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Active Disturbance-Rejection Controller (ADRC)-Based Torque Control for a Pneumatic Rotary Actuator with Positional Interference

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Abstract: The compressibility of air, the uncertainty of dynamic models, and the existence of friction make pneumatic servo systems exhibit strong nonlinearity. Furthermore, the confluence of pneumatic-system nonlinearity and interference from the position system induces oscillations within the system, thereby posing a formidable challenge for achieving precise torque control. This study ensures precise torque control in a pneumatic actuator amid interference from the position system and proposes a novel active disturbance-rejection controller integrated with a Kalman filter. Firstly, in response to the oscillation stemming from the inherent nonlinearity of the pneumatic system and interference from the position system, this paper designs an active disturbance-rejection controller (ADRC) with robust anti-interference capabilities aimed at mitigating system oscillations. Secondly, to address the issue of sensor noise interfering with the ADRC and causing system oscillation, a first-order Kalman filter is designed to provide real-time and more accurate state estimation, effectively reducing oscillations and improving the robustness of the system. Finally, using the Lyapunov stability theory, the effectiveness of both the nonlinear extended observer and the convergence of the nonlinear error-state controller in the ADRC is proven. Experimental results indicate that the proposed controller reduces system oscillations and improves control accuracy.



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Keywords: Kalman filter; torque control; active disturbance-rejection control; oscillation; pneumatic rotary actuator

1. Introduction

Pneumatic rotary actuators are extensively employed in robotics, medicine, polishing, and other relevant fields [1–3] owing to their advantages, such as low cost, cleanliness, and uncomplicated design [4,5]. The precise control of torque in pneumatic rotary actuators is a vital concern in pneumatic servo systems [6]. However, the presence of external disturbance, the compressibility of air, the uncertain dynamic model, and friction render the pneumatic servo system a highly nonlinear system [7,8]. The external disturbance and the nonlinearity in the pneumatic system pose significant challenges to achieving accurate control of torque. Researchers have implemented various control strategies to enhance the control performance of pneumatic-torque servo systems. Sliding-mode controllers are employed for precise force control of the cylinders, using cost functions to counteract the nonlinearity of the systems and disturbances from uncertain models [9,10]. However, they require relatively accurate models and are prone to oscillations on the sliding-mode surfaces. Moreover, backstepping control technology is utilized for controller design and analysis, compensating for the nonlinearity, uncertainty, and external disturbances of the pneumatic system by estimating the inverse model of the system to achieve improved control performance [11,12]. However, it demands a high level of model accuracy. Additionally, adaptive control strategies are applied to force control in pneumatic servo systems,

achieving parameter adaptation to address model uncertainty and friction issues [13,14]. However, these strategies require precise models, and measurement errors and sensor noise can lead to parameter estimation errors. Most of the above methods are based on accurate models, but due to the time-varying characteristics of pneumatic servo systems, obtaining precise models is challenging.

Therefore, some scholars have adopted non-model-based digital control strategies. The improved fuzzy PID controller is applied to constant-force polishing, utilizing a fuzzy-logic strategy to approximate the nonlinearity of the pneumatic system. Moreover, the fuzzy PID strategy, not which does not rely on a model, addresses the issue of model uncertainty [15,16]. An intelligent PID controller, generated through the combination of the Fictitious Reference Iterative Tuning method and the Model-Free Adaptive Control method, avoids the difficulty of obtaining precise models through a data-driven approach [17]. However, the improved PID control strategy mentioned above still requires enhancement in terms of robustness. A novel non-model-based adaptive control, employing a data-driven approach, eliminates the need for process modeling [18]. However, its robustness in the presence of strong external disturbances requires improvement. The aforementioned data-driven control strategy addresses the challenge of obtaining models, but its robustness needs improvement when facing strong external disturbances. Therefore, to address disturbances from external position systems and friction, the system also needs to have strong robustness. This paper proposes an active disturbance-rejection controller integrated with a Kalman filter (ADRCKF) that is not model-based and has strong anti-interference capability.

