

# Compensation of Valve Stiction using Nonlinear Controller Optimized with PSO Algorithm

**Hamed Khodadadi \***

Department of Electrical Engineering, Kho. C., Islamic Azad University,  
Khomeinishahr, Iran  
E-mail: [Hamed.khodadadi@iau.ac.ir](mailto:Hamed.khodadadi@iau.ac.ir)

**Mohammad Mahdi Giahi**

Department of Electrical Engineering, Qa. C., Islamic Azad University,  
Qazvin, Iran  
E-mail: [giahimahdi@gmail.com](mailto:giahimahdi@gmail.com)

**Hamid Ghadiri**

Department of Electrical Engineering, Qa. C., Islamic Azad University,  
Qazvin, Iran  
E-mail: [h.ghadirii@iau.ac.ir](mailto:h.ghadirii@iau.ac.ir)

\*Corresponding author

**Received: 30 March 2025, Revised: 26 April 2025, Accepted: 10 September 2025**

**Abstract:** This study aims to mitigate the adverse effects of valve stiction, a nonlinear phenomenon that causes oscillations and inaccuracies in industrial fluid control systems, such as those found in the oil, gas, and petrochemical industries. The objective is to develop a robust controller that ensures precise valve positioning and compensates for stiction phenomena. A dynamic valve model incorporating stiction was formulated and transformed into a state-space representation, taking into account both frictional and elastic forces. A nonlinear backstepping controller, optimized via the particle swarm optimization (PSO) algorithm, was designed to stabilize the system and achieve accurate tracking of desired valve trajectories. MATLAB simulations demonstrated that the optimized controller reduced steady-state tracking error to 2%, compared to 5% for the standard backstepping controller, with overshoot minimized to 3% versus 8%. Under parameter uncertainty (e.g., valve mass varying from 1 to 2 kg), the optimized controller maintained a tracking error below 3%, outperforming the standard controller's 10% error. Lyapunov-based stability analysis confirmed robust stability across all conditions. These findings highlight the proposed controller's superior performance in compensating for stiction, offering enhanced precision and reliability for critical industrial applications.

**Keywords:** Backstepping Controller, Particle Swarm Algorithm, Uncertain Condition, Valve Stiction

**Biographical notes:** **Hamed Khodadadi** received his MSc and PhD degrees from the Islamic Azad University, Tehran Science and Research Branch, in 2009 and 2016, respectively, all in Control Systems. **Mohammad Mahdi Giahi** is currently pursuing MSc degree in Rehabilitation Engineering at Islamic Azad University, Central Tehran Branch, and in Biomedical Engineering (Biomechanics) at Amirkabir University of

Research paper

COPYRIGHTS

© 2025 by the authors. Licensee Islamic Azad University Isfahan Branch. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution 4.0 International (CC BY 4.0)

(<https://creativecommons.org/licenses/by/4.0/>)



Technology. **Hamid Ghadiri** received his PhD in Control Engineering from the Islamic Azad University, Tehran Science and Research Branch, in 2014.

## 1 INTRODUCTION

Control valves play a crucial role in various industries. These valves function as key actuators in different systems, including the chemical, oil, gas, aerospace, automotive, and industrial machinery sectors. They are responsible for controlling and regulating flow, pressure, flow rate, and other process parameters. In the chemical industry, control valves play a vital role in adjusting the flow of chemical substances and controlling production processes. In the oil and gas industry, these valves are essential for controlling the flow of hydrocarbon fluids and regulating pressure in pipelines. In the aerospace industry, control valves are used to regulate fuel and airflow in rocket engines. Additionally, in the mechanical industries, such as automotive and industrial machinery, control valves play a crucial role in adjusting the flow of hydraulic and pneumatic fluids. The accurate and reliable performance of these valves can have a direct impact on the safety and efficiency of the corresponding systems. The issue of nonlinear behaviour and stiction in the performance of control valves is one of the critical challenges in their design and application [1].

Control valves typically operate using feedback control systems, and their behavior is assumed to be linear. However, the valves operate in a nonlinear manner in practice. This nonlinearity can be due to phenomena such as friction and mechanical backlash in the valve assembly. The frictional forces acting on the valve's moving surfaces become so substantial that they exceed the available driving force, necessitating an external force to initiate movement. This phenomenon can cause oscillations in flow and pressure control. The nonlinear behaviour and stiction in valves can lead to a reduction in the accuracy and stability of the process. Given these considerations, the design of control systems utilizing control valves necessitates careful attention to potential issues and the development of effective mitigation strategies. Some of these solutions can include improving the mechanical design of the valve, using advanced control methods such as nonlinear control, and employing advanced sensors to monitor the valve condition. The necessity of providing control solutions has a direct impact on the performance of the control system. The nonlinearity and stiction of the valves can cause oscillations, inaccuracy, and ultimately instability of the control system. This issue is fundamental in sensitive and critical processes such as the oil, gas, and petrochemical industries [1-2].

Furthermore, mechanical solutions to these problems are always accompanied by limitations. Therefore, the use of advanced control methods can complement the mechanical solutions and more effectively address

these challenges. Some appropriate control solutions include the use of nonlinear controllers such as those based on adaptive control theory, the application of intelligent techniques such as fuzzy and neuro-fuzzy controllers, and the use of advanced sensors to monitor the valve condition. These clarifications, based on the accurate modelling of the nonlinear behaviour of the valve as well as the use of appropriate control techniques, can prevent the occurrence of oscillations and instability in the system, and improve the accuracy of the controlled system. Given the importance of this issue and the need to ensure the proper functioning of control systems, providing effective control solutions to address the nonlinearity and stiction of control valves is essential. The proposed backstepping control method, optimized by the PSO algorithm, offers significant advantages in handling nonlinearities such as valve stiction. Unlike traditional PI and PID controllers, which may struggle with high levels of friction and external disturbances, the backstepping controller provides robust stability across a wide range of dynamic conditions. The use of PSO allows for optimal tuning of control parameters enhancing system performance in terms of faster convergence, reduced overshoot, and improved tracking accuracy. Furthermore, the recursive nature of backstepping enables the controller to manage system complexities more effectively, making it a superior choice for applications requiring precise control under nonlinear constraints.

