Adaptive Position Control of Electrohydraulic Servo Systems with Parameter Uncertainty using Artificial Bee Colony Optimization Algorithm

Abstract

In this paper, we present a robust adaptive backstepping-based controller for precise positioning of the spool valve in an Electro-Hydraulic Servo System (EHSS) under conditions of parameter fluctuations. The Artificial Bee Colony (ABC) algorithm is employed to optimize the controller parameters by simultaneously minimizing both the tracking error and control signal. Simulation results demonstrate that the proposed controller ensures uniform ultimate boundedness of both the tracking error and control signal. Additionally, the robustness and effectiveness of the control scheme are validated through simulations under uncertain conditions. A comparative analysis with sliding mode control further highlights the superior performance of the proposed method.

Keywords: Electro-hydraulic systems, backstepping control, nonlinear systems, adaptive control, artificial bee colony

1 Introduction

The demand for fast, precise, and powerful control systems in industrial applications has made Electro-Hydraulic Servo Systems (EHSS) increasingly popular. EHSS are widely used in diverse industries, ranging from aerospace flight control to manufacturing, and play a crucial role in seismic applications as one of the major components in Vibroseis [1]. However, these applications require high-precision control, which poses significant challenges due to the inherent nonlinearities of the system.

Several factors contribute to the nonlinear behavior of EHSS, such as fluid inflow-outflow in the servo valve, friction in actuator and valve moving parts, and air entrapment within the hydraulic system. Additionally, the system's parameters can vary due to temperature changes, and unknown model errors or perturbations further complicate the controller design process. Numerous methods have been proposed to address these challenges. While linear control theories have been widely used for controller development, these approaches are limited in their ability to handle changing operating conditions and uncertainties, particularly in highly nonlinear systems.

For example, the performance of a linear controller was enhanced using a feedback-feedforward iterative learning controller [2], and adaptive schemes have been employed to manage parameter variations [3, 4]. However, traditional adaptive approaches face significant limitations when the system to be controlled is not linear in parameters or includes uncertain or unmodeled dynamics. This is particularly problematic for EHSS, where critical parameters such as supply pressure and load mass vary with environmental conditions.

Various nonlinear control strategies have been explored to improve the robustness of EHSS controllers. A Lyapunov-based approach was used to develop a feedback linearization controller capable of handling supply pressure uncertainties in EHSS [1], although it did not consider the effects of unknown disturbances at the velocity level. Backstepping, a progressive control design strategy, has emerged as a powerful method for nonlinear systems, offering stabilization and tracking through the introduction of stabilizing functions that counteract nonlinearities [5]. Unlike feedback linearization, backstepping avoids the complete cancellation of useful nonlinearities and can force nonlinear systems to behave like linear systems when transformed into new coordinates.

The backstepping technique has demonstrated particular advantages in avoiding nonlinear cancellation and addressing external perturbations [6, 7].. For instance, backstepping-based neural adaptive techniques have been used for velocity control in EHSS, addressing internal friction and flow nonlinearity, though external disturbances were not considered [8]. Furthermore, EHSS are sensitive to parameter variations caused by temperature fluctuations, such as changes in bulk modulus and viscous friction coefficients, underscoring the need for adaptive controllers that can accommodate such variations.

Friction is another critical consideration in EHSS design. A LuGre model-based adaptive control scheme was proposed to model and estimate frictional effects, offering robustness against uncertainties and disturbance rejection [2]. Additionally, variable structure controllers have been utilized to model friction and load as external disturbances [10], and auto-disturbance rejection controllers have been shown to manage both internal and external disturbances [11]. System identification techniques have also been employed to model EHSS, leading to the development of adaptive Fuzzy PID controllers for position control [12,]. Recent advancements have also leveraged evolutionary algorithms to optimize control performance. Dynamic particle swarm optimization has been applied to enhance closed-loop system tracking performance by optimizing control parameters [14].

Evolutionary techniques like Artificial Bee Colony (ABC) optimization [17, 18] have gained prominence due to their ability to efficiently search for global optima [15, 16]. In this work, we propose the use of ABC to tune controller parameters for optimal performance, particularly in minimizing tracking error and control signal. Significance of ABC have been shown in path planning of multi robot and other control applications [19].

This paper introduces a backstepping-based approach to design a robust adaptive controller for a highly nonlinear EHSS, modeled as a single input single output (SISO) system. The system consists of a four-way spool valve supplying a double-effect linear cylinder with a double-rodded piston, which drives a load modeled by mass, spring, and viscous friction. The proposed adaptive controller ensures practical stability of the closed-loop system and guarantees the uniform ultimate boundedness of the tracking error. ABC is employed to optimize the controller parameters, enhancing both tracking accuracy and control efficiency. The rest of this paper is organized as follows: Section II presents the problem formulation, Section III discusses the adaptive controller design, Section IV focuses on the ABC optimization and its implementation, Section V presents the simulation results, and Section VI concludes the paper.