As a typical data-driven controller, the active disturbance-rejection control technique has become increasingly popular in various fields, such as in satellite cameras [19] and amphibious multi-rotor drones [20], owing to its reduced dependence on precise models and strong disturbance-rejection capability [21]. In practical engineering applications, obtaining precise models is not always feasible. The effectiveness of the active disturbance-rejection controller (ADRC), which does not rely on precise models and boasts robust anti-disturbance capabilities, is credited to the use of an extended observer. The extended-state observer (ESO) is not dependent on a specified model of the observed object and can estimate and compensate for the inner nonlinear part of the system and external disturbance in real time [22]. Extended-state observers can be categorized as linear extended observers and nonlinear extended observers. The linear extended observer is relatively simpler to design, and its parameters are more convenient to adjust compared with a nonlinear extended observer. However, a nonlinear extended-state observer offers better performance for complex nonlinear systems [23]. Thus, this paper proposes a nonlinear ESO for real-time observation of friction in the pneumatic rotary actuator as well as of disturbances from air compressibility and the position system in a complex pneumatic system. It expands these disturbances into a total disturbance for compensation. Although the ADRC demonstrates effective performance in dealing with the complex nonlinearity and external disturbances in pneumatic systems, it also has certain limitations. The ADRC demands a high level of purity in the feedback signal, and the presence of noise can impact its control performance, leading to system oscillations [24]. Therefore, this paper designs a Kalman filter for real-time state estimation to enhance the purity of the feedback signal and improve the performance of the ADRC. The Kalman filter is a recursive filter that continuously updates estimates in real time amidst measurement errors and system noise [25]. Integrating a Kalman filter into an ADRC enables accurate state estimation in the presence of system noise and measurement errors, thereby improving control accuracy and stability. Studying the theory and practice of this field holds great significance as it serves as a source of inspiration for further research work.

This paper presents improvements to the active disturbance-rejection controller by introducing an integrated Kalman-filter-based active disturbance-rejection controller. The objective is to suppress system oscillations in the presence of external position disturbances, ensuring precise control of the aerodynamic torque system. Due to the interference of the position system with the torque system, oscillations occur in the torque system. The torque

sensor is connected to both the torque and position systems, and when the torque system oscillates, the torque sensor vibrates as well. Mechanical vibrations can introduce noise into the torque sensor, and the active disturbance-rejection controller is susceptible to the influence of sensor noise, leading to the drawback of oscillations [23].

This paper integrates a Kalman filter into the active disturbance-rejection controller for real-time filtering and state estimation, effectively mitigating system oscillations and improving system accuracy. In comparison with the standard active disturbance-rejection controller, the integrated Kalman-filter-based active disturbance-rejection controller demonstrates a 34% improvement in control accuracy during a sinusoidal-torque tracking experiment with a frequency of 0.5 Hz.

The main contributions of this article are summarized as follows:

- (1) An active disturbance-rejection torque controller integrated with a Kalman filter is presented.
- (2) The control accuracy of the pneumatic servo system can be greatly enhanced by the NLESO, which estimates and compensates for external disturbances and nonlinearity.
- (3) The Kalman filter is designed to perform real-time filtering, effectively addressing sensor-generated noise and reducing system oscillations; thus, the control precise of the system is advanced.

2. Materials and Methods

2.1. System Structure

The control diagram of the pneumatic-torque servo system based on positional interference is illustrated in Figure 1.

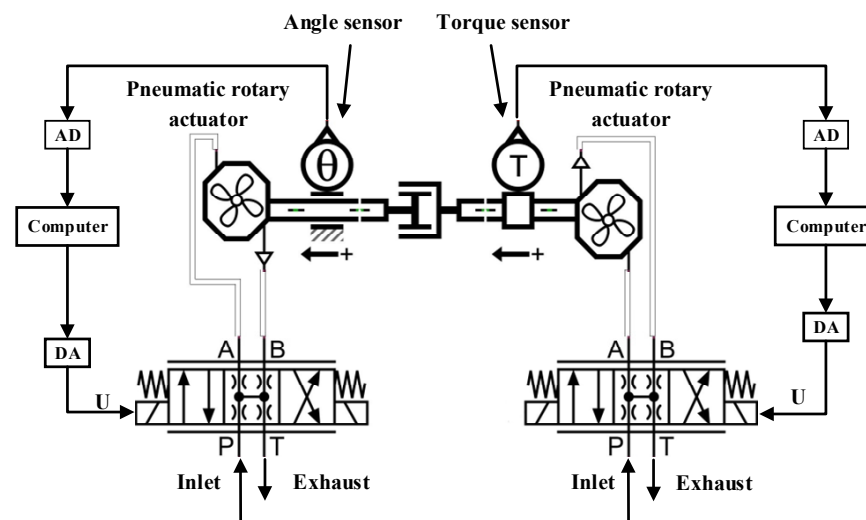


Figure 1. Control diagram of the pneumatic-torque servo system based on positional interference.

