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Optimal Tuning of PID Controllers for Cheetah Optimization Algorithm and Artificial Hummingbird Algorithm

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Abstract

In this study, two modern nature-inspired meta-heuristics, the Cheetah Optimization Algorithm (COA) and the Artificial Hummingbird Algorithm (AHA), are used to optimally tune the Proportional-Integral-Derivative (PID) controller parameters. COA offers a fast and efficient global search strategy inspired by predator-prey dynamics and combines prey localization with swarm-based attack mechanisms, while AHA models the directional memory search and territorial exploration behaviour of hummingbirds, offering a balanced structure between local and global search. Both algorithms were chosen for their potential to produce highly accurate solutions and their fast convergence. In order to evaluate the optimization performance of the algorithms, test functions such as Easom, Michalewicz and Shubert, which are challenging and have multiple local minima, were preferred. With the parameters obtained at the end of the optimization process, PID controllers are designed for three different transfer functions on first and second order dead-time systems and time-delayed systems. In order to comparatively analyse the dynamic characteristics of the systems and the performance of the controllers, the Integrated Time Squared Error (ITSE) function is used as a standard performance metric. The results show that COA and AHA algorithms perform effectively in PID tuning and provide significant improvements according to the system dynamics.

Key words: PID controller, Cheetah Optimization Algorithm, Artificial Hummingbird Algorithm, Parameter setting; Optimization.

1. Introduction

The increase in computer processing power has significantly increased the use of heuristic and meta-heuristic algorithms in engineering problems. Especially in solving nonlinear, non-convex and multidimensional problems, these algorithms are emerging as an alternative to classical methods [1]. The aim is to develop the algorithm that gives the optimal result for each problem. However, not all algorithms have the same success in every problem and some of them may be more effective in certain areas. Therefore, standard control problems such as PID controller tuning are frequently used to evaluate the performance of algorithms. PID controllers are still widely used in industry due to their structural simplicity and acceptable performance in a wide range of applications. Many studies have shown that heuristic algorithms provide superior results in PID tuning, especially for complex systems (time-delayed, higher-order, nonlinear, etc.) [2]. In this context, analyses with PID controllers to test and compare the effectiveness of optimization algorithms provide valuable information for both academic and practical applications. The studies in the literature are shown in Table 1.

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Table 1. Studies in the Literature for Optimum Tuning of PID Controllers

Ref.	Improved Algorithm	Results
[3]	Improved Firefly Algorithm (IFA)	In this paper, an Improved Firefly Algorithm (IFA) is proposed by improving the classical Firefly Algorithm. The algorithm segments the fireflies' paths, evaluates intermediate solutions and improves the solution process. IFA is applied to the design of PID controllers for time-delayed systems and results in lower error and more stable response than conventional methods.
[4]	Firefly Algorithm (FA)	In this study, the Firefly Algorithm (FA) is used to tune the PID controller parameters. FA works with a fitness function to minimize criteria such as rise time, settling time, overshoot and steady state error. Simulations on three different processes show that FA gives better results than the Ziegler-Nichols method.
[5]	Evolutionary Programming (EP)	In this study, the EP algorithm is used to optimize the PID controller gains and the IAE value is minimized. In tests on a fourth-order system with time delay, the proposed method outperforms other conventional methods.
[6]	Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Sine-Cosine Optimization Algorithm (SCA)	In this study, PID controller parameters are optimized by PSO, GA and SCA algorithms and the results are compared with the Ziegler-Nichols method. In the optimization process, the integrated squared error (ISE) function, which is one of the transient response criteria, is minimized. It is shown that meta-heuristic algorithms provide more stable and faster system responses than classical methods.
[7]	Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Fuzzy Logic, Neural Networks, Fuzzy Neural Network (FNN), Internal Model Control (IMC)	This review examines various optimization techniques for tuning PID controller parameters in time-delayed systems. The advantages and limitations of the methods in the literature are evaluated, with particular emphasis on the success of stochastic algorithms such as PSO and GA in nonlinear systems. Furthermore, new generation approaches developed for systems with time delays are comparatively analysed.
[8]	Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Sine-Cosine Optimization (SCA)	In this study, PID controller parameters are optimized using three different meta-heuristic algorithms. The objective is to minimize the integrated squared error (ISE) function, which is one of the transient response criteria. The obtained results are compared with the Ziegler-Nichols method and it is shown that the meta-heuristic algorithms provide lower error, shorter settling time and better system stability.
[9]	Ziegler-Nichols (ZN), Cohen-Coon (CC), Internal Model Control (IMC), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Fuzzy Neural Networks (FNN), Fuzzy-PID, Iterative Feedback Tuning (IFT)	This paper provides a comprehensive review of various optimization techniques for tuning PID controller gains for time-delayed systems. The methods in the literature are evaluated according to their success in nonlinear, higher-order and time-delayed systems. In particular, it is emphasized that stochastic algorithms such as GA and PSO give more effective results than classical methods.

