Received: 21 December 2023 | Revised: 22 April 2024 | Accepted: 28 May 2024

DOI: 10.1049/cth2.12707

IET Control Theory & Applications

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Enhanced precision in robot arm positioning: A nonlinear damping approach for flexible joint manipulators

Amir Hossein Jafari[1] | **Rached Dhaouadi**[2] | **Reza Jafari**[3]

[1]Data Science Program, George Washington University, Washington DC, USA

[2]Department of Electrical Engineering, American University of Sharjah, Sharjah, United Arab Emirates

[3]Computer Science, Virgina Tech, Falls Church, Virginia, USA

Correspondence
Amir Hossein Jafari, Data Science Program, George Washington University, Washington, DC, USA.
Email: ajafari@gwu.edu

Funding information
College of Engineering and the Open Access Program at the American University of Sharjah, Sharjah, UAE

Abstract

This article introduces an advanced nonlinear controller designed for optimizing the performance of a single-link robot arm featuring a flexible joint. The proposed nonlinear control strategy incorporates a Proportional-Integral (PI) controller in conjunction with a nonlinear velocity feedback component, aimed at providing effective nonlinear damping and suppressing vibrations. To validate the controller's performance, extensive simulations are conducted utilizing machine learning techniques within the Python environment. The performance of the proposed nonlinear damping controller is benchmarked against a conventional linear cascaded P-PI control structure, with both controllers fine-tuned using the Nelder-Mead algorithm. Simulation results demonstrate that the nonlinear damping controller yields substantial improvements in the dynamic behavior of the robot axis arm, showcasing superior step and sinusoidal position tracking performance, along with active vibration damping capabilities. This research contributes valuable insights into the enhanced nonlinear control strategies for flexible-joint robot arms, offering promising advancements in their overall dynamic performance.

1 | INTRODUCTION

Designing motion control systems with high dynamic performance requires intricate knowledge of electromechanical subsystem dynamics involving linear and nonlinear transmission attributes. Mechanical transmission elements that cause vibrations and deteriorate performance, such as flexibility of the elements, are undesirable as they restrict the closed-loop bandwidth. Compliance alongside friction limits the precision position and speed control in pointing and tracking servomechanisms [1–5]. Actuated robot joints have usually limited dynamic bandwidth due to the joint transmission elasticity, which affect seriously the tracking accuracy. The joint elasticity is mainly due to the flexibility of the coupling mechanism such as the harmonic drive gear in the joint [1, 6].

Actuated joints encounter dynamic errors such as servo tracking error and elasticity-based errors. These dynamic errors can not be eliminated by traditional methods of calibration as they vary with the motion states and external disturbances [8, 9, 16]. Instead, a dedicated closed loop control system is needed to get a high dynamic accuracy and eliminate all dynamic errors by using cascaded feedback loops to build a position loop that encompasses all the error information in the feedback [10, 11].

In the literature, only a few nonlinear control techniques were proposed for robot arms with flexible joints [12–15]. These represent however a significant advancement in the field of robotics. Traditional control methods struggled with the complex dynamics introduced by flexible joints, leading to issues like vibrations and imprecise positioning. These advanced nonlinear control techniques address these challenges by accounting for the nonlinearity and flexibility of the robot arms.

One notable approach is the use of model-based control techniques, such as adaptive control and robust control, which take into consideration the intricate dynamics of flexible joints [16–19]. Adaptive control continuously updates the control parameters based on real-time feedback, allowing the system to adapt to varying conditions and uncertainties. Robust control, on the other hand, provides a robust and stable performance in the presence of modeling errors and disturbances.

Nonlinear control algorithms have also been designed for example to improve the absolute tracking accuracy of the closed-loop system [20, 21]. Research results confirm that nonlinear damping outperforms in some cases other control algorithms as seen through comparisons with linear control techniques. The nonlinear PI feedback control outperformed the linear PI feedback control system [22–24, 27, 28]. Additionally, research has been conducted on nonlinear PI“D”-type control for flexible-joint robots using motor position measurements, which has been shown to be globally asymptotically stable [25]. Another relevant work is the use of robust stabilization of elastic joint robots through ESP and PID control, with both theoretical and experimental validation [26]. Furthermore, advanced nonlinear control techniques often leverage the power of modern artificial intelligence, particularly deep reinforcement learning (DRL). DRL allows the robot to learn complex control policies through interaction with its environment, gradually improving its performance and adaptability over time. This self-learning capability is especially beneficial in handling the intricate and nonlinear dynamics of flexible-joint robot arms.

These cutting-edge nonlinear control techniques are revolutionizing the field of robotics by enabling robot arms with flexible joints to achieve enhanced precision, stability, and adaptability. By accounting for the intricate dynamics and nonlinearity of such systems, these techniques are ushering in a new era of more capable and versatile robots, opening up opportunities for a wide range of applications in industry, healthcare, and beyond.

On the other hand, Machine Learning (ML) is gaining high interest nowadays in the research community. Machine learning has rapidly evolved to become a key tool in engineering research and practice. It is considered as an important subset of Artificial Intelligence (AI), a vast field of new upcoming technology, that allows models to independently adapt through exposure to new data, identifying patterns and learning from previous computations to reach reliable decisions and results [29–31]. Machine learning relies on a diverse set of tools and frameworks to support various aspects of the machine learning lifecycle, from data preprocessing and model development to deployment and monitoring.

Python is recently recognized as the predominant programming language for machine learning, offering a vast ecosystem of libraries and frameworks. Scikit-learn handles classical machine learning tasks, while TensorFlow, PyTorch, and Keras excel in deep learning. Python’s data manipulation and analysis capabilities are enhanced by NumPy, Pandas, and data visualization tools like Matplotlib. Jupyter Notebooks create an interactive and collaborative environment [32]. Python, with its rich ecosystem of machine learning libraries is used to develop adaptive control systems and predictive maintenance solutions. Python’s popularity has therefore increased recently in control engineering due to its open-source nature, extensive libraries, and the active community of users and developers. It provides control engineers with a flexible and powerful environment for modeling, simulating, and implementing control systems across a wide range of applications [33].