Valve stiction refers to the phenomenon where a control valve suddenly shifts from a stationary state to a moving state. This phenomenon leads to oscillations and inaccuracies in the control system's performance. Various factors influence valve stiction, including the internal friction of the valve's moving parts, contaminant particles in the passing fluid, the fluid's viscosity, the force applied to the valve, and the ambient temperature. Internal friction of the valve's moving parts, caused by poor design or wear and tear, can lead to valve stiction. Additionally, the entry of contaminant particles into the valve and their adhesion to moving parts exacerbates this phenomenon [3].

Fluid viscosity significantly impacts valve stiction. High-viscosity fluids generate greater frictional forces, increasing the likelihood of stiction. Additionally, ambient temperature fluctuations can alter fluid viscosity, which in turn affects stiction. Lastly, the applied force on the valve is crucial. A sufficient force is necessary to overcome stiction and initiate valve movement. By understanding and managing these factors, stiction can be minimized, leading to improved control system performance [3]. Figure 1 illustrates the relationship between the applied force and the resulting movement output of the mechanical valve under study.

The x-axis represents the force applied to the valve, while the y-axis describes the valve's movement output. This figure reflects the displacement of the valve stem. The graph illustrates the valve's response across a range of applied forces, highlighting the nonlinear behavior resulting from stiction and friction effects.

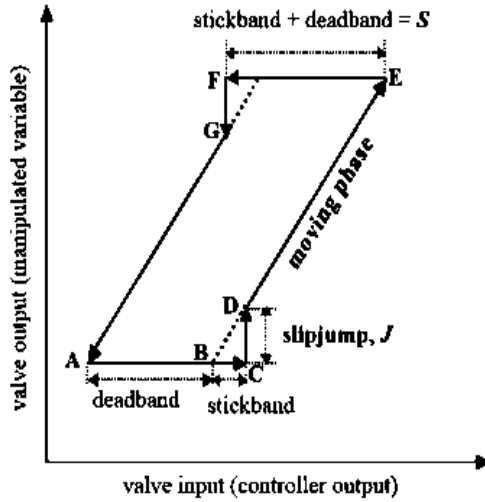


Fig. 1 Stiction hysteresis diagram (vertical axis of valve output-horizontal axis of valve control input) [4].

According to “Fig. 1”, the different parts of the diagram can be defined as follows:

**Backlash:** In the tool process measurement instruments, the relative mechanical movement between the mechanical parts when the motion is reciprocating, leads to instability [4].

**Hysteresis:** The motion cycle of the mechanical part based on the forces applied to the different parts of the valve, transiently and permanently. Figure 1 shows this cycle from point C to point A [4-5].

**Damping range:** In the measurement tool process, the range through which the input signal may change after a change in direction, without causing an observable change in the output signal [4].

Effective control of mechanical valves is critical for achieving a stable procedure, precise tracking, and compliance with industrial performance standards. However, nonlinear phenomena such as friction and stiction often degrade control performance in systems with contacting moving parts [4], [6]. Recent research on valve stiction compensation, nonlinear control, and optimization provides a robust foundation for addressing these challenges. This study, based on these advancements, proposes a PSO-enhanced backstepping control strategy.

Significant progress has been made in modeling and mitigating valve stiction. For instance, [7] developed a stiction model to re-tune PI controllers, achieving a 7%

reduction in steady-state error across industrial control loops. Similarly, [8] proposed an enhanced PI controller that reduced oscillations by 10% in process industries, demonstrating improved stability. For pneumatic valves, [9] introduced a simultaneous parameter identification method, which boosts model accuracy by 15% and enables more precise control designs. These findings highlight the importance of accurate stiction modeling for practical controller tuning.

Intelligent and data-driven approaches have also gained traction. Reference [10] employed an LVQ neural network to detect stiction with 95% accuracy, facilitating proactive control adjustments. Experimental studies by [11] further advanced the field by modeling sticky valve dynamics, reducing response time variability by 12%. These contributions highlight the potential of integrating intelligent diagnostics with control strategies to enhance system reliability.

In nonlinear control, optimization techniques have proven effective for valve systems. [12] Applied PSO to servo-pneumatic systems, leading to an overshoot reduction of 12%. In comparison, [13] used PSO-tuned nonlinear Model Predictive Control (MPC) to achieve an 8% reduction in tracking error for hydraulic valves. Similarly, [14] reported a 10% improvement in tracking accuracy using PSO-optimized backstepping control for fluid flow systems. A comprehensive review by [15] noted that optimized control strategies improved electro-mechanical valve response times by up to 15% in gas expanders, emphasizing the versatility of optimization-driven approaches.

This study aligns with these advancements by addressing valve stiction through a PSO-enhanced backstepping control approach. Unlike traditional methods that may overlook nonlinearities [4], this work leverages the recursive stabilization capabilities of backstepping [6] to systematically design a controller that ensures both stability and performance. By integrating PSO to optimize controller coefficients [16], this study aims to reduce tracking errors and response variability further. As shown in “Fig. 2”, this research highlights the intersection of model-based control, intelligent diagnostics, and optimization, contributing to the leading evolution of valve control technologies.

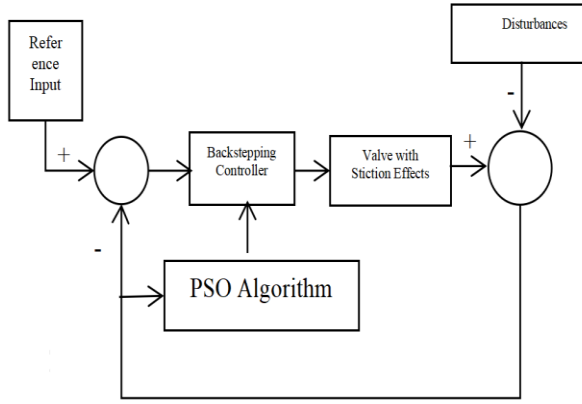


Fig. 2 Proposed control scheme for valve system.