2 System Model and Problem Formulation

The dynamics of the EHSS are highly nonlinear, influenced by factors such as actuator friction and fluid inflow-outflow within the valve. Additionally, complexities like air entrapment, parameter variations, and unknown model errors further complicate the control design process. The EHSS model in Fig. 1 with dynamics given below in 1 is considered.

$$\begin{aligned}
\dot{x}_1 &= \tfrac{4B}{V_t}\left(ku\sqrt{P_d - \text{sign}(u)x_1} - \tfrac{\alpha x_1}{1+\gamma|u|} - Sx_2\right),\\
\dot{x}_2 &= \tfrac{1}{m_t}(Sx_1 - bx_2 - \beta x_3),\\
\dot{x}_3 &= x_2 + d(t).
\end{aligned} \tag{1}$$

where $\beta = (k_l + \Delta\, k_l)$. x_1 is the differential pressure between the two chambers, x_2 and x_3 are the velocity and position of the rod respectively. $k_l + \Delta\, k_l$ denotes the uncertain spring stiffness and b

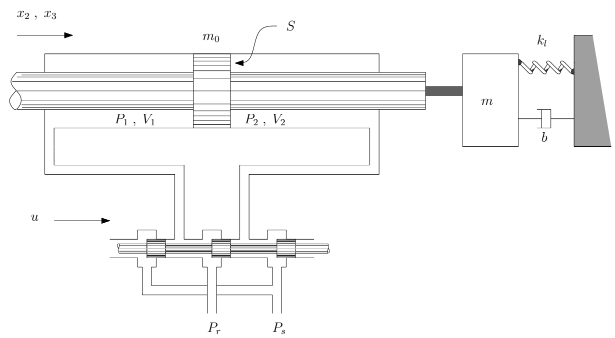

Figure 1: Electro-hydraulic System

is the viscous damping coefficient, V_t is the total volume of the forward and return chambers, P_d is the supply and return pressure difference while m_t is the total mass of the load and piston. B and S are the bulk modulus and net cross-sectional area of one side of the piston respectively. k, γ , α are intrinsic constants of the servo valve; γ and α are used to model the leakage in the servo valve.
In the sequel, we consider the following assumptions hold:

Assumption 1

1. *d(t) is an unknown but bounded disturbance with $|d(t)| < d_{max}$.*
2. *Δk_l is unknown and bounded with $|\Delta k_l| < \Delta k_l^{max}$.*
3. *The spool-valve dynamics are assumed to be sufficiently fast and are thus neglected in the dynamic model.*
4. *All system states are assumed to be available for controller design.*
5. *Reference input $r(t)$ is a known, continuously differentiable, and bounded trajectory.*

The nonlinearities in the system dynamics, particularly with respect to the input u, pose significant challenges in controlling the system's output. To address this, we design a backstepping-based controller that drives the position of the rod to a desired reference trajectory $r(t)$. Utilizing the backstepping approach requires re-indexing the system's state variables to transform the system into its standard strict feedback form, enabling effective controller design. Let

$$\xi_1 = x_3, \quad \xi_2 = x_2, \quad \xi_3 = x_1. \tag{2}$$

The dynamics of the transformed system is then given in Eq. (3)

$$\begin{aligned} \dot{\xi}_1 &= \xi_2 + d(t), \\ \dot{\xi}_2 &= \tfrac{1}{m_t}(S\xi_3 - b\xi_2 - \beta\xi_1), \\ \dot{\xi}_3 &= \tfrac{4B}{V_t}(ku\sqrt{P_d - \text{sign}(u)\xi_3} - \tfrac{\alpha\xi_3}{1+\gamma|u|} - S\xi_2). \end{aligned} \tag{3}$$

Let

$$\begin{aligned} e_1 &= \xi_1 - r, \\ e_2 &= \xi_2 - \dot{r}, \\ e_3 &= f(\xi) - \ddot{r}, \end{aligned} \tag{4}$$

where $f(\xi) = \dot{\xi}_2$, the error dynamics satisfy

$$\begin{aligned} \dot{e}_1 &= e_2 + d, \\ \dot{e}_2 &= e_3, \\ \dot{e}_3 &= (\tfrac{\partial f(\xi)}{\partial \xi})\dot{\xi} - \dddot{r}. \end{aligned} \tag{5}$$