In this paper, we propose a nonlinear controller for a single link robot arm with a flexible joint. The nonlinear control

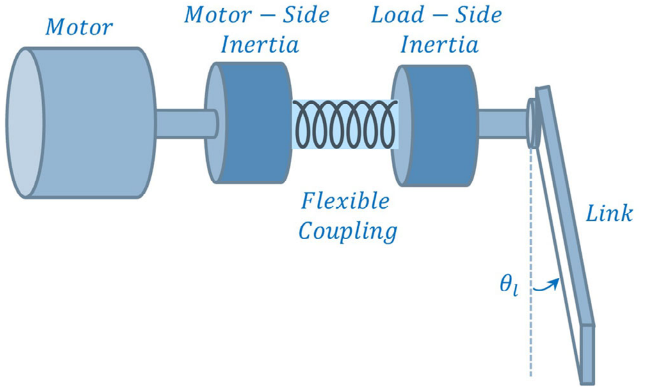


FIGURE 1 Robot axis with flexible joint.

scheme is based on a PI controller combined with a nonlinear PD control action to provide nonlinear damping and vibration suppression. The controller parameters are optimized to achieve high accuracy and good dynamic performance for step and sinusoidal position tracking. Machine learning supported with the Python environment is identified as a promising technique for the optimization and control of elastic drive systems. Theoretical analysis and simulation results show that the proposed nonlinear damping controller can significantly improve the dynamic performance of the flexible-joint arm with effective vibration suppression.

This paper introduces an advanced nonlinear controller designed for optimizing the performance of a single-link robot arm featuring a flexible joint. The proposed nonlinear control strategy incorporates a Proportional-Integral (PI) controller in conjunction with a nonlinear velocity feedback component, aimed at providing effective nonlinear damping and suppressing vibrations. To validate the controller’s performance, extensive simulations are conducted utilizing machine learning techniques within the Python environment. The performance of the proposed nonlinear damping controller is benchmarked against a conventional linear cascaded P-PI control structure, with both controllers fine-tuned using the Nelder-Mead algorithm. The structure of the paper is as follows. Section 2 presents the modeling of the robot axis with a flexible joint. Section 3 describes the proposed nonlinear damping controller, including the controller optimization using the Nelder-Mead algorithm. Section 4 presents the stability analysis of the system using Lyapunov’s direct method and LaSalle’s invariance principle. Section 5 presents the simulation results and discussions comparing the performance of the nonlinear damping controller with the linear cascaded controller. Finally, Section 6 concludes the paper.

2 | MODELING OF THE ROBOT AXIS WITH FLEXIBLE JOINT

The system under consideration is a single-link flexible joint manipulator [1, 6, 10, 18]. It is modeled by a two mass model system with a flexible coupling as shown in Figure 1.

TABLE 1 Mechanical system parameters.

Parameter	Value
$\mathbf{J}_m$ (kg $\cdot$m^2)	0.00143
$\mathbf{J}_l$ (kg $\cdot$m^2)	0.00173
K (N $\cdot$ m/rad)	10.658
f_n (**Hz**)	18.57

The dynamic equations of the two mass model are

$$J_m \frac{d^2\theta_m}{dt^2} = \tau_m - K(\theta_m - \theta_l) - C\left(\frac{d\theta_m}{dt} - \frac{d\theta_l}{dt}\right)$$
$$J_l \frac{d^2\theta_l}{dt^2} = K(\theta_m + \theta_l) + C\left(\frac{d\theta_m}{dt} - \frac{d\theta_l}{dt}\right) - \tau_l, \quad (1)$$

where $J_m = J_{motor} + J_{Mdisk}$ and $J_l = J_{Ldisk} + J_{link}\theta_l$ is the load position, θ_m is the motor position, J_m is the motor side inertia, J_l is the load side inertia, K is the shaft stiffness, C is the damping constant, τ_m is the motor torque, and τ_l is the load torque.

Table 1 shows the key parameters of the flexible joint. The main variable is the natural resonant frequency given by

$$f_n = \frac{1}{2\pi}\sqrt{K\left(\frac{1}{J_m} + \frac{1}{J_l}\right)}. \quad (2)$$

Next, defining, $x_1(t) = \theta_l(t)$, $x_2(t) = \frac{d\theta_l(t)}{dt}$, $x_3(t) = \theta_m(t)$, $x_4 = \frac{d\theta_m(t)}{dt}$ as the state variables of the system and the control system input as $u(t) = \tau_m(t)$, the system equations can be written as

$$\dot{x}_1 = x_2,$$
$$\dot{x}_2 = \frac{1}{J_l}\left[K(x_3 - x_1) + C(x_4 - x_2) - Mg\frac{d}{2}sinx_1\right], \quad (3)$$
$$\dot{x}_3 = x_4,$$
$$\dot{x}_4 = \frac{1}{J_m}[u - K(x_3 - x_1) - C(x_4 - x_2)].$$

The control goal is to design a nonlinear controller that can effectively damp the vibrations in the robot arm with flexible joint and achieve high precision position tracking performance. The key challenges are the nonlinear dynamics introduced by the flexible joint and the need to actively suppress the oscillations and vibrations to ensure fast and accurate positioning. Traditional linear control methods often struggle with these challenges, motivating the need for advanced nonlinear control techniques.

The proposed nonlinear damping controller aims to address these challenges by modulating the damping action as a function of the position error. By incorporating a nonlinear velocity feedback component, the controller can adaptively adjust the damping to provide high damping when the error is large, and lower damping as the system approaches the desired position. This allows for fast transient response without excessive overshoot or oscillations.