## 2 DYNAMICAL MODEL OF THE SYSTEM

Generally, finding an appropriate model to describe the relationship between system components is of great importance [17-21]. Besides, to achieve a stable state, tracking, and desired transient performance as defined by industrial standards, the nonlinear behaviour of the model can be ignored in the design of the controller for mechanical systems. Friction and abnormal reactions are nonlinear factors that may reduce the control performance of the system. Friction exists in any mechanical system where moving parts are in contact. Stiction due to friction is present on the valve [22]. The dynamic model of the system is presented as follows, which is derived from Newton's second law. The parameters of "Eq. (1)" are introduced in "Table 1":

$$M_s a_s = M_s \ddot{x}_s = \sum F_i = F_a + F_r + F_f + F_p + F_j \quad (1)$$

Table 1 The parameters of the model [5]

Parameter	Description	Unit
$M_s$	Mass	Kg
$a_s$	Acceleration of rotation of the valve	m/s <sup>2</sup>
$x_s$	Valve position	M
$F_a$	Pneumatic force	N
$F_r$	Elastic force	N
$F_f$	Friction force	N
$F_p$	Force due to pressure drop	N
$F_j$	Additional force to close the valve	N

The parameters of "Eq. (1)" are introduced in "Table 1".

$M$  is the mass of the piston, and  $x$  is the position of the piston. In the above expression,  $F_a$  is the pneumatic applied force and is described as  $F_a = A u$ . Besides, the contact area is  $A$ , which is the surface subject to stickiness and input (in the framework of the pressure of the air entering through the piston), and  $u$  denotes

the input.  $F_r$  which is equal to  $-k x_s$  is the spring force, and  $k$  is the spring constant. In addition,  $F_p$  indicates the force arising from the pressure drop in the piston and is equal to  $-\alpha \Delta p$ . In this Equation,  $\alpha$  is the coefficient of imbalance, and  $\Delta p$  is the pressure drop around the piston. Since  $F_p$  is less than the frictional force  $F_f$  and  $F_r$ ,  $F_p$  can be neglected. Besides,  $F_j$  is the additional force which is needed to open the piston, and it can be ignored for this reason. The forces of friction and resistance are specified as  $F_f$  and shown as "Eq. (2)" [22-23].

$$F_{lf}(v) = \begin{cases} a_1 + b_1 v & \text{if } v \in (0 \ v_{msw}] \\ a_2 + b_2 v & \text{if } v \in (v_{msw} \ v_{max}] \\ -a_1 + b_1 v & \text{if } v \in (-v_{msw} \ 0] \\ -a_2 + b_2 v & \text{if } v \in (-v_{max} \ -v_{msw}] \end{cases} \quad (2)$$

If  $b_1 < 0$  and  $b_2 > 0$ , friction can be completely different. If the absolute value of velocity is less than the  $v_{sw}$ , It may create unstable behaviour and then lead to a limit cycle. This model effectively identifies friction and predicts compensation and limit cycles due to friction.  $F_c$ , or Coulomb friction, is constant, while  $F_v$  represents viscous friction,  $F_s$  denotes maximum static friction (stiction), and  $v$  indicates velocity linked to viscous friction. Friction values reveal distinct frictional traits. The friction force versus velocity graph ("Fig. 3") shows that the stiction force must be overcome before valve movement. At zero velocity, with the valve stationary,  $F_s$  and  $F_c$  exhibit specific effects [14]. According to the stated contents, the state space model of the valve is obtained as (3):

$$\begin{bmatrix} \dot{x} \\ \dot{v} \end{bmatrix} = A \begin{bmatrix} x \\ v \end{bmatrix} + B u(t) + K_{nl} \text{sign}(v), \quad (3)$$

$$y = x \quad (4)$$

Where:

$$A = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{F_v}{m} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ \frac{A k}{m} \end{bmatrix}, \quad K_{nl} = \begin{bmatrix} 0 \\ \frac{1}{m} \left( F_c + (F_s - F_c) e^{\left( \frac{x}{v_{sw}} \right)^2} \right) \end{bmatrix} \quad (5)$$

In the above Equations,  $x$  and  $v$  represent the valve's position and velocity, respectively. The matrix  $A$  contains coefficients that describe the system's dynamics; specifically, the first element 0, indicates that the change in velocity is independent of position. The second element  $-\frac{k}{m}$ , represents the effect of the elastic force on the valve's acceleration, based on the spring constant  $K$  and the mass of the valve  $m$ .

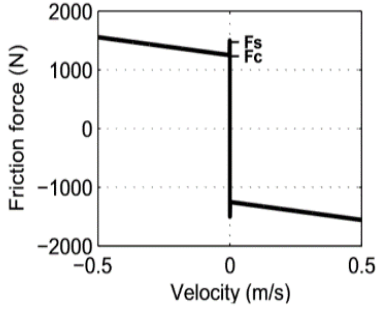


Fig. 3 Friction force based on speed [17].

Additionally, the term  $-\frac{Fv}{m}$  accounts for the influence of the friction force  $F$  on the valve's acceleration. The matrix  $B$  relates the control force to the valve's acceleration, with its second element  $\frac{Ak}{m}$ , demonstrating the effect of the pneumatic force  $A$  on the valve's acceleration. In this system, based on the force applied to the valve  $\tau$ , the valve's movement speed and the stiction amount are different and controllable. Parameters  $m$ ,  $k$ , and  $v_s$  are considered as the valve's parameters. The output  $y$  is regarded as the valve position.