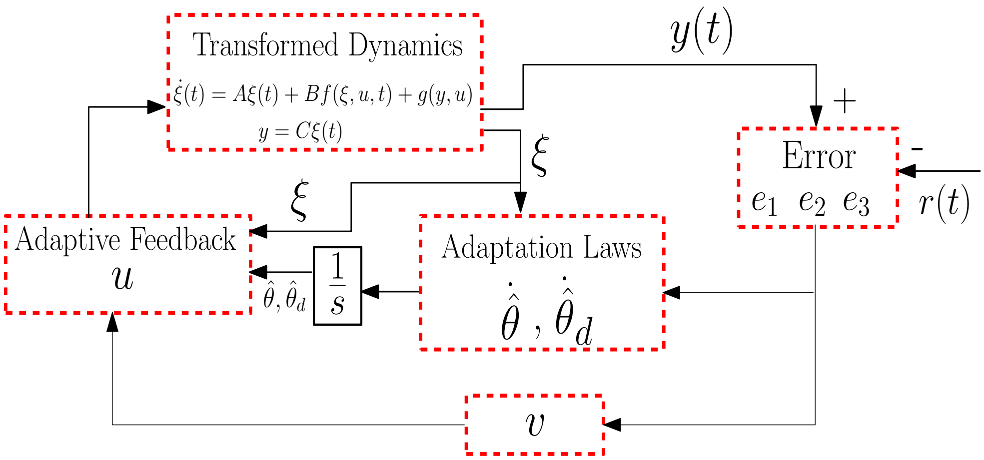

Figure 2: Adaptive Control Scheme

3 Adaptive Control Law Design

In many cases, EHSS parameters are prone to variations due to temperature fluctuations. Since the design of the backstepping controller depends on the actual system parameters, it becomes crucial to develop a controller that adapts to these changes. To address the issue of parameter variation, adaptive control schemes are typically employed. In this section, we propose a backstepping-based adaptive technique that is robust against uncertainties in system parameters and external disturbances. Specifically, we assume that the load parameters, such as β and b, are unknown nonlinear functions. These parameters will be estimated through the adaptive scheme. The schematic diagram of the proposed backstepping-based adaptive strategy is illustrated in Fig 2 below.

We also considered a scenario in which a more complex vibrator-ground model arises due to non-ideal contact stiffness at the boundary interaction between the vibrator's baseplate and the ground, as depicted in Fig. 3. To account for this, we replaced the parameters β and b as defined in (6). This modification allows for a more accurate representation of the system dynamics under such conditions.

$$\begin{aligned} \beta &= \gamma_3\xi_1^2 + \gamma_4\xi_2^2 + \gamma_5\xi_3^2 = \theta^T\phi(\xi) \\ b &= b_0 + \Delta f(\xi, b_0) \end{aligned} \tag{6}$$

where $\Delta f(\xi, b_0)$ is unknown but bounded nonlinear function that satisfies (7)

$$\sup_{t\geq 0} |\Delta f(\xi, b_0)| \leq F_{max} \tag{7}$$

Now, the error dynamics are given as:

$$\begin{aligned} \dot{e}_1 &= e_2 + d, \\ \dot{e}_2 &= e_3, \\ \dot{e}_3 &= \tfrac{b_0}{m_t^2}\theta^T\phi(\xi)\xi_1 + (-\tfrac{1}{m_t}\theta^T\phi(\xi) + \tfrac{b_0^2}{m_t^2} - \tfrac{4BS^2}{m_tV_t})\xi_2 \\ &\quad + (-\tfrac{b_0S}{m_t^2} - \tfrac{4BS\alpha}{m_tV_t(1+\gamma|u|)})\xi_3 + \Delta F_1\theta^T\phi(\xi)\xi_1 \\ &\quad + \Delta F_2\xi_2 - \Delta F_3\xi_3 - \theta_d^T\phi(\xi)d(t) - \dddot{r} + Am(t)u. \end{aligned} \tag{8}$$

where, $\theta_d^T\phi(\xi) = \frac{\beta}{m_t}$ and ξ is a state vector comprising of ξ_1, ξ_2 and ξ_3. Now, the goal is to design an adaptive feedback such that:

$$\lim_{t\to\infty} |\xi_1 - r(t)| \leq \delta \tag{9}$$

where, δ is a sufficiently small positive number. The design objective is to minimize δ while simultaneously ensuring a smooth control law. The following section outlines the control design schemes

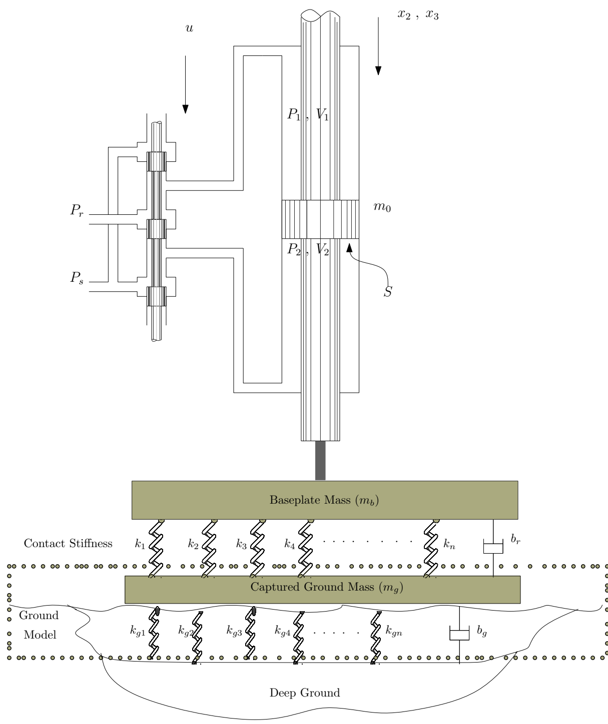

Figure 3: A more detailed vibrator-ground model prototype [20]

used to achieve this balance.

$$\begin{aligned} \Delta F_1 &= \frac{\Delta f(\xi,b_0)}{m_t^2} \leq F_{max} \\ \Delta F_2 &= \frac{1}{m_t^2}(2b_0\Delta f(\xi,b_0) + \Delta f^2(\xi,b_0)) \leq F_{max}^3 \\ \Delta F_3 &= \frac{S}{m_t^2}\Delta f(\xi,b_0) \leq F_{max} \end{aligned} \tag{10}$$