3 | PROPOSED NONLINEAR DAMPING CONTROLLER

3.1 | Nonlinear control law formulation

Nonlinear damping control refers to a feedback control system where an additional nonlinearity is deliberately inserted in the feedback loop to modify and improve the overall system performance. for the robot arm with flexible joint, the objective is to damp the vibrations due to the elastic coupling and obtain a damped response. Nonlinear damping has long been recognized as an effective technique to optimize servomechanisms performance [22, 23]. In the past few years the general interest has been observed again in systems using nonlinear elements [24, 27, 28]. The nonlinear based controllers have appealing advantages of simple intuitive structure and high performance while involving only a few control parameters. In this paper, the proposed nonlinear damping controller is based on nonlinear derivative control action combined with a PI controller as shown in Figure 2.

The objective of the nonlinear damping controller is to adjust the robot arm position from an initial value to a final value in the shortest possible time and with minimum oscillations. when a large error appears as a result of a sudden change in the reference position, then a high acceleration is needed, and this, in turn, is achieved by decreasing the system damping. As the system position approaches the desired reference, the error becomes small and the acceleration should be reduced rapidly to prevent overshoot, which requires a high damping. The system damping is, therefore modulated as a function of the position error. We propose a linear PI controller combined with a three-parameters nonlinear derivative controller, which is a function of the robot arm position error e as illustrated in Figure 2. The nonlinear controller is defined as

$$\tau_m(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau - \big(K_d + K_n\Gamma(e)\big)\omega_m(t), \quad (4)$$

$$e(t) = \theta_r(t) - \theta_l(t), \quad (5)$$

$$\Gamma(e) = 1 + tanh\big(-\beta e^2\big), \quad (6)$$

$$tanh(-x) = \frac{\exp^{-2x} - 1}{\exp^{-2x} + 1}, \quad (7)$$

where $K_p, K_i, K_d, K_n, \beta$ are the controller parameters and $tanh$ is the hyperbolic tangent function. Figure 3 shows a plot of the nonlinear function $f(e)$.

The main contribution of this paper is to propose an alternative approach to synthesize the nonlinear damping function

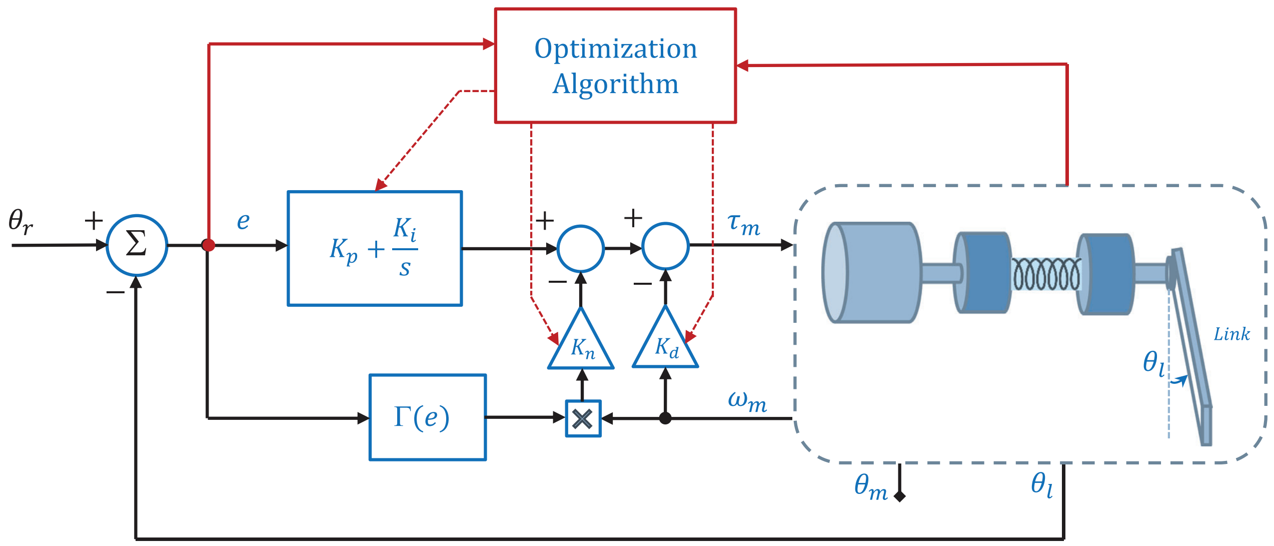


FIGURE 2 Nonlinear damping controller with optimization.

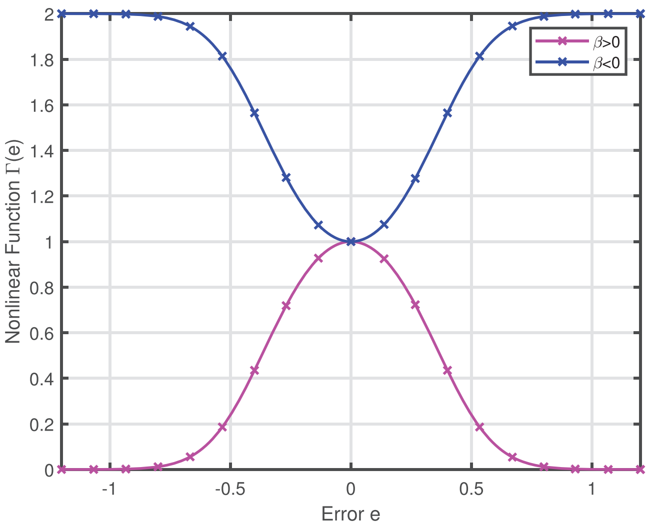


FIGURE 3 Nonlinear damping function for $\beta = \pm 4$.

based on motor velocity feedback control. An appropriate choice of the nonlinear function and corresponding gains allow to modulate the damping action as a function of angular position error.

3.2 | Controller optimization

In our analysis, it is assumed that the robot arm parameters are unknown or only a nominal model is known. In addition system parameters may change such as the load carried at the tip of the link. Therefore, the controller parameters should be optimized without the need for the system model parameters.

