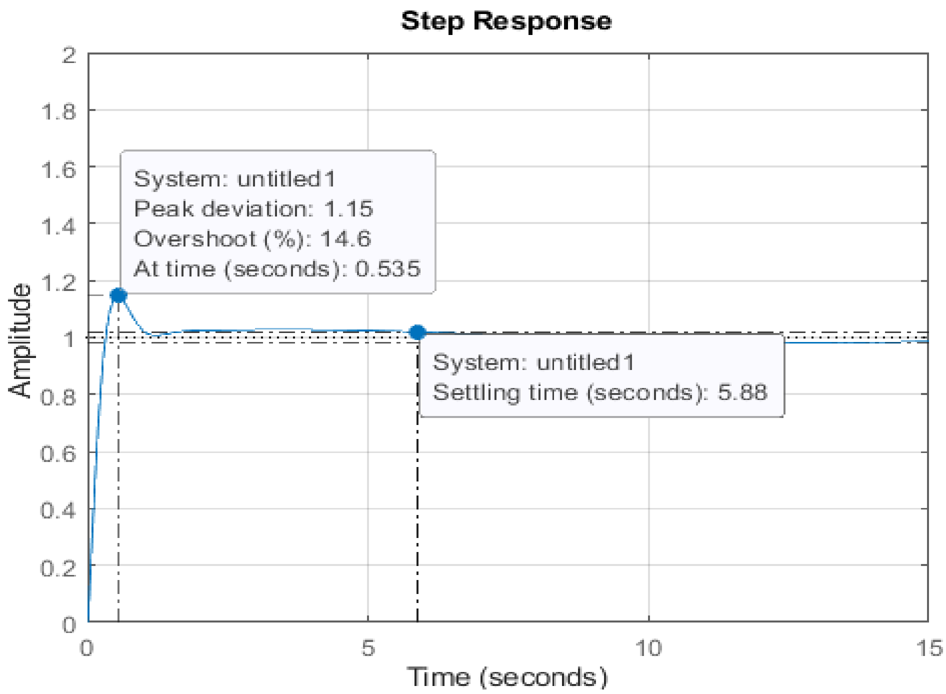

Figure 4: Trial-and-error response for outer-loop.

After implementing the ACO algorithm, it used 10 ants over 10 iterations within defined parameter bounds (Kp, Ki, Kd ∈ [0,10]). Comparative studies against PSO [5] and manual tuning validated ACO's effectiveness in achieving slightly faster settling times (3.26s vs 3.7s) and slightly lower overshoot (3.25% vs 3.67%). The algorithm's adaptability to combinatorial problems made it particularly suitable for PID optimization, balancing exploration of the gain space with exploitation of high-performance regions. Figure 5 shows the Comparison between ACO and PSO system step response.