Theorem 1 *Given that*

$$\begin{aligned} \alpha_4 &= \tfrac{3}{2} + \lambda, \\ \alpha_5 &= 1 + \tfrac{1}{\lambda^3} + \tfrac{1}{2\lambda}, \\ \alpha_6 &= \tfrac{1}{\lambda^4}. \end{aligned} \tag{11}$$

and

$$\begin{aligned} h(e) &= \alpha_4 e_1 + \alpha_5 e_2 + \alpha_6 e_3 \\ g(e,\xi) &= e_2 + \lambda e_1 + \alpha_4 e_2 + \alpha_5 e_3 \\ &\quad + \alpha_6(\tfrac{b_0^2}{m_t^2} - \tfrac{4BS^2}{m_t V_t})\xi_2 - \tfrac{b_0 S}{m_t^2}\xi_3 \\ A_1 &= \tfrac{\alpha_6 b_0}{m_t^2}, \quad A_2 = \tfrac{\alpha_6}{m_t} \quad A_3 = \tfrac{4BS\alpha\alpha_6}{m_t V_t} \\ \tilde{\theta} &= \theta - \hat{\theta} \end{aligned} \tag{12}$$

and let the adaptation law be given as

$$\begin{aligned} \dot{\hat{\theta}} &= \gamma_6(A_1 h(e)\phi(\xi)\xi_1 - A_2 h(e)\phi(\xi)\xi_2 \\ &\quad + \alpha_6 F_{max}|\xi_1|\phi(\xi)) \\ \dot{\hat{\theta}}_d &= -\gamma_7\alpha_6\phi(\xi)d_{max} \end{aligned} \tag{13}$$

and let the adaptive feedback be given as

$$u = \left(\frac{m_t V_t}{4\alpha_3 SBkmin(\sqrt{P_d - \xi_3}, \sqrt{P_d + \xi_3})}\right)v \tag{14}$$

where,

$$v = -\left(|g(e,\xi)| + |\alpha_4 - \alpha_6 \hat{\theta}_d^T \phi(\xi)| d_{max} + \Phi(\xi, \hat{\theta}) + \alpha_6 |\xi_3| F_{max} + \alpha_6 |\xi_2| F_{max}^3\right) - k_o h(e) \tag{15}$$

Then, system (3) *under the adaptive feedback control law given in* (14) *is practically stable and the solution of the error dynamic* (8) *is globally uniformly ultimately bounded with ultimate bound satisfying the following condition*

$$||e||^2 \leq \frac{d_{max}^2}{\lambda\, \sigma_{min}(\phi\phi^T)} \leq \frac{d_{max}^2}{2\,(\lambda + \lambda^5)\; \sigma_{min}(\phi\phi^T)} \tag{16}$$

with

$$\phi = \begin{bmatrix} 1 & \lambda & \frac{\alpha_1}{\lambda^2} \\ 0 & 1 & \frac{\alpha_2}{\lambda^2} \\ 0 & 0 & \frac{\alpha_3}{\lambda^2} \end{bmatrix} \tag{17}$$

Proof 1 *To demonstrate the boundedness of the error dynamics, we will again select the Lyapunov functions as follows:*

$$\begin{aligned} &V_1 = \tfrac{1}{2} e_1^2, \quad V_2 = \tfrac{1}{2\lambda^4}(e_2 + \lambda e_1)^2 \\ &V_3 = \tfrac{1}{2}(\alpha_4 e_1 + \alpha_5 e_2 + \alpha_6 e_3)^2 \\ &V_4 = \tfrac{1}{2\gamma_6} \tilde{\theta}^T \tilde{\theta}^T + \tfrac{1}{2\gamma_7} \tilde{\theta}_d^{\,2}, \end{aligned} \tag{18}$$

and again using the Young's inequality with $\lambda > 0$ *then,*

$$\dot{V} = \dot{V}_1 + \dot{V}_2 + \dot{V}_3 + \dot{V}_4 \tag{19}$$

Therefore, the derivative of the Lyapunov function is thus given:

$$\begin{aligned} \dot{V} \leq & -\tfrac{\lambda}{2} e_1^2 + (\tfrac{1}{2\lambda} + \tfrac{1}{2\lambda^5}) d^2 - (e_2 + \lambda e_1)^2 \\ & + h(e)[g(e,\xi) + A_1 \tilde{\theta}^T \phi(\xi)\xi_1 + A_1 \hat{\theta}^T \phi(\xi)\xi_1 \\ & - A_2 \tilde{\theta}^T \phi(\xi)\xi_2 - A_2 \hat{\theta}^T \phi(\xi)\xi_2 - \tfrac{A_3}{1+\gamma|u|})\xi_3 \\ & + \alpha_4 d + \alpha_6 \Delta F_1 \tilde{\theta}^T \phi(\xi)\xi_1 + \alpha_6 \Delta F_1 \hat{\theta}^T \phi(\xi)\xi_1 \\ & + \alpha_6 \Delta F_2 \xi_2 - \alpha_6 \Delta F_3 \xi_3 - \alpha_6 \tilde{\theta}_d^T \phi(\xi) d(t) \\ & - \alpha_6 \hat{\theta}_d^T \phi(\xi) d(t) - \alpha_6 \dddot{r} + \alpha_6 A m(t) u] \\ & - \tfrac{1}{\gamma_6} \tilde{\theta}^T \dot{\hat{\theta}} - \tfrac{1}{\gamma_7} \tilde{\theta}_d \dot{\hat{\theta}}_d \end{aligned} \tag{20}$$