The principle of the structure of the torque control experiment is as follows:

The controller of a computer issues control commands, and through the DA card, it generates a voltage-signal input to the pneumatic servo valve that controls the opening area of the valve. This achieves the adjustment of the gas flow to the pneumatic rotary actuator, controlling the output torque of the pneumatic rotary actuator. The AD card converts the torque signal collected by the torque sensor into a digital quantity input to the computer. The controller of the computer, based on the collected torque signal and the desired signal, performs subtraction and further calculations to achieve closed-loop feedback control. The control principles on the left for the position system and on the right for the torque system are similar.

The execution device comprises two pneumatic rotary actuators (Festo, Esslingen, Germany, DRVS-40-180-P). This system is also equipped with an angle encoder (OMRON-

E6C3-A), a torque sensor (QLN-10 (10–100 Nm)), and two proportional valves (Festo, MPYE-5-1/4-010-B). In addition to these devices, there is also an industrial computer (Advantech, Taiwan, China, 510H), two data-acquisition cards (Advantech, PCI-1716, and PCI-1784), and a D/A card (Advantech, PCI-1723). The parameters of the system are shown in Table 1.

Table 1. Parameters of the system.

Parameter Name	Parameter Value
Valve frequency	80 Hz
Valve working pressure	0–1 MPa
Valve flow rate	1400 L/min
Valve control voltage (u_1)	0–10 V
Valve nominal diameter	8 mm
Valve dead-zone voltage	4.9–5.1 V
Flow coefficient (C_1)	0.142
Adiabatic index of air (k)	1.4
Effective cross-sectional area of the orifice (A_u)	0.00502 m ²
Angular displacement (D_m)	0–180 degrees
Working pressure (p_c)	0.2–0.8 MPa
Ideal gas constant (R)	287
Internal volume (V)	0.00275 m ³

2.2. Dynamic Model

To simplify the mathematical model appropriately, the following assumptions have been made [8]:

- (1) The gas in the system follows the ideal gas equation of state.
- (2) The flow of gas is assumed to be an isentropic process.
- (3) There is no effect of piping on air-pressure transfer.
- (4) The gas temperature remains constant during the flow.
- (5) The actuator and the outside world, as well as between the two chambers, have no leakage.

To simplify the modeling complexity, the valve is approximated by a first-order model as presented below:

$$\dot{A}_u = -k_1 A_u + k_2 u_1 \quad (1)$$

where k_1 and k_2 are coefficients to be determined. A_u is the effective cross-sectional area of the proportional servo valve orifice, while u_1 is the control variable.

The gas-flow equation through the valve port can be obtained from the above assumptions as follows:

$$\dot{m} = C_1 A_u \frac{P_u}{\sqrt{T}} \varphi(P_u, P_d) \quad (2)$$

$$\varphi(p_u, p_d) = \begin{cases} \sqrt{\frac{k}{R} \left(\frac{2}{k+1} \right)^{\frac{k+1}{k-1}}} & , \frac{p_d}{p_u} \leq 0.5283 \\ \sqrt{\frac{2k}{(k-1)} \frac{1}{R} \left[\left(\frac{p_d}{p_u} \right)^{\frac{2}{k}} - \left(\frac{p_d}{p_u} \right)^{\frac{k+1}{k}} \right]} & , \frac{p_d}{p_u} > 0.5283 \end{cases} \quad (3)$$

where φ is the flow function of gas passing through a small hole, and $\dot{m}$ is the mass-flow rate passing through the valve. C_1 , k , and T are the flow coefficient, diatomic index of the gas, and gas temperature, respectively. P_1 and P_2 are the pressures of the inflowing and outflowing gas, respectively.

The expression for the ideal gas-state equation is as follows:

$$p = \rho RT \quad (4)$$

Differentiating both sides of Equation (4):

$$\dot{p} = \dot{\rho} RT \quad (5)$$

where p is the gas pressure, ρ is the gas density, R is the ideal gas constant, and T is the temperature.

The mass-flow equation is as follows:

$$\dot{m} = \frac{d}{dt}(\rho V) \quad (6)$$

$$\dot{m}_{in} - \dot{m}_{out} = \dot{\rho} V + \rho \dot{V} \quad (7)$$

where $\dot{m}_{in}$ and $\dot{m}_{out}$ represent the mass-flow rates into and out of the pneumatic rotary actuator, respectively.

$$\dot{\rho} = \frac{\dot{m}_{in} - \dot{m}_{out}}{V} - \frac{\rho \dot{V}}{V} \quad (8)$$