In this study, firstly, information about COA and AHA will be given and how the performance is achieved with the modification will be shown and analysed in 3 test functions. Then, the controller design for some dead-time systems in the literature will be realized with this developed algorithm.

2. Cheetah Optimization Algorithm

COA was first introduced by Akbari in 2022 [10]. This algorithm is based on the hunting behaviour of cheetahs. The cheetah constantly checks the areas frequented by its prey and observes its surroundings. When it spots its prey, it hides in a suitable spot and waits for the prey to approach. When the prey is close enough, it attacks.

The cheetah moves to find its prey. This movement is shown by the formula;

$$X_{\mathrm{i},j}^{t+1} = X_{\mathrm{i},j}^{t} + r_{\mathrm{i},j}^{-1} \,.\, a_{\mathrm{i},j}^{t} \tag{1}$$

Here, $X_{\mathrm{i},j}^{t+1}$ is the new position of the cheetah, $r_{\mathrm{i},j}^{-1}$ is the randomness coefficient and $a_{\mathrm{i},j}^{t}$the step size.

The cheetah does not move and stays still, so as not to spot the prey and startle it;

$$X_{\mathrm{i},j}^{t+1} = X_{\mathrm{i},j}^{t} \tag{2}$$

When the prey escapes, the cheetah gives chase. Sometimes they hunt in groups and act in coordination. This is expressed as follows;

$$X_{i,j}^{t+1} = X_{B,j}^{t} + r_{i,j} \, . \, \beta_{i,j}^{t} \tag{3}$$

Where $X_{B,j}^{t}$ represents the best location, $r_{i,j}$ represents the coefficient of direction change, and $\beta_{i,j}^{t}$ represents the interaction factor.

3. Artificial Hummingbird Algorithm

The Artificial Hummingbird method (AHA) [11] is an optimization method inspired by nature that simulates hummingbird foraging behaviours. The method uses axial, diagonal, and omnidirectional flight capabilities to implement guided feeding and migration procedures.

$$X_j = LB + r \times (UB - LB), j = 1,2, \dots, N \tag{4}$$

Initial solutions were determined using r (a number between 0 and 1) randomly chosen between the lower boundary (LB) and the upper boundary (UB) of the search space.

$$VT_{j,i} = \begin{cases} 0, & if \quad j \neq i \\ null & \quad\; j = i \end{cases}, j = 1, \dots, N, i = 1, \dots, N \tag{5}$$

Where $VT_{j,i}$ = $null$ indicates that the hummingbird consumed the food at that location.

- Axial Flight;

$$D^i = \begin{cases} 1, & if \quad i = R \\ 0, & \quad\quad else \end{cases}, \; i = 1, \dots, d, \tag{6}$$

- Diagonal Flight;

$$D^i = \begin{cases} 1, & if \; i = P(j) \\ 0, & \quad\quad else \end{cases}, \; j \in [1, k] \, , \; i = 1, \dots, d, \tag{7}$$

$$P = randperm(k), k \in [2, [\, r1(d - 2),] + 1]$$

- Versatile Flight;

$$D^i = 1 \quad i = 1, \dots, d \tag{8}$$

The updated position is calculated by determining the fitness function $f(X)$;

$$V_i(t+1) = X_{i,t}(t) + a \times D \times (X_i(t) - X_{i,t}(t)), \quad a \in N(0,1) \tag{9}$$

The hummingbird leaves the worst food source and migrates to a random place;

$$X_w(t+1) = LB + r \times (UB - LB) \tag{10}$$

In this context, X_w represents the solution point with the lowest fitness value.

4. Analyses

4.1. Test Functions

In this study, COA and AHA are used for the optimal tuning of PID controller parameters and the differences between them are compared. The proposed algorithms are tested on test functions for one hundred trials. Then, the PID controller design with four different transfer functions was realized. These analyses were performed on a 12th Gen Intel(R) Core (TM) i7-12650H 2.30 GHz, 64-bit, 16GB RAM computer using MATLAB 2024a. Table 1 presents the basic parameters of COA and AHA proposed in this study and their specific values for each algorithm.