To eliminate the parametric error, the update laws are selected as shown in (13)*. Given that* $F_{max} = \sup_{t \geq 0} |\Delta F_1|$ *and* $d_{max} = \sup_{t\geq 0} |d(t)|$*, and to ensure a uniformly ultimately bounded tracking error, adaptive feedback "*u*" is chosen as given in* (14) *and* v *is given as follows:*

$$v = -(|g(e,\xi)| + |\alpha_4 - \alpha_6 \hat{\theta}_d^T \phi(\xi)| d_{max} + \Phi(\xi, \hat{\theta}) + \alpha_6 |\xi_3| F_{max} + \alpha_6 |\xi_2| F_{max}^3) - k_o h(e) \tag{21}$$

Ultimately,

$$\begin{aligned} \dot{V} \leq & -\tfrac{\lambda}{2} e_1^2 + (\tfrac{1}{2\lambda} + \tfrac{1}{2\lambda^5}) d^2 - (e_2 + \lambda e_1)^2 \\ & - (\alpha_1 e_1 + \alpha_2 e_2 + \alpha_3 e_3)^2 \end{aligned} \tag{22}$$

Therefore,for $\dot{V} \leq 0$*, it is sufficient to verify that* $-V + \frac{1}{\lambda} d_{max}^2 \leq 0$*. Which means that* $\dot{V} \geq 0$ *if* e *is such that* $V \leq \frac{1}{\lambda} d_{max}^2$*. This will lead to increasing* e *until* $V \geq \frac{1}{\lambda} d_{max}^2$*.*
Let $z = \phi^T e$*, with*

$$\phi = \begin{bmatrix} \frac{1}{\sqrt{2}} & \lambda & \alpha_1 \\ 0 & 1 & \alpha_2 \\ 0 & 0 & \alpha_3 \end{bmatrix} \tag{23}$$

Using (23), V can be rewritten as $V = z^T z = ||z||^2$. On the other hand,

$$\sigma_{min}(\phi\phi^T)||e||^2 \leq V = ||z||^2 \leq \sigma_{max}(\phi\phi^T)||e||^2 \tag{24}$$

where $\sigma_{min}(\phi\phi^T)$ and $\sigma_{max}(\phi\phi^T)$ represent the max and min singular values of $\phi\phi^T$ respectively. Since the Lyapunov function satisfies (22) for all $t \in \Re_{\geq 0}$, this implies that the whole time during which the adaptation take place is finite. During the finite time, the variables $\hat{\theta}$ and $\hat{\theta}_d$ cannot escape to infinity since the adaptation laws in (13) are well defined. For any bounded conditions $e(0)$, $\hat{\theta}(0)$ and $\hat{\theta}_d(0)$ and by making use of (22), we infer that e, $\hat{\theta}$ and $\hat{\theta}_d$ are bounded for all $t \in \Re_{\geq 0}$. The proof ends here.

Remark 1 *The parameter λ is a design parameter introduced in Young's inequality. It should be selected as large as possible to reduce the ultimate bound in the tracking error dynamics. However, a trade-off must be considered: increasing λ results in a more oscillatory transient response and a higher control input. Additionally, ϵ must be chosen to be sufficiently small, and its selection is independent of the system's parameters and the disturbance bounds.*

The proposed controller has parameters that must be carefully selected for optimal closed-loop system performance. In this work, the ABC technique is employed to optimally set the controller parameters λ and γ_1 based on the minimization of a preassigned objective function. The proper selection of these parameters will effectively minimize the objective function, which is defined in terms of the error and control signal.

$$Obj = \sum_{t=0}^{t_{sim}} \left(\Gamma_1 e_1^2(t) + \Gamma_2 u^2(t)\right) \tag{25}$$

where the tracking error $e_1(t) = \xi_1 - r(t)$ and $u(t)$ is the control signal, Γ_1 and Γ_2 are weighting parameters. The controller's parameters are selected within the bounds:

$$\lambda^{min} \leq \lambda \leq \lambda^{max}$$
$$\gamma_1^{min} \leq \gamma_1 \leq \gamma_1^{max}$$