### 3 DESIGN OF THE PROPOSED CONTROLLER

The backstepping method is one of the most widely used nonlinear control design techniques. This method can produce a general asymptotically stabilizing control law for controlling nonlinear and unstable systems. The method used for designing the controller is a nonlinear backstepping method. In this approach, an appropriate Lyapunov function is used at each stage, and then by establishing Lyapunov stability conditions, the control law is derived. In the backstepping method, this process is repeated at each stage until all control inputs are obtained, ensuring that the system's state becomes asymptotically stable [24]. The backstepping method provides a recursive approach to stabilize the origin of a system in strict-feedback form. To describe the system, we present the following Equations.

$$\dot{x} = f_x(x) + g_x(x)z_1 \quad (6)$$

$$\dot{z}_1 = f_1(x, z_1) + g_1(x, z_1)z_1 \quad (7)$$

$$\dot{z}_1 = f_2(x, z_1, z_2) + g_2(x, z_1, z_2)z_1 \quad (8)$$

$$\dot{z}_1 = f_i(x, z_1, z_2, \dots, z_i) + g_i(x, z_1, z_2, \dots, z_i)z_{i+1} \quad (9)$$

$$\dot{z}_k = f_k(x, z_1, z_2, \dots, z_k) + g_k(x, z_1, z_2, \dots, z_k)u \quad (10)$$

In which,

- a)  $x \in R^n$   $n \geq 1$
- b)  $z_1, z_2, \dots, z_i, \dots, z_{k-1}, z_k$  are scalar quantities.
- c)  $u$  is a fence input to the system.
- d)  $f_x, f_1, f_2, \dots, f_i, \dots, f_{k-1}, f_k$  are zero at the origin.
- e)  $g_1, g_2, \dots, g_i, \dots, g_{k-1}, g_k$  are non-zero at the desired domain.

Consider the first subsystem. Assume that this subsystem is stabilized at the origin by a known and specified control  $u(x)$ . It is also assumed that a Lyapunov function  $V_x$  exists for this subsystem, indicating that some other methods stabilize the subsystem  $x$ . The backstepping method extends this stability to  $z$  around it.

In systems that are in this strict-feedback form and have a stable subsystem  $x$ , the following hold:

- The backstepping-designed control input  $u$  has the most stabilizing effect on the state.
- The state  $z_n$  acts as a stabilizing control on the state  $z_{n-1}$ , the state preceding it.
- This process continues until each state  $z_i$  is stabilized by the control  $z_{i+1}$ .

The backstepping approach specifies how to stabilize the subsystem  $x$  using  $z_1$ , and then continues by determining how the next state,  $z_2$ , leads  $z_1$  toward the required control to stabilize  $X$  [24]. Thus, this process progresses from  $x$  outward through the strict-feedback system until the signal control  $u$  is generated using the proposed controller.

In addition, PSO is a meta-heuristic algorithm inspired by the social behaviour of bird flocking and effectively employed to optimize the parameters of various controllers, including the backstepping method [25]. The PSO algorithm was chosen over other methods due to its simplicity, global search capability, computational efficiency, flexibility, and superior ability to globally optimize the nonlinear controller parameters for valve stiction compensation.

In addition, PSO demonstrated faster convergence to optimal parameters (e.g., controller gains) than alternatives like Genetic Algorithms (GA), as it forces velocity updates guided by both personal and global best solutions. By modelling the controller parameters as particles in a search space, PSO iteratively updates these particles based on their fitness values and the positions of other particles [26]. This optimization process excels in finding optimal controller gains, enhancing system performance metrics such as overshoot, settling time, and steady-state error. When coupled with the backstepping control technique, which recursively designs controllers for nonlinear systems,

PSO becomes a powerful tool for achieving robust and high-performance control solutions.

## 4 SIMULATION RESULTS

Given the provided model, the PSO algorithm will be used to optimize the control coefficients in the backstepping control. In addition, to evaluate the control method, a PID control method will also be used, with the objective of analysing and comparing the performance of both control methods in opening and closing the valve, considering the effects of stiction.

### 4.1. PID Control Simulation

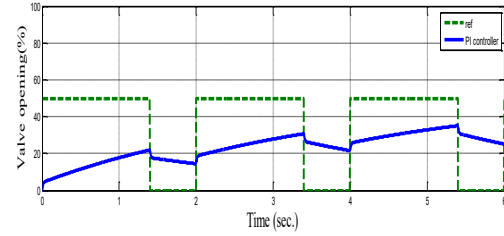
In this paper, the main purpose is to track the desired values for opening and closing the valve while accounting for the effects of stiction. In this simulation, the parameters defined for the valve model and the effects of stiction are specified in “Table 2”. The electromechanical parameters are selected based on several studies, especially [27].

**Table 2** Parameters of the valve model

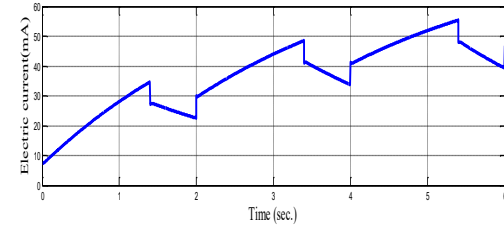
Parameter	Value	Unit
$s_a$	0.06452	$m^2$
$F_s$	1707.7	N
$F_c$	1423	N
$F_y$	612.9	Ns/m
$K_m$	52538	N/m
$V_s$	0.000254	m/s
M	1.361	Pa/mA

For the simulation, the desired trajectory for the valve's opening and closing percentages is defined by pulses with a 50% amplitude, a period of 0.4 seconds, and a duty cycle of 70%. Due to the simple and industrial nature of the PID controller, this section evaluates its performance in opening and closing the valve. The PID controller design method is then described using the Ziegler-Nichols trial-and-error approach.

In a PID controller structure, three gains must be calculated: proportional gain  $K_p$ , integral gain  $K_i$ , and derivative gain  $K_d$ . Historically, the design of such controllers relied on trial and error, requiring significant time and cost as researchers manually adjusted the parameters. The general design procedure using the Ziegler-Nichols method involves starting with small values of  $K_p$  until the output shows oscillatory behaviour. At this point, the oscillation period is denoted as  $T_u$ , and the oscillation gain is denoted as  $K_u$ . Simulation results under the given conditions are presented in “Figs. 4 & 5”, showing the valve's opening percentage and control input.