Python is a versatile programming language that can be effectively used for this task. Python offers control system design tools through libraries like Control System Toolbox and control packages in SciPy. Python offer as well powerful optimization libraries, such as SciPy's optimization module and open-source optimization libraries like Gekko, that can be used for tuning control system parameters to achieve desired performance. As such it can be used effectively for the optimization of the nonlinear robot arm with flexible joint.

The Nelder-Mead optimization (NMO) algorithm is used to optimize the nonlinear controller gains and to improve the tracking performance. Nelder-Mead optimization, also known as the simplex method, is a popular iterative optimization algorithm used for finding the minimum (or maximum) of an objective function, particularly in cases where the function is not differentiable or its derivatives are hard to compute.

The NMO algorithm has also the advantage of easy implementation and little prior knowledge of the optimization problem. As such, it is generally referred to as a pattern search algorithm and is used as a local or global search procedure for challenging nonlinear and potentially noisy and multi-modal optimization problems where the gradient of the function is unknown or cannot be reasonably computed.

A starting point must be provided to the algorithm, which may be the endpoint of another global optimization algorithm or a random point drawn from the domain. Given that the algorithm may get stuck in local optima, it may benefit from multiple restarts with different starting points.

The algorithm works by using a shape structure (called a simplex) composed of $n + 1$ points (vertices), where n is the number of input dimensions to the function. For example, on a two-dimensional problem that may be plotted as a surface, the shape structure would be composed of three points represented as a triangle. The cost functions at the points of the shape structure are evaluated and simple rules are used to decide how to move the points of the shape based on their relative evaluation. This includes operations such as "reflection," "expansion," "contraction," and "shrinkage" of the simplex shape on the surface of the objective function. The search stops when the points converge on an optimum, when a minimum difference between evaluations is observed, or when a maximum number of function evaluations are performed.

The cost function used for minimization is the sum of squares of errors:

$$SSE = \sum_{k=1}^{N} e(kT)^2, \tag{8}$$

where T, is the sampling time, and N, is the total number of samples.

4 | STABILITY ANALYSIS

4.1 | Local asymptotic stability

First, the stability analysis of the nonlinear damping controller can be carried out using local asymptotic stability analysis, which involves linearizing the system around the equilibrium point ($X = 0$) and examining the stability of the linear system. This linearization can be done using the first-order Taylor expansion of the nonlinear system equations (3)−(7). Define a new state variable x_5 as follows.

$$x_5(t) = \int_0^t e(\tau)d\tau. \tag{9}$$

The nonlinear closed loop system equations are therefore written as

$$\dot{X}(t) = f\big(X(t), r(t), t\big), \tag{10}$$

which is detailed as follows.

$$\begin{aligned}
\dot{x}_1 &= x_2,\\
\dot{x}_2 &= \frac{K}{J_l}(x_3 - x_1) + \frac{C}{J_l}(x_4 - x_2) - \frac{Mgd}{2Jl} sinx_1,\\
\dot{x}_3 &= x_4,\\
\dot{x}_4 &= -\frac{K}{J_m}(x_3 - x_1) - \frac{C}{J_m}(x_4 - x_2)\\
&\quad + \frac{K_p}{J_m}(r - x_1) + \frac{K_i}{J_m}z + -\frac{1}{J_m}\left[K_d + K_n tanh\left(-\beta e^2\right)\right]x4,\\
\dot{x}_5 &= r - x_1.
\end{aligned} \tag{11}$$

This nonlinear system can be linearized in the following form:

$$\dot{X}(t) = AX(t) + Bu(t), \tag{12}$$

where A is the Jacobian matrix evaluated at the equilibrium point.

$$A = \frac{\partial f}{\partial X}\Big|_{X=0} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ -\left(\frac{K}{J_l} + \frac{Mgd}{2J_l}\right) & -\frac{C}{J_l} & \frac{K}{J_l} & \frac{C}{J_l} & 0 \\ 0 & 0 & 0 & 1 & 0 \\ \frac{K-K_p}{J_m} & \frac{C}{J_m} & \frac{-K}{J_m} & -\left(\frac{C+K_d+K_n}{J_m}\right) & \frac{K_i}{J_m} \\ -1 & 0 & 0 & 0 & 0 \end{pmatrix}. \tag{13}$$

The eigenvalues of the system matrix A are next obtained by solving the characteristic equation. Assuming that the system damping C is negligible, we get

$$\begin{aligned}
\Delta(s) &= s^5 + \left(\frac{K_d + K_n}{J_m}\right)s^4 + \left(\frac{K}{J_m} + \frac{K}{J_l} + \frac{Mgd}{2J_l}\right)s^3\\
&\quad + \frac{(K_d + K_n)}{J_m J_l}\left(K + \frac{Mgd}{2J_l}\right)s^2\\
&\quad + \frac{K}{J_m J_l}\left(K_p + \frac{Mgd}{2J_l}\right)s + \frac{KK_i}{J_m J_l},
\end{aligned} \tag{14}$$

where, s is the Laplace operator.

If all eigenvalues have negative real parts, the linearized system is locally asymptotically stable. Using the Routh stability criterion, the following stability conditions are obtained.

Condition C1:

$$K_i > 0. \tag{15}$$

Condition C2:

$$K_d + K_n > 0. \tag{16}$$

Condition C3:

$$J_m K_i + (K_d + K_n)\big(K - K_p\big) > 0. \tag{17}$$

Condition C4:

$$\begin{aligned}
&K(K_d + K_n)^2\big(K - K_p\big)\left(K_p + \frac{Mgd}{2J_l}\right)\\
&\quad + KK_i\left[J_m\left(2K_p - K + \frac{Mgd}{2J_l}\right) - J_l K\right]\\
&\quad (K_d + K_n) - J_m^2 K_i^2 K > 0.
\end{aligned} \tag{18}$$

4.2 | Global asymptotic stability

Since our robot arm is a mechanical system, we can use the concepts of potential and kinetic energy to analyse stability.