4 ABC Algorithm

The Artificial Bees Colony (ABC) is a meta-heuristic approach inspired by the work of [17]. This algorithm mimics the structured behavior of natural bee colonies, which are typically divided into three groups: employed, onlooker, and scout bees. Employed bees are primarily responsible for searching for food, identifying the best food sources as optimal solutions. They communicate information about these sources and their nectar quantity to other bees through systematic dances. Onlooker bees evaluate food sources based on the characteristics of these dances, such as length, type, and the speed of the employed bees' movements, using this information to assess food quality. Scout bees are selected from the onlooker group to initiate new food searches. Depending on the quality of the food sources, onlooker and scout bees may switch roles with the employed bees [18]. As detailed in [18], the employed and onlooker bees are tasked with exploring the solution space to identify optimal parameters, while the scout bees oversee the overall search process. A summary of the ABC algorithm is presented in the flowchart in Fig. 4. In this context, the solution to the optimization problem corresponds to the position of the food source, and the amount of nectar relative to quality is referred to as the objective function of the optimization procedure. The position of the food source within the search space can be described as follows:

$$x_{ij}^{new} = x_{ij}^{old} + u(x_{ij}^{old} - x_{kj}) \tag{26}$$

The probability of onlooker bees for choosing a food source:

$$P_i = \frac{fitness_1}{\sum_{i=1}^{E_b} fitness_i} \tag{27}$$

where, x is a candidate solution, P_i is the probability of onlooker solution, $i = 1, 2, \cdots, E_b$ is the half of the colony size, $j = 1, 2, \cdots, D$ and and j is the number of positions with D dimension where D refers to number of parameters to be optimized, $fitness_i$ is the fitness function, k is a random number where $k \in (1, 2, \cdots, E_b)$, u is random number between 0 and 1.

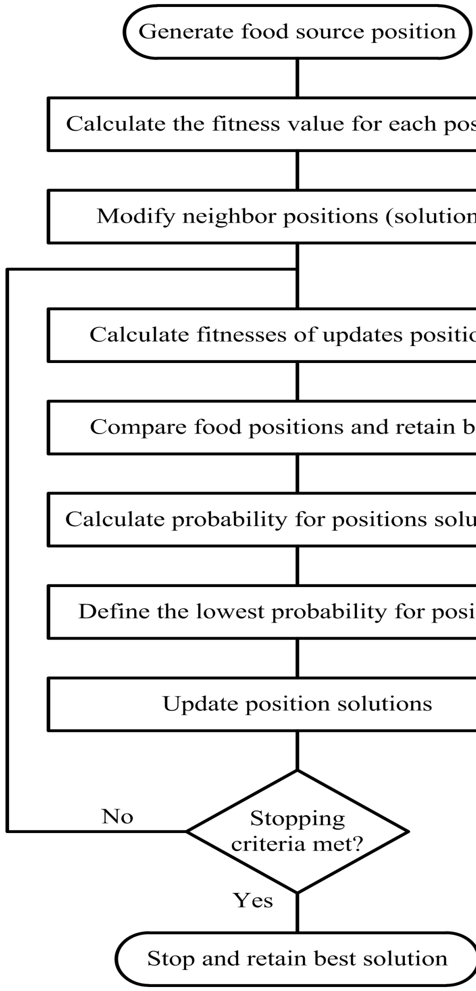

Figure 4: Artificial Bee Colony Algorithm

5 Results and Discussions

The problem is divided into two stages. In the first stage, the proposed backstepping controller (BSC) is implemented without the ABC algorithm. In the second stage, the ABC algorithm is integrated with the proposed controller for optimal parameter tuning. The tracking capability of both stages is evaluated using constant, sinusoidal, and the sum of sinusoidal reference inputs. The objective function for the optimization procedure is formulated as follows:

$$Obj = \sum_{t=0.01}^{20} \Gamma_1 e_1^2(t) + \Gamma_2 u^2(t) \tag{28}$$

$$9 \leq \lambda \leq 16$$
$$10^{-7} \leq \gamma_1 \leq 10^{-10}$$

In the optimization algorithm, the parameters to be optimized are λ and γ_1. The population size is set to 50, and the number of generations is set to 100, with the search space constrained as specified in (28). The weighted values for Γ_1 and Γ_1 are both chosen to be 1. For experimental purposes, F_{max} is selected to be 10. The adaptive backstepping controller with the ABC-based optimizer is applied to the system model in (3). It is important to note that this is a minimization task. The parameters of the system model are provided in Table 1

.

Table 1: Numerical values for simulations

Parameters	Value	Units
B	$2.2e9$	Pa
P_r	$1e5$	Pa
V_t	$1e{-}3$	m^3
S	$1.5e{-}3$	m^2
γ	8571	s^{-1}
b	590	$kg\ s^{-1}$
Δk_l	2500	Nm^{-1}
k_l	12500	Nm^{-1}
P_s	$300e5$	Pa
m_t	70	kg
k	$5.12e{-}5$	$m^3s^{-1}A^{-1}Pa^{1/2}$
α	$4.1816e-12$	$m^3s^{-1}Pa^{-1}$

Table 2: Minimum objective function with optimal parameters.