Table 2. Specific Values for the Proposed Algorithms

Parameters	Meaning	COA	AHA
n	Number of Individuals	50	50
α	Step Size	0.5	-
β	Search coefficient	0.8	-
λ	Coefficient of flight	-	0.5
MaxIter	Max Iteration	100	100

Test functions were used to evaluate the proposed algorithms. There is different test functions used in the literature to measure the success of such optimization problems. By selecting 3 of them, iterations were continued until the difference between the optimal and absolute values was below 1e-6 and the results obtained were compared [3]. The mathematical modelling of the test functions is described by the following equations.

- Easrom test function:

$$f(x,y) = -\cos(x)\cos(y)\exp\left(-(x-\pi)^2-(y-\pi)^2\right) ; x \in [0,\pi], y \in [0,\pi]$$

The global minimum value of this function in the specified range is f*=-1 [12].

- Michaelwicz test function:

$$f(x,y) = -\sin(x)\, sin\left(\frac{x^2}{\pi}\right)^{2m} - \sin(y)\, sin\left(\frac{2y^2}{\pi}\right)^{2m} ;\ x \in [0{,}5], y \in [0{,}5]$$

In this selected range, the global minimum takes the value f*=-1. 801 [12].

- Shubert test function:

$$f(x,y) = -\sum_{i=1}^{5} i cos[(i+1)x+1] \sum_{i=1}^{5} cos[(i+1)y+1] ;\ x \in [-10{,}10], y \in [-10{,}10]$$

The global minimum of this test function is f*=-180.7309 [12].

COA and AHA were tested with these 3 different test signals and the results are shown in Table 2. When we look at the table, COA converges faster by far for the Easom function. It is more stable with lower mean and lower standard deviation. When we look at the Michalewicz function, the average iteration and distribution for both algorithms are very similar. However, the minimum value is 12 for AHA and 28 for COA. This shows that AHA converges very fast in some cases, but in general it is much more variable. When we look at the Shubert function, both algorithms go almost to the maximum number of iterations. This function may be a challenge because it contains multiple local minima. The difference in minima (73 vs 56) suggests that AHA had a few slightly luckier runs, but there was no significant difference in overall success.

Table 3. Comparison Analysis of Test Functions

	Easom (COA)	Easom (AHA)	Michalewicz (COA)	Michalewicz (AHA)	Shubert (COA)	Shubert (AHA)
Average	**21.00**	87.03	**88.87**	89.60	**97.37**	97.50
Standard Deviation	**6.7262**	28.2531	**23.8164**	24.1498	**7.1606**	9.6660
Minimum	11	**11**	28	**12**	73	**56**
Maximum	39	100	100	100	100	100

4.2. PID Controller Design

PID controllers are one of the most widely used and preferred controller types in industrial control applications. Due to their simplicity, flexibility and wide range of applications, they are frequently encountered in process control and automation systems. The mathematical model of the PID controller is expressed in Equation 11. In this expression, K_p is the proportional gain, K_i is the integral gain and K_d is the derivative gain coefficient:

$$G(s) = K_p + \frac{K_i}{s} + K_d s \tag{11}$$

Each of these gains directly affects the transient and permanent behaviour of the system. K_p increases the system's instantaneous response to error, K_i removes the permanent error and K_d suppresses the overreaction, resulting in a more balanced response. However, incorrect selection of these parameters can lead to problems such as excessive oscillation, slow response or instability. Therefore, the correct tuning of PID gains is critical to improve system performance. Many methods have been developed to determine the PID gains. One of the most well-known of these is the Ziegler-Nichols method, which adjusts according to the step or frequency response of the system. It is frequently used in industry because it is practical and fast. However, since it does not give the best result in every system, modern optimization and adaptive algorithms can also be preferred. As a result, accurate tuning of PID gains is of great importance to improve the stability and performance of the system. In this study, the proposed algorithms will be used to design a controller for the system given in Figure-1. The algorithm aims to minimize a given objective function. The ITAE specified in Equation 12 penalizes especially long-term errors by weighting the error over time and provides a faster response of the system.

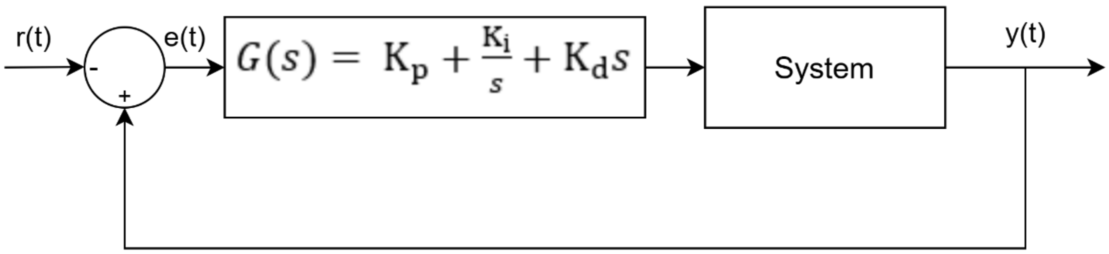

Figure 1. System Model

$$\mathrm{ITAE} = \int t \mid e(t) \mid dt = \int t \mid r(t) - y(t) \mid dt \qquad (12)$$