4.2.1 | Open loop system

For the uncontrolled system, the total energy is the sum of the potential energy and kinetic energy, which can be written as

$$E(X) = \frac{1}{2}J_l x_2^2 + \frac{1}{2}J_m x_4^2, \quad P(X) = \frac{1}{2}K(x_3 - x_1)^2 + \frac{Mgd}{2}\left(1 - cos(x_1)\right). \tag{19}$$

For the robot arm, the equilibrium point is $x_{10} = 0$, $x_{20} = 0$, $x_{30} = 0$, $x_{40} = 0$. Next, define the Lyapunov function V_0

$$V_0(X) = E(X) + P(X) = \frac{1}{2}J_l x_2^2 + \frac{1}{2}J_m x_4^2 + \frac{1}{2}K(x_3 - x_1)^2 + \frac{Mgd}{2}\left(1 - cos(x_1)\right). \tag{20}$$

The directional derivative of V_0 gives

$$\dot{V}_0 = \frac{dV_0}{dX}\dot{X} = -C(x_4 - x_2)^2 + x_4 u. \tag{21}$$

This is always negative for the unforced system ($u = 0$), which implies that that the energy is decreasing if the system is perturbed from its equilibrium point. This proves the stability of the equilibrium point [37].

4.2.2 | Closed loop system

The objective now is to provide conditions on the nonlinear damping controller gains $K_p, K_i, K_d, K_n, \beta$, guaranteeing global asymptotic stability of the unique equilibrium point [34–36]. To carry out the stability analysis, we consider the following Lyapunov function candidates:

$$V(X) = V_0(X) + V_1(X) + V_2(X) = V_0(X) + \frac{1}{2}\left(e - \lambda z\right)^2 + \alpha\, ln\left[cosh(-\beta e^2)\right]. \tag{22}$$

The second term is included in the Lyapunov function candidate to take into account the state variable z induced by the integral action. The third term is useful to take into account the nonlinear derivative function. The time derivative of the Lyapunov functions candidate along the trajectories of the closed-loop system (8) can be written as

$$\dot{V}_0 = -C(x_4 - x_2)^2 - K_p x_1 x_4 + K_i x_4 x_5 - (K_d + K_n)x_4^2 - K_n x_4^2\, tanh(-\beta e^2), \tag{23}$$

$$\dot{V}_1 = x_1 x_2 - \lambda x_1^2 + \lambda x_2 x_5 - \lambda^2 x_1 x_5, \tag{24}$$

$$\dot{V}_2 = -2\alpha\beta\, x_1 x_2\, tanh(-\beta e^2). \tag{25}$$

Therefore, the time derivative of the total Lyapunov function candidate V is

$$\dot{V} = -C(x_4 - x_2)^2 - K_p x_1 x_4 + K_i x_4 x_5 - (K_d + K_n)x_4^2 - K_n x_4^2\, tanh(-\beta e^2) + x_1 x_2 - \lambda x_1^2 + \lambda x_2 x_5 - \lambda^2 x_1 x_5 - 2\alpha\beta\, x_1 x_2\, tanh(-\beta e^2). \tag{26}$$

This can be written as

$$\dot{V} \leq X^T P X - K_n x_4^2\, tanh(-\beta e^2), \tag{27}$$

where,

$$X^T = [x_1 \quad x_2 \quad x_4 \quad x_5], \tag{28}$$

and

$$P = \begin{bmatrix} -\lambda & \frac{1}{2} - \alpha\beta & -\frac{K_p}{2} & -\frac{\lambda^2}{2} \\ \frac{1}{2} - \alpha\beta & -C & C & \frac{\lambda}{2} \\ -\frac{K_p}{2} & C & -(K_d + K_n + C) & \frac{K_i}{2} \\ -\frac{\lambda^2}{2} & \frac{\lambda}{2} & \frac{K_i}{2} & 0 \end{bmatrix}, \tag{29}$$

where we have used the property $\left|tanh\left(-\beta e^2\right)\right| \leq 1$.

As observed, P is a symmetric matrix. Then, P can be shown to be negative definite iff its naturally ordered (leading) principal minors alternate in sign starting with a negative number.

Define the variable

$$\gamma = \left(\frac{1}{2} - \alpha\,\beta\right). \tag{30}$$

Then, the naturally ordered principle minors of the matrix P lead to the following conditions:

Condition ND1:

$$-\lambda < 0, \tag{31}$$

Condition ND2:

$$\lambda\, C - \gamma^2 > 0, \tag{32}$$

Condition ND3:

$$CK_p^2 - 4C\gamma K_p + 4\gamma^2(K_d + K_n + C) - 4\lambda\, C(K_d + K_n) < 0, \tag{33}$$

Condition ND4:

$$\left(\gamma^2 - \lambda\, C\right)K_i^2 + 2\lambda^2 C(\gamma - 1)K_i + \frac{\lambda^2}{4}K_p^2 - \lambda^3 CK_p + \frac{\lambda}{2}(\gamma - 2\lambda\, C)K_p K_i + \lambda^3(2\gamma - \lambda\, C)(K_d + K_n + C) + \lambda^3 C^2 > 0. \tag{34}$$

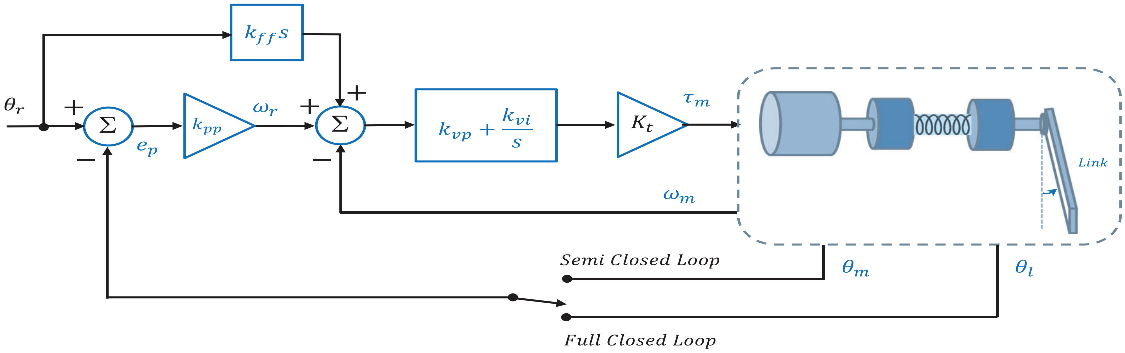


FIGURE 4 Standard PPI cascade control of a robot arm with flexible joint.