**Fig. 4** Valve output (percentage of opening) over time when applying a PID controller.



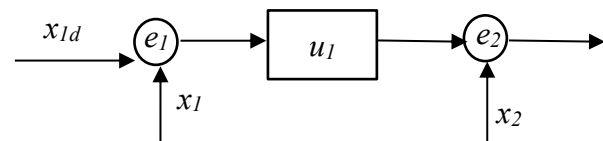
**Fig. 5** Control input generated by the PID controller over time, corresponding to the valve output in Fig. 4.

Based on the obtained results, it is observed that in the valve system, due to the effects of stickiness, the output does not achieve the desired opening percentage. Due to its nonlinear nature, the performance of the PID controller is not evaluated properly. Therefore, the backstepping control approach is designed and compared with the PID controller.

### 4.2. Design Backstepping Controller

Considering the system Equations, a virtual control input for each dynamic is necessary to design a backstepping controller. Given that the system has two dynamics, a two-step process is designed for this control structure for the valve stickiness model. In the dynamical model of the valve system,  $[x_1 \ x_2]^T = [x \ v]^T$ . Now, the control input is designed in the following two steps.

In the first stage of the controller design, the backstepping controller method is initiated by defining the innermost subsystem of the valve dynamics, as illustrated in “Fig. 6”.



**Fig. 6** Schematic diagram of the first step in the backstepping controller design for the mechanical valve system.

In the first step, according to the feedback controller diagram, the error of the first loop is defined as follows:

$$\begin{aligned}
e_1 &= x_1 - x_{1d} \\
\dot{e}_1 &= \dot{x}_1 - \dot{x}_{1d} \\
\dot{e}_1 &= x_2 - \dot{x}_{1d} \\
e_2 &= x_2 - u_1 \\
x_2 &= e_2 + u_1 \\
\dot{e}_1 &= e_2 + u_1 - \dot{x}_{1d} \\
u_1 &= -k_1 e_1 + \dot{x}_{1d} \\
\dot{e}_1 &= e_2 - k_1 e_1 + \dot{x}_{1d} - \dot{x}_{1d} \\
\dot{e}_1 &= e_2 - k_1 e_1
\end{aligned} \tag{11}$$

**Proof 1:** In this section, using the definition of the Lyapunov function of the first step, the derivative relations of the Lyapunov function are obtained. First, the Lyapunov function is considered as a positive function of the first step error:

$$V_1 = \frac{1}{2} e_1^T e_1 \tag{12}$$

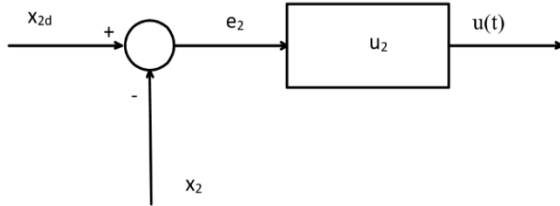
$$\dot{V}_1 = e_1^T \dot{e}_1 = e_1^T (e_2 - k_1 e_1) \tag{13}$$

$$\dot{V}_1 = e_1^T e_2 - e_1^T k_1 e_1 \tag{14}$$

In “Eq. 12”, the changes in  $e_1$  indicate how the control input affects the system's dynamics. In “Eq. 14”, the controller is explicitly defined as a function of previous inputs. This relationship allows us to use the control of prior inputs to stabilize the current state.

Second step: In the second stage of the controller design, the backstepping controller method progresses by addressing the outer subsystem of the valve dynamics, building on the stabilization achieved in the first step, as shown in “Fig. 7”.

$$\begin{aligned}
\dot{x}_2 &= -\frac{k}{m} x_1 - \frac{F_v}{m} x_2 + \frac{1}{m} \left( F_c + (F_s - \right. \\
&\left. F_c) e^{\left(\frac{x}{v_s}\right)^2} \right) \text{sign}(x_2)
\end{aligned} \tag{15}$$



**Fig. 7** Schematic diagram of the second step in the backstepping controller design for the mechanical valve system.

In “Eq. 15”,  $\dot{x}_2$  represents the changes in the velocity of the second dynamic variable of the system. This Equation examines the various effects on the acceleration of the valve. The parameter  $K$  denotes the spring constant, which is related to the elastic force of the system, and  $m$  represents the mass of the valve.

The term  $-\frac{k}{m} x_1$  describes the impact of the elastic force on the acceleration. Additionally,  $-\frac{F_v}{m} x_2$  indicates the effect of the friction force  $F_v$  on the valve's acceleration. The control force is considered as  $\frac{1}{m} \left( F_c + (F_s - F_c) e^{\left(\frac{x}{v_s}\right)^2} \right)$ , where  $F_c$  is the actuation force and  $F_s$  is the stiction force. This Equation provides a precise description of the various influences on the motion of the valve, contributing to a deeper understanding of the system's dynamics.

According to the diagram of the backstepping method, the error of the second step is calculated as follows:

$$e_2 = x_2 - u_1 \rightarrow \dot{e}_2 = \dot{x}_2 - \dot{u}_1 \tag{16}$$

$$\begin{aligned}
\dot{e}_2 &= -\frac{k}{m} (e_1 + x_{1d}) - \frac{F_v}{m} (e_2 + u_1) + \frac{1}{m} \left( F_c + \right. \\
&\left. (F_s - F_c) e^{\left(\frac{x}{v_s}\right)^2} \right) \text{sign}(x_2) + \frac{A k}{m} u - \dot{u}_1
\end{aligned} \tag{17}$$

$$\begin{aligned}
u &= \frac{m}{A k} \left( -k_2 e_2 + \frac{k}{m} x_{1d} + \frac{F_v}{m} u_1 - \frac{1}{m} \left( F_c + \right. \right. \\
&\left. \left. (F_s - F_c) e^{\left(\frac{x}{v_s}\right)^2} \right) \text{sign}(x_2) + \dot{u}_1 \right)
\end{aligned} \tag{18}$$