Substituting Equation (8) into Equation (5) yields the pressure-differential equation inside the pneumatic rotary actuator:

$$\dot{p}_c = \frac{RT}{V_c}(\dot{m}_{in} - \dot{m}_{out}) - \frac{p_c \dot{V}_c}{V_c} \quad (9)$$

where V_c and p_c represent the total volume and internal pressure of the pneumatic rotary actuator, respectively.

$$\dot{p}_c = \frac{RT}{V_0 + A_c \theta_c} C_1 A_u \frac{P_u}{\sqrt{T}} \varphi(P_u, P_d) - \frac{p_c A_c \dot{\theta}_c}{V_0 + A_c \theta_c} \quad (10)$$

where A_c is the effective area of the fan blade, and V_0 and θ_c are the ineffective volume and rotation angle.

$$T_c = p_c D_m \quad (11)$$

$$\dot{T}_c = \frac{RT}{V_0 + A_c \theta_c} C_1 A_u D_m \frac{P_u}{\sqrt{T}} \varphi(P_u, P_d) - \frac{F_c A_c \dot{\theta}_c}{V_0 + A_c \theta_c} \quad (12)$$

where T_c is the system output torque, and D_m is the displacement of the pneumatic rotary actuator, respectively.

The simplified second-order model of the torque control system is as follows:

$$\begin{cases} \dot{A}_u = -k_A A_u + k_B u_1 \\ \dot{T}_c = \frac{RT}{V_0 + A_c \theta_c} C_1 A_u D_m \frac{P_u}{\sqrt{T}} \varphi(P_u, P_d) - \frac{F_c A_c \dot{\theta}_c}{V_0 + A_c \theta_c} \end{cases} \quad (13)$$

Differentiating T_c and transforming Equation (4) into a normalized form of the equation of state:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = a_0 + a_1 x_1 + a_2 x_2 + b_1 u \\ y = x_1 \end{cases} \quad (14)$$

where x_1 and y denote torque, while x_2 represents the derivative of the torque.

$$\text{Let } f(x_1, x_2) = a_0 + a_1 x_1 + a_2 x_2$$

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(x_1, x_2) + b_1 u_1 \\ y = x_1 \end{cases} \quad (15)$$

where b_1 is a gain variable adjusted based on the system inertia to compensate for the system total nonlinearity, u_1 is the control voltage generated by the controller, $f(x_1, x_2)$ is the total nonlinearity of the pneumatic-torque servo system, and $f(0, 0) = 0$.

2.3. Design of an Active Disturbance-Rejection Controller Integrated with a Kalman Filter

This paper presents an active disturbance-rejection torque controller integrated with a Kalman filter (ADRCKF) to enhance the torque control precision of a pneumatic rotary actuator. The algorithm diagram of the ADRCKF is presented in Figure 2.

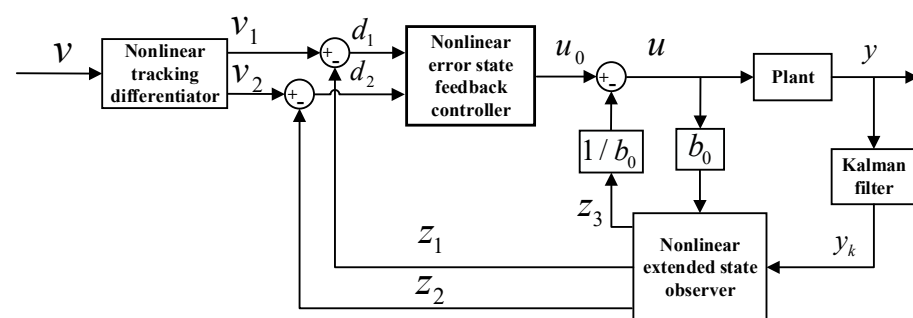


Figure 2. Algorithm diagram of the active disturbance-rejection torque controller integrated with a Kalman filter.

The algorithm in Figure 2 is explained as follows: The feedback value y is transmitted to a Kalman filter to generate the signal y_k . y_k , along with the control input u multiplied by the gain b_0 , is input into the nonlinear extended-state observer to generate the observed value z_1 of y , as well as the first derivative z_2 and the second derivative z_3 of the observed value z_1 . The desired signal v is conveyed to a nonlinear tracking differentiator to generate the transitional signal v_1 of the desired signal and its derivative v_2 . d_1 is obtained by taking the difference between v_1 and z_1 , and d_2 is obtained by taking the difference between v_2 and z_2 . d_1 and d_2 are input into the nonlinear error-state feedback controller to generate the control signal u_0 . The final control signal u is obtained by subtracting the nonlinear compensation term z_3/b_0 from u_0 , and u is passed to the control object to produce the output y .