These stability conditions can be fulfilled by freely choosing both the controller parameters $(K_p, K_i, K_d, K_n, \beta)$ and the parameters associated with the Lyapunov function (λ, α). Then, $\dot{V}$ is a globally negative definite function. We can therefore conclude that the equilibrium point of the closed-loop system (11) is stable [37].

5 | SIMULATION RESULTS AND DISCUSSIONS

The standard position control of an actuated joint uses a (Proportional & PI) PPI cascade control structure as shown in Figure 4 with an outer position loop based on a proportional controller (k_{pp}) and an inner velocity loop with a PI controller (k_{vp}, k_{vi}). An additional velocity feedforward gain (k_{ff}) is used for the inner velocity loop. Velocity feedback can be from the motor side encoder (semi-closed loop) or from the link side encoder (full closed loop). In our case, the load position is used for feedback.

The PPI control scheme will be used as a benchmark and its performance will be compared to the proposed nonlinear damping controller.

5.1 | Step-reference tracking

At first, a step reference input was used to analyse the performance of the nonlinear damping controller. The results indicate that the response of the nonlinear system is superior to the linear system.

Figure 5 shows the optimized step response of the robot arm with full closed loop feedback. The robot arm angle follows the step reference with a fast and controlled response. The small overshoot and zero steady state error confirm that the mechanical vibrations have been actively damped. The overshoot for the nonlinear damping control is decreased by 11.4 percent compare to the linear controller. The nonlinear damping function is also shown in Figure 5b indicating the modulation of the damping as a function of the system position error. The optimized gains are shown in Tables 2 and 3. The controller gains

TABLE 2 Optimized controller gains for step response.

Nonlinear damping controller		Linear PPI controller	
Parameter	Value	Parameter	Value
K_p	11.237	k_{pp}	33.453
K_i	5.503	k_{vp}	0.183
K_d	−0.436	k_{vi}	0.432
K_n	0.467	k_{ff}	0.0
β	−50.553		

TABLE 3 Optimized controller gains for sinusoidal response.

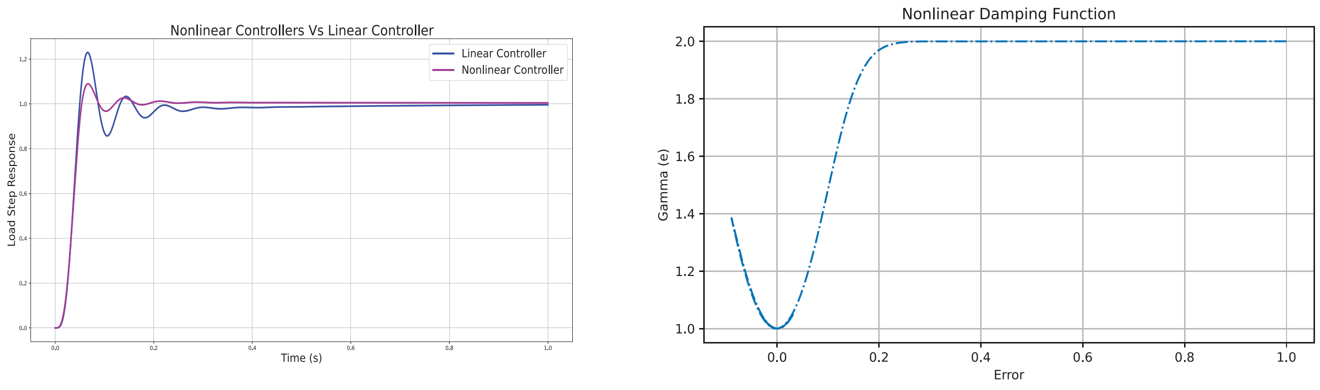
Nonlinear damping controller		Linear PPI controller	
Parameter	Value	Parameter	Value
K_p	10.26	k_{pp}	50.0
K_i	2.09e-8	k_{vp}	0.194
K_d	−6.02e-2	k_{vi}	0.0
K_n	8.74e-2	k_{ff}	0.0
β	−299.92		

also satisfy the stability conditions 15–18, which confirms the asymptotic stability of the nonlinear damping control system.

5.2 | Sinusoidal-reference tracking

The performance of the proposed nonlinear damping controller is next analyzed under sinusoidal reference tracking shown in Figure 6. This is the error residuals with respect to the reference position which compares the linear controller with nonlinear controller. We used Nelder-Mead algorithm to optimize the linear controller gains.

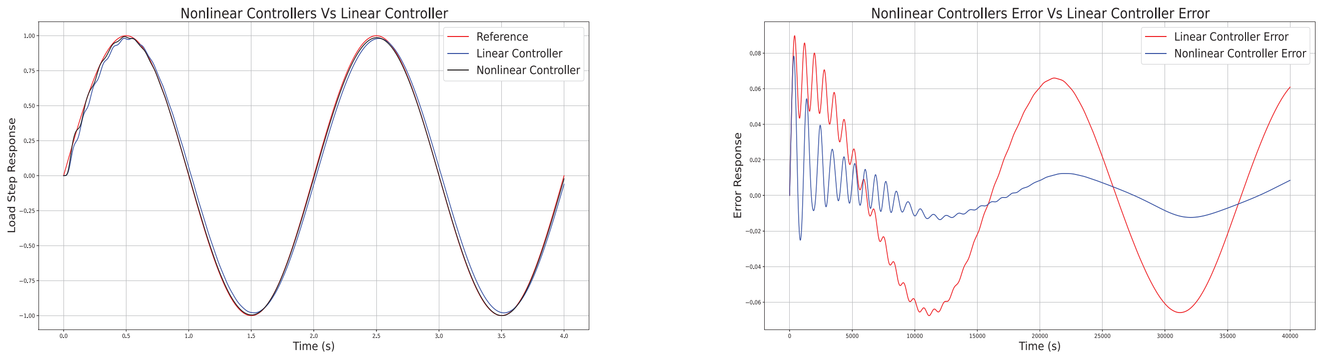
As a further indication, the angular position error of the system was recorded as shown in Figure 6b. The curves clearly indicate that the nonlinear control system's response is superior to the linear system's response.