Experiment No	1	2	3	4	5	6	7	8
$Objective$	2.1368	2.1368	2.1368	2.1368	2.1369	2.1368	2.1368	2.1369
γ_1	10^{-10}	10^{-10}	10^{-10}	10^{-10}	10^{-10}	10^{-10}	10^{-10}	10^{-10}
λ	13.5585	13.5580	13.5583	13.5585	13.5580	13.5585	13.5581	13.5589

The simulation was conducted for 20 seconds, with error and control signal values captured every 0.01 seconds. In the first set of experiments, the reference input was a step function defined as $r(t) = 0.2$. The simulation was repeated eight times with different initial populations to ensure the robustness of the proposed solution. As indicated in Table 2, the objective functions were consistently close across all experiments. Figure 5 illustrates the output performance of the proposed backstepping controller (BSC) with optimized parameters $\gamma_1 \leq 10^{-10}$ and $\lambda \leq 13.5585$. Although the steady-state error is not zero due to the disturbance ($d(t) = 0.1$), both the error and control signal remain bounded, and the output performance closely tracks the reference. The performance of the proposed controller was compared with that of a sliding mode controller (SMC). While the SMC achieved a smaller tracking error, it exhibited output chattering even in steady state. In contrast, the proposed controller, tuned with the ABC algorithm, produced a smooth control signal and eliminated transient oscillations. The ABC algorithm effectively found the best compromise solution by minimizing both tracking error and output oscillations in transient and steady states. Furthermore, as shown in Fig. 6, the control signal for the ABC-based BSC is minimized and smooth compared to both the SMC and the BSC without ABC tuning.

It is important to note that the proposed adaptive design does not require differentiating $m(t)$, which allows the scheme to effectively handle various types of slowly time-varying $m(t)$ and $d(t)$. The issue at hand is a robust adaptive control problem for Electric-Hydraulic Servo Systems (EHSS). As shown in Fig.5, the adaptive backstepping controller (BSC) achieves bounded error tracking even in the presence of input nonlinearity, parameter uncertainties, and unknown but bounded disturbances. Figure7 illustrates the output performance when the reference input is changed to $r(t) = 0.3$. The results indicate that the BSC tuned with the ABC algorithm provides better tracking accuracy, a smoother response, and fewer transient oscillations compared to both the SMC and the BSC without tuning. Moreover, Fig. 8 further supports this finding, revealing that the SMC control signal is non-smooth, while the control signals from the BSC are smooth, underscoring the advantages of the proposed approach.

Figure 9 illustrates the excellent tracking performance of the proposed ABC-based backstepping controller (BSC) for a sum of sinusoidal reference inputs, particularly in comparison to the BSC

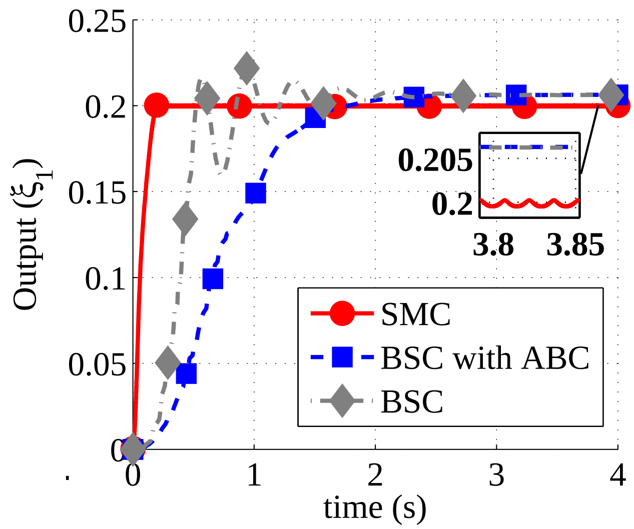

Figure 5: Output performance of adaptive backstepping after ABC optimization with $r = 0.2$m

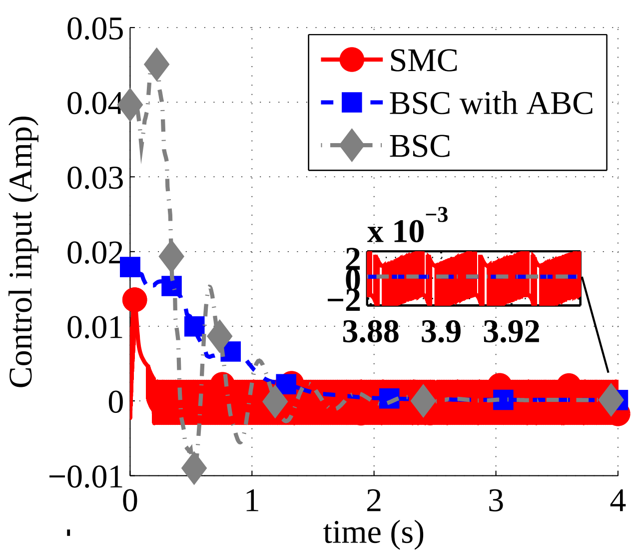

Figure 6: Control input of adaptive backstepping after ABC optimization with $r = 0.2$m

without ABC. Notably, the sliding mode controller (SMC) experienced instability with sinusoidal references, preventing a direct comparison with the BSC in these experiments. Additionally, Fig. 10 highlights the superior tracking accuracy of the ABC-based BSC when the reference input was switched to a sinusoidal signal. In summary, the proposed solution demonstrates robustness against parameter uncertainties and disturbances, provided the ultimate bound satisfies the condition $||e||^2 \leq \frac{d_{max}^2}{2(\lambda+\lambda^5)\,\sigma_{min}(\phi\phi^T)}$. It is important to note that the results presented in this paper pertain to scenarios involving non-ideal contact stiffness at the boundary interaction between the vibrator's baseplate and the ground. The parameters β and b, which correspond to load and frictional characteristics, have been modeled as nonlinear functions to create a more realistic vibrator-ground interaction model. As demonstrated, the tracking error converges to a neighborhood of the origin in steady states, further underscoring the robustness of the backstepping-based adaptive controller.