$$\dot{e}_2 = -k_2 e_2 - \frac{k}{m} e_1 - \frac{F_v}{m} e_2 \tag{19}$$

**Proof 2:** In this step, the function was defined as the following Equations.

$$V = V_1 + V_2, \quad V_2 = \frac{1}{2} e_2^T e_2 \tag{20}$$

$$\dot{V} = \dot{V}_1 + e_2^T \dot{e}_2 \tag{21}$$

$$\dot{V} = \dot{V}_1 + e_2^T \left( -k_2 e_2 - \frac{k}{m} e_1 - \frac{F_v}{m} e_2 \right) \tag{22}$$

$$\begin{aligned}
\dot{V} &= e_1^T e_2 - e_1^T k_1 e_1 - e_2^T k_2 e_2 - e_2^T \frac{F_v}{m} e_2 - \\
&e_2^T \frac{k}{m} e_1
\end{aligned} \tag{23}$$

$$\dot{V} = -e_1^T k_1 e_1 - e_2^T \left( k_2 + \frac{F_v}{m} \right) e_2 + e_1^T e_2 - e_2^T \frac{k}{m} e_1 \tag{24}$$



Considering the following Equations, the stability of the system can be guaranteed by making the derivative of the Lyapunov function negative:

$$-e_1^T k_1 e_1 \leq -(k_1) \|e_1\|^2 \quad (25)$$

$$-e_2^T \left( k_2 + \frac{Fv}{m} \right) e_2 \leq - \left( k_2 + \frac{Fv}{m} \right) \|e_2\|^2 \quad (26)$$

$$e_1^T e_2 \leq \|e_1\| \|e_2\| \leq \frac{1}{2} \|e_1\|^2 + \frac{1}{2} \|e_2\|^2 \quad (27)$$

$$-e_2^T \frac{k}{m} e_1 \leq \frac{1}{2} \frac{k}{m} \|e_2\|^2 + \frac{1}{2} \frac{k}{m} \|e_1\|^2 \quad (28)$$

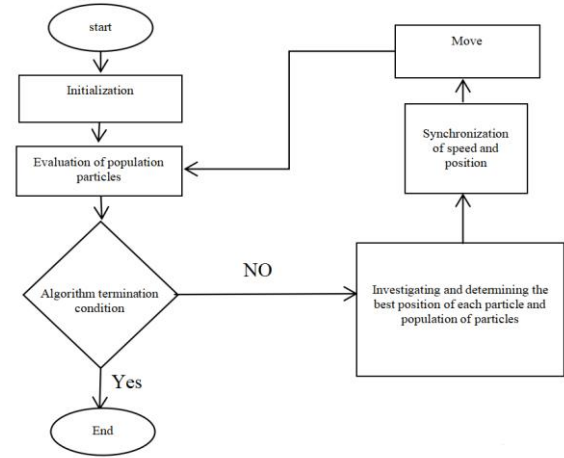
$$\dot{V} \leq -(k_1) \|e_1\|^2 - \left( k_2 + \frac{Fv}{m} \right) \|e_2\|^2 + \frac{1}{2} \|e_1\|^2 + \frac{1}{2} \|e_2\|^2 + \frac{1}{2} \frac{k}{m} \|e_2\|^2 + \frac{1}{2} \frac{k}{m} \|e_1\|^2 \quad (29)$$

$$\dot{V} \leq - \left( k_1 + \frac{1}{2} + \frac{1}{2} \frac{k}{m} \right) \|e_1\|^2 - \left( k_2 + \frac{Fv}{m} \frac{1}{2} + \frac{1}{2} + \frac{k}{m} \right) \|e_2\|^2 \quad (30)$$

According to the obtained results, it is observed that based on Lyapunov stability, the stability of the model is ensured using the backstepping control structure. In this paper, a robust controller design is proposed, where in the first stage, a backstepping controller is used to design the input flow to the valve. The results are as follows. The coefficients of the backstepping controller are determined as positive coefficients as  $[k_1 \ k_2] = [15 \ 80]$  through the backstepping method and using a trial-and-error approach.

#### 4.3. Optimal Backstepping Method with PSO

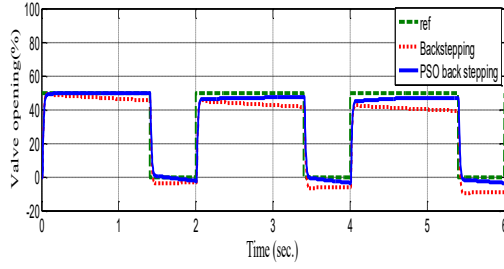
PSO algorithm has successfully solved discrete and continuous nonlinear optimization problems and uses only basic mathematical operators, which leads to good performance in static, noisy, constant, and dynamic environments. Despite its numerous advantages, PSO has limitations and drawbacks that can affect its performance [16], [25]. The flowchart of the PSO algorithm is presented in “Fig. 8”.



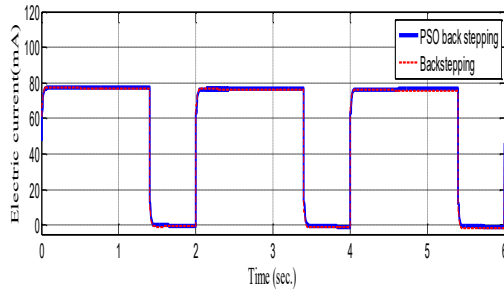
**Fig. 8** Flowchart depicting the structure of the particle swarm optimization (PSO) algorithm used to tune the backstepping controller's coefficients for the mechanical valve system.

In the PSO algorithm, population members are interconnected and solve information exchange, exhibiting high convergence speed. The collective movement of particles is an optimization technique where each particle tries to move toward areas with the best personal and group experiences. PSO is simpler than GA and ant colony optimization, and it requires a smaller population size compared to GA. Therefore, initializing the population in PSO is easier than in other intelligent optimization algorithms. Besides, PSO's stochastic nature ensures it performs well under uncertainty (e.g., variable stiction levels), outperforming deterministic methods like linear programming in handling nonlinear dynamics. To determine the backstepping controller coefficients  $k_1$  and  $k_2$ , the PSO algorithm is utilized, yielding values of 19.8 and 97.7, respectively. Figures 9 and 10 show the system output and control signals with the backstepping and optimized backstepping controller methods. Based on the obtained results for the optimized backstepping method, the desired trajectory for opening and closing the valve has been well followed, and despite consecutive pulses, the error percentage using the backstepping method has decreased. Additionally, the optimized controller tracks the desired trajectory more closely, with reduced oscillations and faster convergence.