2.3.1. Kalman Filter

The Kalman filter is a powerful tool for estimating system states and has gained widespread popularity across different domains, mainly due to its ability to accurately estimate system states even in the presence of uncertainties and noise. The Kalman filter is proposed to perform real-time filtering of signals fed back to the nonlinear extended-state observer (ESO), improving the observation accuracy of the ESO and effectively suppressing the chatter caused by noise signals.

For discrete systems:

$$\begin{aligned} x(n) &= Ax(n-1) + Bu(n) + w(n) \\ y(n) &= Hx(n) + v(n) \end{aligned} \quad (16)$$

where $w(n)$ represents the process noise signal, and $v(n)$ represents the measurement noise signal.

The discrete formula of the first-order Kalman filter recursive algorithm is presented below:

$$K_k(n) = \frac{P(n)}{P(n) + R} \quad (17)$$

$$P(n) = P(n-1) + Q \quad (18)$$

$$P(n) = (1 - HK_k(n))P(n) \quad (19)$$

$$x(n) = Ax(n-1) + K_k(n)(y_v(n) - HAx(n-1)) \quad (20)$$

$$y_k(n) = Cx(n) \quad (21)$$

The estimation error is characterized by the following covariance:

$$errcov(n) = HP(n)H^T \quad (22)$$

The parameters A , B , C , Q , and R are all variables that can be adjusted to achieve the desired filtering behavior. For instance, the balance between the influence of process noise and measurement noise on the filter is determined by the values of the covariance matrices Q and R ; these, therefore, influence the ability of the filter to accurately estimate the system state. Similarly, the parameters A , B , and C affect the propagation of the state estimate over time and, therefore, the response of the filter to changes in the system dynamics. By properly adjusting these parameters, the Kalman filter can be optimized for a particular system and improve its accuracy and efficiency. In this paper, $A = 1$, $B = 1$, $H = 1$, $Q = 0.01$, $R = 11$, $C = 1$.

2.3.2. Nonlinear Tracking Differentiator

The purpose of designing the nonlinear tracking differentiator (TD) in this article is to arrange the transition process and generate a smooth and continuous signal of the input signal and its differential signal. The nonlinear function $f_{hst}(\cdot)$ is proposed for filtering and fast-tracking. Let $\lambda = v_1 - v$; then, a second-order TD is designed as follows:

$$\begin{cases} \dot{v}_1(n) = v_2(n) \\ \dot{v}_2(n) = hf_{hst}(\lambda, v_2, r, h_0) \end{cases} \quad (23)$$

where λ is an error between a transition signal and a desired input signal. v , v_1 , and v_2 represent the desired input signals, the smoothed transition signal of the input signal v , and the derivative signal of the transition signal v_1 , respectively. The expression for the $f_{hst}(\lambda, v_2, r, h_0)$ function is as follows:

$$f_{hst}(\lambda, v_2, r, h_0) = \begin{cases} -r \operatorname{sign}(a) & |a| > d \\ -ra/d & |a| \leq d \end{cases} \quad (24)$$

where $d = rh$, $\varepsilon = hd$, $\phi = v_1 + hv_2$, $\phi = \sqrt{d^2 + 8r|\phi|}$.

$$a = \begin{cases} v_2 + \frac{(\phi-d)}{2} \operatorname{sign}(\phi) & |\phi| > \varepsilon \\ v_2 + \phi/h & |\phi| \leq \varepsilon \end{cases} \quad (25)$$

where the parameters r , h and h_0 are all positive real numbers, r represents the filtering factor, and h represents the sampling step. The response speed of the transient process is able to be adjusted by modifying the value of r . In practice, the adopted step size h_0 is set larger than h to prevent overshooting.

2.3.3. Nonlinear Extended-State Observer

To address dynamic external disturbances and internal nonlinearity, a nonlinear extended-state observer (ESO) is introduced to perform real-time estimation of the internal nonlinearity and dynamic external disturbances within the torque system and to expand them into total nonlinearity for real-time compensation. The total nonlinearity is expanded into a new state variable x_3 ; $f(x_1, x_2) = x_3$. The pneumatic-torque servo control system (15) is extended as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 + bu_1 \\ \dot{x}_3 = \omega(n) \end{cases} \quad (26)$$

where $\omega(n)$ is the derivative of x_3 . In practice, $\omega(n)$ is delimited. Defining $e_k = z_k - x_k$ and $k = 1, 2, 3$, the expression for the second-order ESO is as follows:

$$\begin{cases} \dot{z}_1 = z_2 - \beta_1 e_1 \\ \dot{z}_2 = z_3 - \beta_2 fal(e_1, \sigma_1, \delta) + b_1 u_1 \\ \dot{z}_3 = -\beta_3 fal(e_1, \sigma_2, \delta) \end{cases} \quad (27)$$

where z_k is the observed value of x_k for $k = 1, 2, 3$. In addition, the performance of the ESO can be adjusted by tuning the three gains β_1 , β_2 , and β_3 . The nonlinear function $fal(\cdot)$ is proposed to reduce signal oscillation. The nonlinear function $fal(e, \sigma, \delta)$ is given by the following expression:

$$fal(e, \sigma, \delta) = \begin{cases} e/\delta^{1-\sigma}, & |e| \leq \delta \\ |e|^\delta sign(e), & |e| > \delta \end{cases} \quad (28)$$

where σ and δ are two given positive parameters, and e is the error value. The parameter σ is a value constrained within a specified range: $\sigma \in (0, 1)$. Parameter δ is the sampling step-size of the function, and tuning both σ and δ adjusts the performance of the function.

Remark 1. The saturation function $fal(\cdot)$ is a monotonically smooth, continuously increasing odd function. However, it is not smooth and not differentiable at $e = \pm\delta$.

According to Formulas (26) and (27), the error equations of ESO are as follows:

$$\begin{cases} \dot{e}_1 = e_2 - \beta_1 e_1 \\ \dot{e}_2 = e_3 - \beta_2 fal(\sigma_1) + b_1 u_1 \\ \dot{e}_3 = -\beta_3 fal(\sigma_2) - \omega(n) \end{cases} \quad (29)$$

where $fal(\sigma_k) = fal(e_1, \sigma_k, \delta)$; $k = 1, 2$.

The self-stabilizing region method has been employed to prove the convergence of the system (29), as in [26–28]. However, this method is considered too intricate. In this paper, the Lyapunov function is proposed to demonstrate the convergence of the ESO.

Theorem 1. If Lyapunov-like lemma

- (1) $V(0) = 0$
- (2) $V(t) > 0 \quad t > 0$
- (3) $\dot{V}(t) \leq 0 \quad t > 0$

then $\lim_{t \rightarrow \infty} V(t) = 0$.

Proof. The design of the Lyapunov function is as follows:

$$\begin{aligned}
 V_k(t) &= V_1(t) + V_2(t) + V_3(t) \\
 V_1(t) &= \frac{1}{2}e_1^2, V_2(t) = \frac{1}{2}e_2^2, V_3(t) = \frac{1}{2}e_3^2 \\
 V_k(t) &= \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 + \frac{1}{2}e_3^2 \\
 \dot{V}_k(t) &= e_1\dot{e}_1 + e_2\dot{e}_2 + e_3\dot{e}_3 \\
 &= e_1(e_2 - \beta_1 e_1) + e_2(e_3 - \beta_2 fal(\sigma_1)) \\
 &\quad + e_3(-\beta_3 fal(\sigma_2) - \omega(n))
 \end{aligned}$$

where $\omega(n)$ is delimited in practice, such as in [29–31]. There exist parameters β_1 , β_2 , and β_3 that are sufficiently large to satisfy $\dot{V}_k(t) \leq 0$. The effectiveness of the ESO has been demonstrated, leading to the convergence of the observed values of z_1 , z_2 , and z_3 to x_1 , x_2 , and x_3 , respectively.

When $e = \pm\delta$, the derivative of the function $fal(e, \sigma, \delta)$ does not exist. This is because when $|e| = \delta$, the left and right derivatives are not equal, but both its left and right derivatives exist and are bounded. Therefore, when $|e| \leq \delta$, the derivation is based on $fal(e, \sigma, \delta) = e/\delta^{1-\sigma}$, and when $|e| > \delta$, the derivation is based on $fal(e, \sigma, \delta) = |e|^\delta sign(e)$, which still satisfies the above analysis of $\dot{V}_k(t)$. $\square$

2.3.4. Nonlinear Error-State Feedback Controller

The following equations define the error signals between a tracking differentiator and an extended-state observer:

$$\begin{cases} d_1 = v_1 - z_1 \\ d_2 = v_2 - z_2 \end{cases} \quad (30)$$

where v_1 and v_2 represent the torque and its differential signal, respectively, while z_1 and z_2 denote the corresponding observation output signals.