In this study, PID controller design is performed on three systems with different dynamic characteristics. Their equations are given below. The systems include time-delayed, second-order, multipole and complex pole structures. This diversity is chosen to evaluate the performance of the PID controller in different system responses.

$$G_1(s) = \frac{1}{11s+1} e^{-3.5s}, \qquad G_2(s) = \frac{27}{(s+1)(s+3)^3}, \qquad G_2(s) = \frac{4.228(s+0.5)^{-1}}{s^2+1.64s+8.456}$$

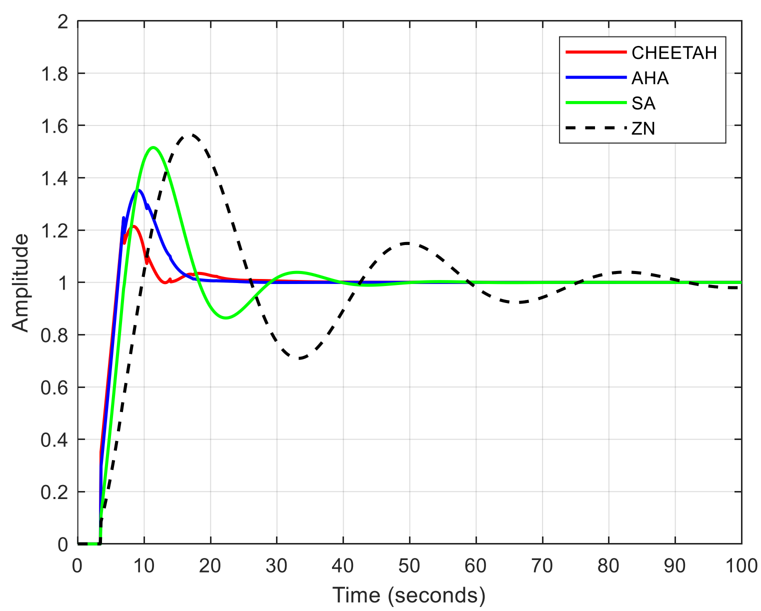

Figure 2. G_1 System

Figure 2 compares the step responses of four different PID tuning methods for the G1 system, where the COA and AHA algorithms give a faster and damped response, while the ZN method shows high oscillation and long settling time. The parameters in Table 4 show that the COA algorithm provides the best performance with the lowest ITAE value. Although the SA algorithm performs better than the ZN method, it performs worse than the proposed algorithms as shown in the graph and table.

Table 4. Controller Parameters and Error Values for G_1 System

Controllers	K_p	K_i	K_d	ITAE
COA	3.1507	0.3160	3.8687	8.7713
AHA	3.1158	0.4240	3.2633	12.7497
SA	2.5840	0.4295	1.2125	26.3585
ZN	1.2000	0.3820	0.9425	96.4960