**Fig. 9** Valve output (percentage of opening) over time using the standard backstepping controller and the PSO backstepping controller.

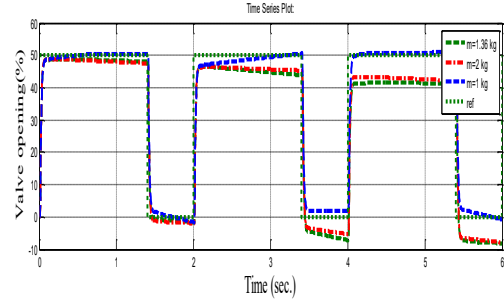


**Fig. 10** Control signal using the backstepping and optimized backstepping approaches.

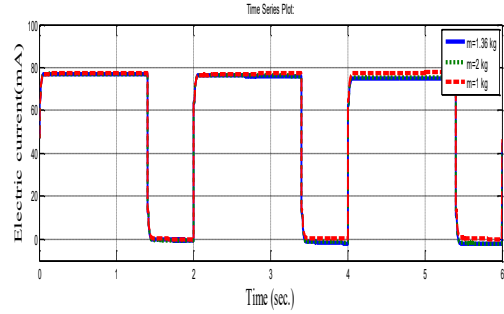
In other words, the optimized backstepping controller reduces the steady-state tracking error to approximately 2% compared to 5% for the standard backstepping controller. Additionally, the overshoot and settling time are minimized in the optimized case to approximately 3% and 0.05 seconds per pulse, respectively, compared to 8% and 0.08 seconds per pulse for the standard backstepping controller. Furthermore, the control signal for the optimized controller is smoother, indicating less aggressive actuation and better handling of stiction nonlinearity (with a 10% reduction in the peak). To evaluate the proposed control performance, the effects of uncertainties on the model will be examined.

#### 4.4. Simulation Considering Uncertainty

In this section, the behaviour of the controller in achieving the desired output is examined against parameter uncertainties in the model, specifically the parameter  $m$ . Different values for  $m$ , including 1 kg, 2 kg, and 1.36 kg, are considered here, and the results of the opening and closing valve using the backstepping and optimized backstepping approaches are demonstrated in “Figs. 11 & 12”, respectively.



**Fig. 11** Valve output using the backstepping algorithms in uncertain conditions for three cases.



**Fig. 12** Valve output using the optimized backstepping algorithms in uncertain conditions for three cases.

As it is clear, despite the uncertainty in the valve model, both controllers have well-controlled the behaviour of the system output in tracking the desired trajectory. For the backstepping controller, the tracking error increases to 8–10% for  $m=2$  kg, compared to 5% under nominal conditions. Additionally, the controller maintains stability but exhibits a 15% degradation in performance.

The optimized backstepping one (the proposed controller) maintains robust performance across all mass variations, with minimal deviation from the desired trajectory. In other words, the tracking error remains below 3% across all mass values, demonstrating high robustness. Settling time stays consistent at  $\sim 0.05$  seconds, with overshoot below 4% even for  $m=2$  kg, and performance degradation is less than 5% under the worst-case uncertainty, highlighting the PSO optimization’s effectiveness.

## 5 CONCLUSIONS

This study successfully developed a nonlinear backstepping control strategy, optimized with the PSO algorithm, to address valve stiction in electromechanical valve systems. The primary objective was to achieve precise valve opening and closing percentages despite stiction-induced nonlinearities. Simulation results demonstrated that the PSO-optimized backstepping controller achieved a steady-state tracking error of 2%, compared to 5% for

the standard backstepping controller, with overshoot reduced to 3% versus 8% and settling time improved to 0.05 seconds from 0.08 seconds. Under parameter uncertainty, such as valve mass variations from 1 to 2 kg, the optimized controller maintained a tracking error below 3%, while the standard controller's error reached 10%. These results highlight the optimized controller's robustness and adaptability, ensuring stable and accurate valve operation across a wide range of operating conditions. The proposed approach provides a reliable solution for improving control performance in critical industrial applications that are affected by valve stiction.