(a) Step response for nonlinear damping

(b) Nonlinear damping function

FIGURE 5 Step response and nonlinear damping.



(a) Sinusoidal response

(b) Angular position errors

FIGURE 6 Sinusoidal response and error.

6 | CONCLUSIONS

A new and optimized nonlinear damping controller has been proposed for a single link robot arm with a flexible joint. The nonlinear control scheme is based on a PI controller combined with a nonlinear PD control action to provide nonlinear damping and active vibration suppression. A nonlinear function have been proposed for the nonlinear angular velocity gain, which increases with the increase of absolute position error and decreases with the decrease of absolute position error. The parameters of the closed loop system are optimized under the Python environment using the numpy library. The proposed scheme has been validated to provide superior command tracking for step reference and sine reference signals.

AUTHOR CONTRIBUTIONS

Amir Hossein Jafari: Conceptualization; data curation; formal analysis; methodology; software; supervision; visualization; writing—original draft; writing—review and editing. **Rached Dhaouadi**: Conceptualization; investigation; resources; software; supervision; validation; visualization; writing—original draft; writing—review and editing. **Reza Jafari**: Conceptualization; methodology; writing—original draft; writing—review and editing.

ACKNOWLEDGEMENTS

This paper represents the opinions of the authors and does not mean to represent the position or opinions of the American University of Sharjah.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

ORCID

Amir Hossein Jafari https://orcid.org/0000-0002-1730-4807

REFERENCES

1. Luca, A.D., Book, W.: Robots with flexible elements. In: Siciliano B., Khatib O. (eds.) Springer Handbook of Robotics, pp. 287–319. Springer, Berlin, Heidelberg (2008). https://doi.org/10.1007/978-3-540-30301-5-14