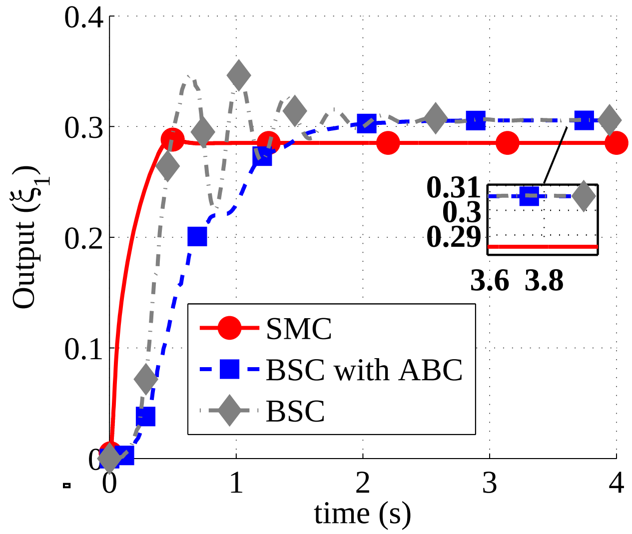

Figure 7: Output performance of adaptive backstepping after ABC optimization with $r = 0.3$m

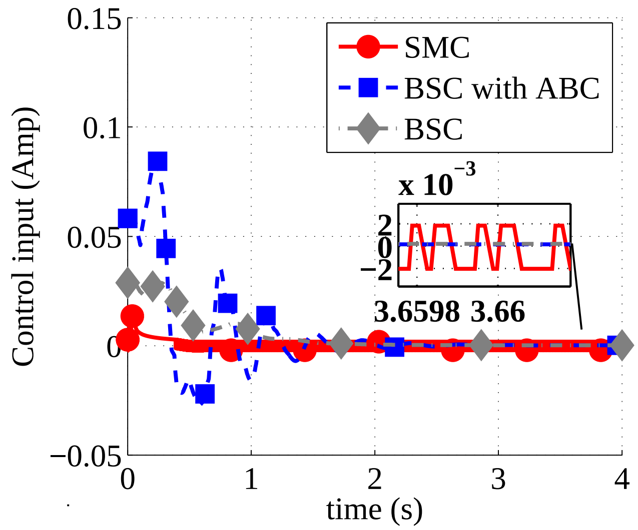

Figure 8: Control input of adaptive backstepping after ABC optimization with $r = 0.3$m

6 CONCLUSION

In this work, we have presented a robust backstepping-based adaptive controller for Electric-Hydraulic Servo Systems (EHSS) with uncertain and partially known parameters. The Artificial Bees Colony (ABC) algorithm is integrated into the closed-loop system to optimize the controller's parameters and adaptation gain while minimizing tracking error, control signal, and ensuring smoothness. Various experiments were conducted to validate the tracking capabilities and robustness of the proposed controller. The results demonstrate that the proposed control approach guarantees uniform ultimate boundedness of both the error and the control signal.

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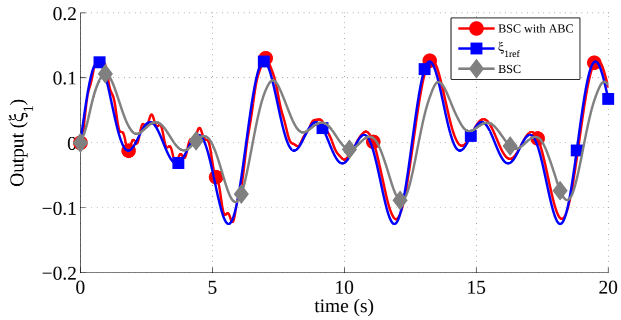

Figure 9: Output performance of adaptive backstepping after ABC optimization with $r = 0.05(sin(t) + sin(2t) + sin(3t))$m

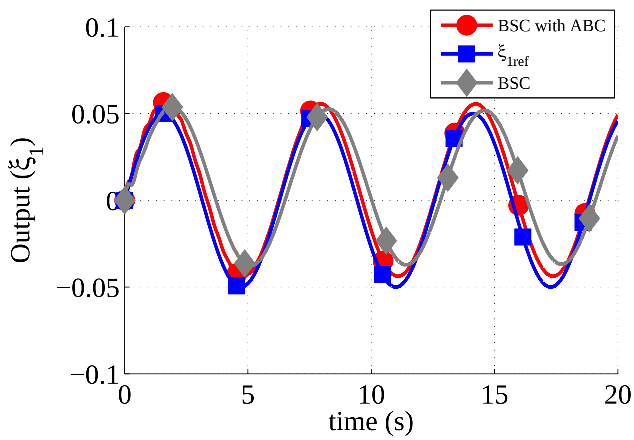

Figure 10: Output performance of adaptive backstepping after ABC optimization with $r = 0.05sin(t)$m

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