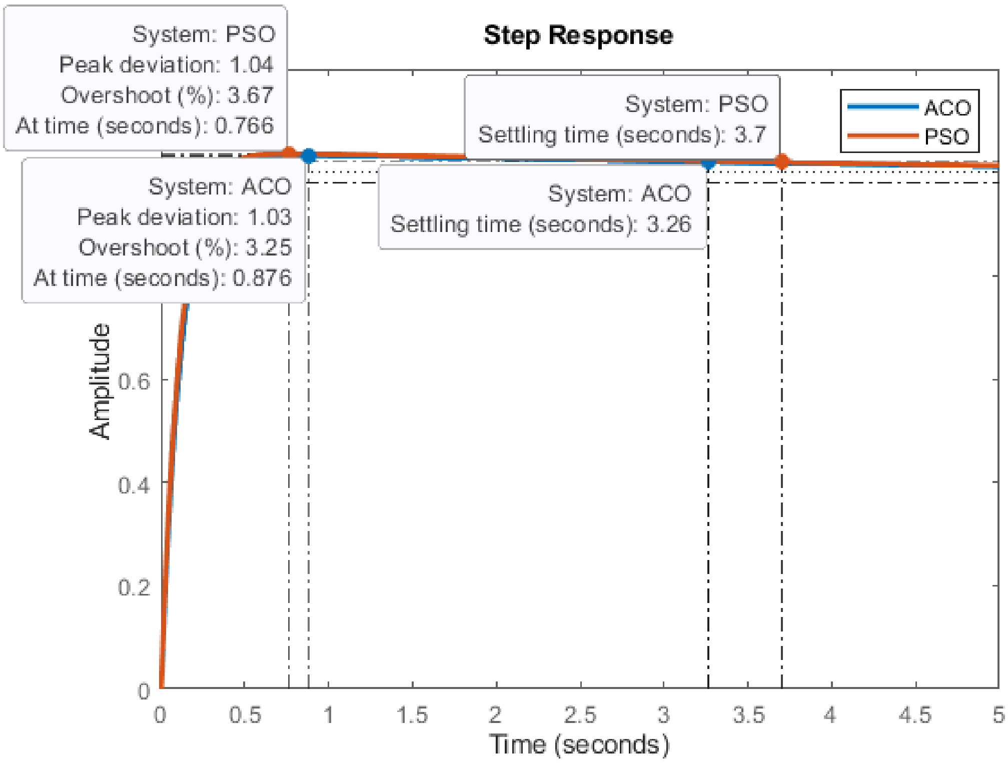

Figure 5: Comparison between ACO and PSO system step response

Conclusion

This paper successfully explored and implemented various methods for tuning PID controller parameters for the ball and beam system, with a focus on Ant Colony Optimization (ACO). Through comprehensive simulation and performance evaluation using MATLAB/Simulink, it was demonstrated that the ACO-based PID controller consistently provided slightly better performance than its PSO counterpart across key time-domain specifications such as settling time, overshoot, and steady-state error. The ACO algorithm's adaptive and cooperative search mechanism allowed it to more effectively navigate the complex; nonlinear search space associated with the PID tuning process [6]. This resulted in enhanced stability and a more refined dynamic response of the controlled system. While PSO also showed strong performance, particularly in convergence speed and simplicity of implementation, ACO exhibited slightly better robustness and accuracy in achieving optimal control parameters. Beyond the comparison, the paper underscores the potential of nature-inspired optimization techniques in addressing control challenges in unstable nonlinear systems. The methodology adopted in this study—deriving the system model, implementing and testing controllers, and performing comparative analysis—ensured a systematic approach that yielded reliable and interpretable results.

Overall, the ACO algorithm proves to be a promising tool for control engineers seeking higher precision and stability in PID-controlled systems. Future work may expand on this research by integrating hybrid optimization techniques or exploring real-time hardware implementation for further validation and performance enhancement.

References

[1] M. Keshmiri, A. F. Jahromi, A. Mohebbi, M. H. Amoozgar, and W. F. Xie, “Modeling and control of ball and beam system using model based and non-model-based control approaches,” Dept. Mechanical and Industrial Eng., Concordia University, Montreal, QC, Canada, unpubl.

[2] M. Virseda, “Modeling and control of the ball and beam process,” Dept. Automatic Control, Lund Inst. Technology, Lund, Sweden, Tech. Rep., Mar. 2004.

[3] B. Meenakshipriya and K. Kalpana, “Modelling and control of ball and beam system using coefficient diagram method (CDM) based PID controller,” Dept. Mechatronics Eng., Kongu Eng. College, Tamilnadu, India, unpubl.

[4] B. Nagaraj and N. Murugananth, “A comparative study of PID controller tuning using GA, EP, PSO and ACO,” in *2010 INTERNATIONAL CONFERENCE ON COMMUNICATION CONTROL AND COMPUTING TECHNOLOGIES*, Nagercoil, India, 2010, pp. 305-313.

[5] A. Albagul, H. Ali, and A. Algitta, “Optimization of PID parameters based on particle swarm optimization for ball and beam system,” *Int. J. Eng. Technol. Manag. Res.*, vol. 5, no. 9, pp. 59–69, 2018.

[6] M. Dorigo, M. Birattari, and T. Stutzle, “Ant colony optimization,” *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28-39, Nov. 2006.

[7] R. A. Hanifah, S. F. Toha, and S. Ahmad, “PID-Ant colony optimization (ACO) control for electric power assist steering system for electric vehicle,” in *2013 IEEE International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA)*, Kuala Lumpur, Malaysia, 2013, pp. 1-5.