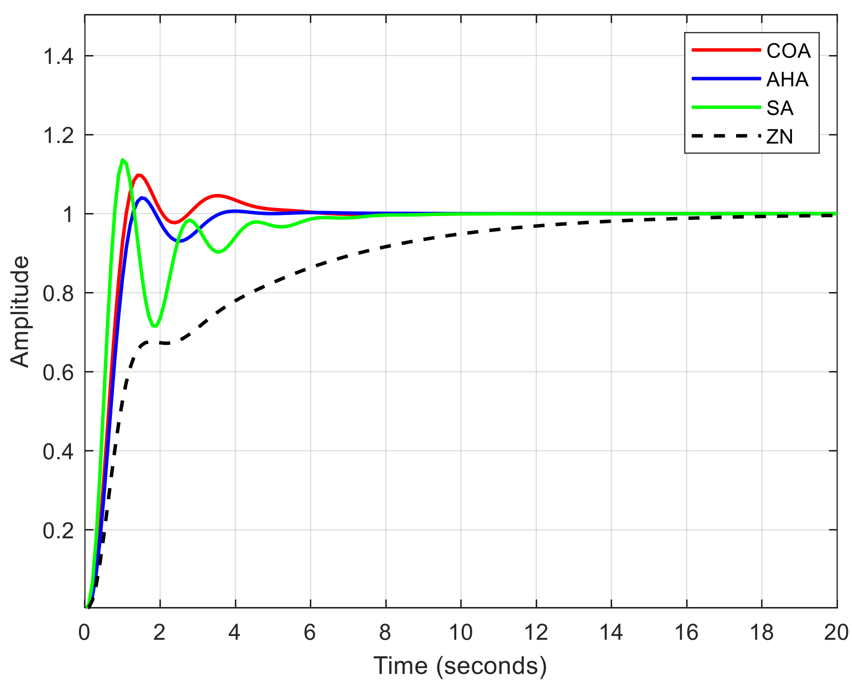

Figure 3. G_2 System

According to Figure 3 and Table 5 for the G2 system, the lowest ITAE value of 0.1540 was obtained by COA and this algorithm gave the fastest and most balanced response. AHA also performed well with low overshoot and short settling time. The SA algorithm produced relatively more overshoots and oscillations, while the ZN method showed the poorest control performance with the highest ITAE value.

Table 5. Controller Parameters and Error Values for G_2 System

Controllers	K_p	K_i	K_d	ITAE
COA	2.5787	1.9356	1.5926	0.1540
AHA	2.4335	1.3682	1.3438	0.1742
SA	3.2896	1.2174	2.8733	0.2128
ZN	1.2000	0.3820	0.9425	1.5097

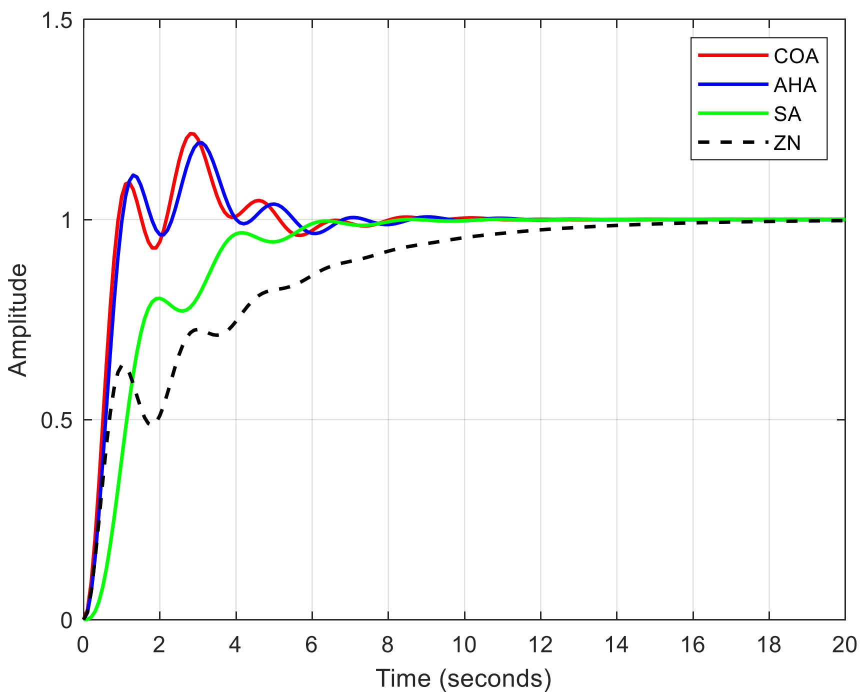

Figure 4. G_3 System

According to the results shown in Figure 4 and Table 6 for the G3 system, COA exhibited the best control performance with the lowest ITAE value of 0.1995 and provided a fast, damped behavior in the system response. The AHA algorithm also performed well with a low ITAE value, but produced more oscillations compared to COA. The ZN and SA algorithms have lower gains and delayed system responses, with the ZN method in particular showing the poorest performance with the highest ITAE value.

Table 6. Controller Parameters and Error Values for G_3 System

Controllers	K_p	K_i	K_d	ITAE
COA	2.4408	3.3095	1.1597	0.1995
AHA	2.3146	2.8388	0.8194	0.2139
SA	1.2371	0.6170	0.0000	0.6656
ZN	1.2000	0.3820	0.9425	1.6721

4. Conclusions and Discussion

In this study, Cheetah Optimization Algorithm (COA) and Artificial Hummingbird Algorithm (AHA) are proposed and their performances are evaluated. For this purpose, both algorithms are run on three different test functions under certain constraints and the results are compared. In addition, controller designs for three different systems with dead time are realized using the proposed algorithms and the results are compared with some widely used algorithms and methods in the literature. As a result of the comparisons, Cheetah Optimization Algorithm and Artificial Hummingbird Algorithm are found to have superior performance in terms of both test functions and control system designs.

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