2. Li, X., et al.: A new mechanical resonance suppression method for large optical telescope by using nonlinear active disturbance rejection control. IEEE Access 7, 94400–94414 (2019). https://doi.org/10.1109/ACCESS.2019.2928050
3. Xie, L., Qiu, Z., Zhang, X.: Development of a 3-PRR precision tracking system with full closed-loop measurement and control. Sensors 19(8), 1756 (2019). https://doi.org/10.3390/s19081756
4. Gordon, D.J., Erkorkmaz, K.: Accurate control of ball screw drives using pole-placement vibration damping and a novel trajectory prefilter. Precis. Eng. 37(2), 308–322 (2013). https://doi.org/10.1016/j.precisioneng.2012.09.009
5. Liu, H., Wang, Y., Shan, X.: Full closed loop-based dynamic accuracy enhancement for elastic joints. J. Power Electron. 22, 959–969 (2022). https://doi.org/10.1007/s43236-022-00438-6
6. Khan, I.U., Dhaouadi, R.: Robust control of elastic drives through immersion and invariance. IEEE Trans. Ind. Electron. 62(3), 1572–1580 (2015). https://doi.org/10.1109/TIE.2014.2363435
7. Patel, R., Kumar, V.: Multilayer neuro PID controller based on back propagation algorithm. Procedia Comput. Sci. 54, 207–214 (2015). https://doi.org/10.1016/j.procs.2015.06.023
8. Anh, H.P.H.: Online tuning gain scheduling MIMO neural PID control of the 2-axes pneumatic artificial muscle (PAM) robot arm. Expert Syst. Appl. 37(9), 6547–6560 (2010). https://doi.org/10.1016/j.eswa.2010.02.131
9. Chertovskikh, P.A., Seredkin, A.V., Gobyzov, O.A., Styuf, A.S., Pashkevich, M.G., Tokarev, M.P.: An adaptive PID controller with an online auto-tuning by a pretrained neural network. J. Phys. Conf. Ser. 1359, 012090 (2019)
10. Dhaouadi, R., Ghorbel, F.H., Gandhim, P.S.: A new dynamic model of hysteresis in harmonic drives. IEEE Trans. Ind. Electron. 50(6), 1165–1171 (2003). https://doi.org/10.1109/TIE.2003.819661
11. Jafari, R., Dhaouadi, R.: Adaptive PID control of a nonlinear servomechanism using recurrent neural networks. In: Advances in Reinforcement Learning. IntechOpen, London (2011). https://doi.org/10.5772/13020
12. Tuan, H.M., Sanfilippo, F., Hao, N.V.: Modelling and control of a 2-DOF robot arm with elastic joints for safe human-robot interaction. Front. Rob. AI 8, 679304 (2021). https://doi.org/10.3389/frobt.2021.679304
13. Taghirad, H.D., Khosravi, M.A.: A robust linear controller for flexible joint manipulators. In: 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566), vol. 3, pp. 2936-2941. IEEE, Piscataway (2004). https://doi.org/10.1109/IROS.2004.1389855
14. Izadbakhsh, A., Masoumi, M.: FAT-based robust adaptive control of flexible-joint robots: Singular perturbation approach. In: 2017 IEEE International Conference on Industrial Technology (ICIT), pp. 803-808. IEEE, Piscataway (2017). https://doi.org/10.1109/ICIT.2017.7915462
15. Spurgeon, S.K., Yao, L., Lu, X.Y.: Robust tracking via sliding mode control for elastic joint manipulators. Proc. Inst. Mech. Eng. Part I: J. Syst. Control Eng. 215(4), 405–417 (2001)
16. Reichensdörfer, E., Günther, J., Diepold, K.: Recurrent neural networks for PID auto-tuning. Adaptive Control and Identification of Nonlinear Systems. Technical Report, Technische Universität München, Munich, Germany (2017)
17. Chaoui, H., Sicard, P., Gueaieb, W.: ANN-based adaptive control of robotic manipulators with friction and joint elasticity. IEEE Trans. Ind. Electron. 56, 3174–3187 (2009)
18. Talole, S.E., Kolhe, J.P., Phadke, S.B.: Extended-state-observer-based control of flexible-joint system with experimental validation. IEEE Trans. Ind. Electron. 57(4), 1411–1419 (2010). https://doi.org/10.1109/TIE.2009.2029528
19. Ullah, H., Malik, F.M., Raza, A., Mazhar, N., Khan, R., Saeed, A., Ahmad, I.: Robust output feedback control of single-link flexible-joint robot manipulator with matched disturbances using high gain observer. Sensors 21, 3252 (2021). https://doi.org/10.3390/s21093252
20. Izadbakhsh, A.: A note on the nonlinear control of electrical flexible-joint robots. Nonlinear Dyn. 89, 2753–2767 (2017). https://doi.org/10.1007/s11071-017-3623-x
21. Jafari, A.H., Dhaouadi, R., Jhemi, A.: Nonlinear friction estimation in elastic drive systems using a dynamic neural network-based observer. J. Adv. Comput. Intell. Intell. Informat. 17(4), 637–646 (2013). https://doi.org/10.20965/jaciii.2013.p0637
22. Dhaouadi, R., Kubo, K.: A nonlinear control method for good dynamic performance elastic drives. IEEE Trans. Ind. Electron. 46(4), 868–870 (1999). https://doi.org/10.1109/TIE.1999.778264
23. Tian, Y.-C., Tadé, M.O., Tang, J.: A nonlinear PID controller with applications. IFAC Proc. Vol. 32(2), 2657–2661 (1999). https://doi.org/10.1016/S1474-6670(17)56452-6
24. Son, Y.D., Bin, S.D., Jin, G.G.: Stability analysis of a nonlinear PID controller. Int. J. Control Autom. Syst. 19, 3400–3408 (2021). https://doi.org/10.1007/s12555-020-0599-y
25. Moyrón, J., Moreno–Valenzuela, J., Sandoval, J.: Nonlinear PI"D"-type control of flexible joint robots by using motor position measurements is globally asymptotically stable. IEEE Trans. Autom. Control 68(6), 3648–3655 (2023). https://doi.org/10.1109/TAC.2022.3194043
26. Keppler, M., Raschel, C., Wandinger, D., Stemmer, A., Ott, C.: Robust stabilization of elastic joint robots by ESP and PID control: Theory and experiments. IEEE Rob. Autom. Lett. 7(3), 8283–8290 (2022). https://doi.org/10.1109/LRA.2022.3187277
27. Zheng, C., Su, Y., Mercorelli, P.: A simple nonlinear PD control for faster and high-precision positioning of servomechanisms with actuator saturation. Mech. Syst. Sig. Process. 121, 215–226 (2019). https://doi.org/10.1016/j.ymssp.2018.11.017
28. Salton, A.T., Eckhard, D., Flores, J.V., Fernandes, G., Azevedo, G.: Disturbance observer and nonlinear damping control for fast tracking quadrotor vehicles. In: 2016 IEEE Conference on Control Applications (CCA), pp. 705–710. IEEE, Piscataway (2016). https://doi.org/10.1109/CCA.2016.7587901
29. Van Vuuren, J.J., Tang, L., Al-Bahadly, I., Arif, K.M.: A 3-stage machine learning-based novel object grasping methodology. IEEE Access 8, 74216–74236 (2020). https://doi.org/10.1109/ACCESS.2020.2987341
30. Kalousdian, N.K., et al.: Learning robotic manipulation of natural materials with variable properties for construction tasks. IEEE Rob. Autom. Lett. 7(2), 5749–5756 (2022). https://doi.org/10.1109/LRA.2022.3159288
31. Alhousani, N., Saveriano, M., Sevinc, I., Abdulkuddus, T., Kose, H., Abu-Dakka, F.J.: Geometric reinforcement learning for robotic manipulation. IEEE Access 11, 111492–111505 (2023). https://doi.org/10.1109/ACCESS.2023.3322654
32. Blank, J., Deb, K.: Pymoo: Multi-objective optimization in python. IEEE Access 8, 89497–89509 (2020). https://doi.org/10.1109/ACCESS.2020.2990567
33. Fuller, S., Greiner, B., Moore, J., Murray, R., van Paassen, R., Yorke, R.: The python control systems library (python-control). In: 2021 60th IEEE Conference on Decision and Control (CDC), pp. 4875-4881. IEEE, Piscataway (2021). https://doi.org/10.1109/CDC45484.2021.9683368
34. Su, Y., Müller, P.C., Zheng, C.: Global asymptotic saturated PID control for robot manipulators. IEEE Trans. Control Syst. Technol. 18(6), 1280–1288 (2010). https://doi.org/10.1109/TCST.2009.2035924
35. Pervozvanski, A.A., Freidovich, L.B.: Robust stabilization of robotic manipulators by PID controllers. Dyn. Control 9, 203–222 (1999). https://doi.org/10.1023/A:1008321920742
36. Kelly, R.: Global positioning of robot manipulators via PD control plus a class of nonlinear integral actions. IEEE Trans. Autom. Control 43(7), 934–938 (1998). https://doi.org/10.1109/9.701091
37. Slotine, J.-J.E., Li, W.: Applied Nonlinear Control. Prentice Hall, Upper Saddle River, NJ (1991)

How to cite this article: Jafari, A.H., Dhaouadi, R., Jafari, R.: Enhanced precision in robot arm positioning: A nonlinear damping approach for flexible joint manipulators. IET Control Theory Appl. 18, 1968–1976 (2024). https://doi.org/10.1049/cth2.12707