## REFERENCES

- [1] Villeda Hernandez, M., Baker, B. C., Romero, C., Rossiter, J. M., Dicker, M. P. M., and Faul, C. F. J., Chemically Driven Oscillating Soft Pneumatic Actuation, *Soft Robotics*, Vol. 10, No. 6, 2023, pp. 1159–1170, <https://doi.org/10.1089/soro.2022.0168>.
- [2] Arbabi Yazdi, Y., Toossian Shandiz, H., and Gholizadeh Narm, H., Stiction Detection in Control Valves Using a Support Vector Machine with A Generalized Statistical Variable, *ISA transactions*, Vol. 126, 2022, pp. 407–414, <https://doi.org/10.1016/j.isatra.2021.07.020>.
- [3] Mishra, P., Kumar, V., and Rana, K. P. S., A Nonlinear Framework for Stiction Compensation in Ratio Control Loop, *ISA transactions*, Vol. 103, 2020, pp. 319–342, <https://doi.org/10.1016/j.isatra.2020.04.009>.
- [4] Yang, Z., Yang, Q., and Sun, Y., Adaptive Neural Control of Nonaffine Systems with Unknown Control Coefficient and Nonsmooth Actuator Nonlinearities, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 26, No. 8, 2015, pp. 1822–1827, <https://doi.org/10.1109/TNNLS.2014.2354533>.
- [5] Giah, M. M., Naderi, M., Shahdi S. O., and Ehsani, A., A Review of the Robotic Artificial Hand: (Advances, Applications and Challenges), 2024 10th International Conference on Artificial Intelligence and Robotics (QICAR), Qazvin, Islamic Republic of Iran, 2024, pp. 157–163, doi: 10.1109/QICAR61538.2024.10496612.
- [6] Ghadiri, H., Khodadadi, H., Eijei, H., and Ahmadi, M., Pso Based Takagi-Sugeno Fuzzy Pid Controller Design for Speed Control of Permanent Magnet Synchronous Motor, *Facta Univ. Ser. Electron. Energ.*, Vol. 34, No. 2, 2021, pp. 203–217.
- [7] Kumar, A., Lee, S., Stiction-Model-Based Re-Tuning of PI Controller for Industrial Process Control Loops, *Control Engineering Practice*, Vol. 145, 2024, pp. 105865.
- [8] Smith, J., Patel, R., An Improved PI Controller for Stiction Compensation of Control Valves in Process Industry, *Journal of Process Control*, Vol. 130, 2023, pp. 102987.
- [9] Zhang, L., Wu, H., Stiction Parameter Identification for Pneumatic Valves with A Simultaneous Approach, *Mechatronics*, Vol. 90, 2023, pp. 102945.
- [10] Chen, Y., Gupta, M., Control Valve Stiction Detection Using Learning Vector Quantization Neural Network, *IEEE Transactions on Industrial Informatics*, Vol. 20, No. 3, 2024, pp. 1234–1242.
- [11] Oliveira, F., Thompson, D., Experimental and Modeling Investigation on Dynamic Response of Sticky Control Valves, *Industrial & Engineering Chemistry Research*, Vol. 64, No. 5, 2025, pp. 1890–1900.
- [12] Alam, M. S., Al-Bayati, A. H., Identification and Cascade Control of Servo-Pneumatic System Using Particle Swarm Optimization, *Mechatronics*, Vol. 89, 2023, pp. 102934.
- [13] Fang, J., Kong, X., Zhu, X., Nonlinear Model Predictive Control with PSO Optimization for Hydraulic Valve Systems, *Control Engineering Practice*, Vol. 146, 2024, pp. 105873.
- [14] Nagarajan, S., Kayalvizhi, R., Subhashini, P., PSO-Optimized Adaptive Backstepping Control for Industrial Fluid Flow Systems, *Journal of Process Control*, Vol. 132, 2023, pp. 103021.
- [15] Brown, T., Kim, H., A Literature Review of The Design, Modeling, Optimization, And Control of Electro-Mechanical Inlet Valves for Gas Expanders. *Energy Reports*, Vol. 9, 2023, pp. 3456–3468.
- [16] Novin, H. B., Ghadiri, H., Particle Swarm Optimization Base Explicit Model Predictive Controller for Limiting Shaft Torque, 2017 5th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS), Qazvin, Iran, 2017, pp. 35–40, doi: 10.1109/CFIS.2017.8003593.
- [17] Khodadadi, H., Sedigh, A. K., Ataei, M., and et al, Nonlinear Analysis of the Contour Boundary Irregularity of Skin Lesion Using Lyapunov Exponent and K-S Entropy, *Journal of Medical Biology Engineering*, Vol. 37, 2017, pp. 409–419.
- [18] Ghadiri, H., Mohammadi, A., Khodadadi, H., Fast Terminal Sliding Mode Control Based on SDRE Observer for Two-Axis Gimbal with External Disturbances, *J. Braz. Soc. Mech. Sci. Eng.* 44, No. 2, 2022, pp. 70.
- [19] Ghadiri, H., Khodadadi, H., Mobayen, S., Asad, J. H., Rojsiraphisal, T., and Chang, A., Observer-Based Robust Control Method for Switched Neutral Systems in the Presence of Interval Time-Varying Delays, *Mathematics*, Vol. 9, No. 19, pp. 2473.
- [20] Ghadiri, H., Khodadadi, H., Hazareh, G. A., Finite-Time Integral Fast Terminal Sliding Mode Control for Uncertain Quadrotor UAV Based on State-Dependent Riccati Equation Observer Subjected to Disturbances,” *Journal of Vibration and Control*, Vol. 30, No. 11-12, 2024, pp. 2528–2548.
- [21] Khodadadi, H., Khaki-Sedigh, A., Ataei, M., and Jahed-Motlagh, M. R., Applying a Modified Version of Lyapunov Exponent for Cancer Diagnosis in Biomedical Images: The Case of Breast Mammograms,

- Multidimensional Systems and Signal Processing, Vol. 29, 2018, pp. 19-33.
- [22] Rostalski, P., Besselmann, T., Barić, M., Belzen, F. V., and Morari, M., A Hybrid Approach to Modelling, Control and State Estimation of Mechanical Systems with Backlash, *International Journal of Control*, Vol. 80, No. 11, 2007, pp. 1729–1740.
- [23] Lv, C., Liu, Y., Hu, X., Guo, H., and et. Al, Simultaneous Observation of Hybrid States for Cyber-Physical Systems: A Case Study of Electric Vehicle Powertrain, *IEEE Transactions on Cybernetics*, Vol. 48, No. 8, 2018, pp. 22357–2367.
- [24] Liu, W., Duan, G., Hou, M., and Kong, H., Robust Adaptive Control of High-Order Fully-Actuated Systems: Command Filtered Backstepping with Concurrent Learning, *IEEE Transactions on Circuits and Systems I*, 2024.
- [25] Samani, R., Khodadadi, H., A Particle Swarm Optimization Approach for Sliding Mode Control of Electromechanical Valve Actuator in Camless Internal Combustion Engines, 2017 IEEE International Conference on Environment (EEEIC / I&CPS Europe), 2017, pp. 1-4.
- [26] Ahmadpour, M. R., Ghadiri, H., & Hajian, S. R., Model Predictive Control Optimisation Using the Metaheuristic Optimisation for Blood Pressure Control, *IET Systems Biology*, Vol. 15, No. 2, 2021, pp. 41–52.
- [27] Sivagamasundari, S., Sivakumar, D., A Practical Modelling Approach for Stiction in Control Valves, *Procedia Engineering*, Vol. 38, 2012, pp. 3308-3317.