The controlled variable u of the following is the formulation of the nonlinear error-state feedback controller (NLEF):

$$u_2 = \alpha_1 fal(d_1, \sigma_3, \delta) + \alpha_2 fal(d_2, \sigma_4, \delta) \quad (31)$$

$$u_1 = u_2 - z_3/b_1 \quad (32)$$

where α_1 and α_2 are two control gains, while z_3/b_1 represents the compensation for the system (15) nonlinearity.

The errors between the input and output signals are as follows:

$$\begin{cases} g_1 = v_1 - x_1 \\ g_2 = v_2 - x_2. \end{cases} \quad (33)$$

By incorporating system (15) into system (33), the error system is redefined:

$$\begin{cases} \dot{g}_1 = g_2 \\ \dot{g}_2 = v_3 - f(x_1, x_2) - b_1 u_1 \end{cases} \quad (34)$$

where v_3 denotes the derivative of v_2 , which is both continuous and delimited.

By combining Equations (30) and (33), we obtain:

$$\begin{cases} d_1 = g_1 - e_1 \\ d_2 = g_2 - e_2. \end{cases} \quad (35)$$

To simplify the expression, we denote $fal(d_1, \sigma_3, \delta)$ as $fal(d_1)$ and $fal(d_2, \sigma_3, \delta)$ as $fal(d_2)$. Furthermore, by using Equations (26) and (34), we have:

$$\begin{aligned}\dot{g}_2 &= v_3 - b_1\alpha_1 fal(g_1 - e_1) - b_1\alpha_2 fal(g_2 - e_2) + e_3 \\ e_3 &= z_3 - f(x_1, x_2).\end{aligned}\quad (36)$$

Theorem 2. By selecting appropriate gain variables α_1 and α_2 , the nonlinear error-state feedback controller (32) is stable and convergent, and the error system (34) is also convergent, resulting in the convergence of the output signals x_1 and x_2 to v_1 and v_2 , respectively.

In [32], examples of stability analysis for data-driven controllers are presented. This study employs the Lyapunov stability theory for the stability analysis of the controller.

Proof. Let the Lyapunov function be designed as:

$$V = \frac{1}{2}(g_1 - e_1)^2 + \frac{1}{2}(g_2 - e_2)^2 + (g_1 - e_1)(g_2 - e_2).$$

The derivative of V is given by:

$$\begin{aligned}\dot{V} &= (g_1 - e_1)(g_2 - e_2) + \beta_1 e_1(g_1 - e_1) \\ &\quad + (g_1 - e_1 + g_2 - e_2)(v_3 + \beta_2 fal(\sigma_1)) + (g_2 - e_2)^2 + \beta_1 e_1(g_2 - e_2) \\ &\quad - (g_1 - e_1 + g_2 - e_2)(b_1\alpha_1 fal(g_1 - e_1) + b_1\alpha_2 fal(g_2 - e_2)).\end{aligned}$$

Setting

$$\psi(g_1 - e_1, g_2 - e_2) = (g_1 - e_1 + g_2 - e_2)(fal(g_1 - e_1) + fal(g_2 - e_2)), \quad (37)$$

We have

$$\begin{aligned}\dot{V} &= -b_1\alpha_1\psi(g_1 - e_1, g_2 - e_2) - b_1\alpha_2\psi(g_1 - e_1, g_2 - e_2) \\ &\quad - \beta_1 e_1^2 + \beta_1 e_1 g_1 + (g_2 - e_2)^2 \\ &\quad + (g_1 - e_1)(g_2 - e_2) + \beta_1 e_1(g_2 - e_2) \\ &\quad + (g_1 - e_1 + g_2 - e_2)(v_3 + \beta_2 fal(\sigma_1)).\end{aligned}$$

From (35), we have

$$\psi(g_1 - e_1, g_2 - e_2) = \psi(d_1, d_2) = (d_1 + d_2)(fal(d_1) + fal(d_2)). \quad (38)$$

$fal(\cdot)$ is an odd function and monotonically increasing. To simplify the analysis, let $\delta_1 = \delta_2$. The analysis is then as follows:

- (1) If $(d_1 + d_2) > 0$, then $(fal(d_1) + fal(d_2)) > 0$.
- (2) If $(d_1 + d_2) \leq 0$, then $(fal(d_1) + fal(d_2)) \leq 0$.

Therefore, the conclusion is as follows:

$$(d_1 + d_2)(fal(d_1) + fal(d_2)) \geq 0. \quad (39)$$

The boundedness of e_1 , e_2 , and e_3 is guaranteed by the proven convergence of the ESO. Additionally, v_3 , d_1 , and d_2 are also bounded.

Letting

$$\dot{M} = \beta_1 e_1 g_1 + d_2^2 + d_1 d_2 + \beta_1 e_1 d_2 + (d_1 + d_2)(v_3 + \beta_2 f_1); \quad (40)$$

obviously, H is also bounded.

$$\dot{V} = -b_1\alpha_1\psi(g_1 - e_1, g_2 - e_2) - b_1\alpha_2\psi(g_1 - e_1, g_2 - e_2) - \beta_1e_1^2 + \dot{M}. \quad (41)$$

There exist sufficiently large values of α_1 and α_2 such that there exists a region where $\dot{V} < 0$ holds. According to the proof provided above, it can be inferred that the stability of the closed-loop system (34) can be guaranteed by judicious selection of the parameters α_1 and α_2 in the ADRCKF. $\square$

3. Results

3.1. Simulation Result

This study utilizes Amesim and Simulink for combined simulation to validate the feasibility of the algorithm. The physical model designed in Amesim is depicted in Figure 3, while the mathematical model of the algorithm designed in Simulink is presented in Figure 4.

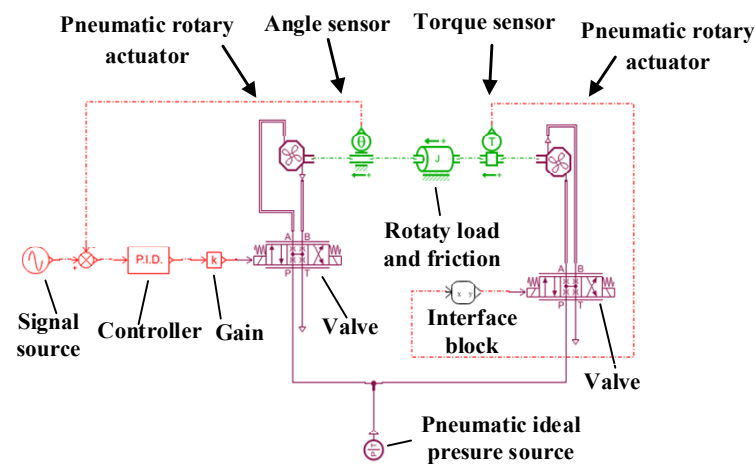


Figure 3. The physical model designed in Amesim.

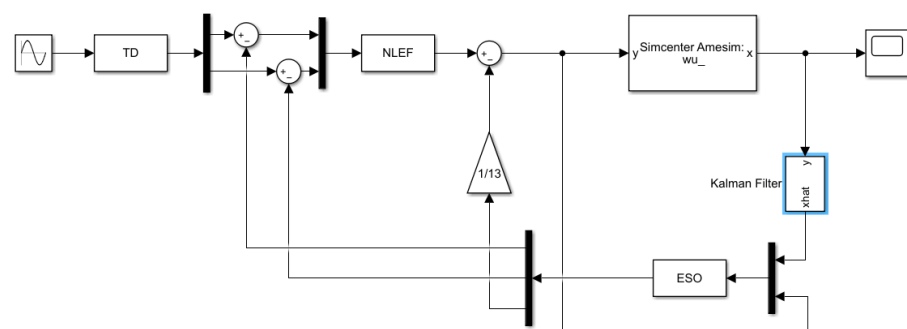


Figure 4. The mathematical model of the algorithm designed in Simulink.

The specific working principles are explained using the active disturbance-rejection controller with integrated Kalman filter (ADRCKF) as an example. The angle sensor in Figure 3 captures the actual output angle and the expected angle signal and calculates the difference to obtain the error, which is then input into the PID controller to obtain the control quantity. The control quantity is multiplied by a gain to generate a control voltage that is input to the valve. The control voltage regulates the opening area of the valve interface, controlling gas flow. Changes in flow impact the position output, achieving closed-loop control of the position. This constitutes the position-disturbance control part on the position side. The position disturbance is applied to the torque control part, introducing an additional position disturbance. The primary objective of this paper is to achieve precise

torque control under external position disturbance. The control principle on the torque side is as follows: The torque sensor in Figure 3 captures the actual torque output signal, which is then transmitted to the Interface block. The Interface block, through the control Simulink algorithm in Figure 4, generates a control quantity that is transferred to the valve. By controlling the voltage of the valve, the opening area of the valve is regulated, achieving flow control. Changes in flow influence the torque output, realizing closed-loop control of torque. The algorithm principles in Figure 4 were already explained when introducing Figure 2 and will not be reiterated here.

Due to the interference of the position system with the torque system, oscillations occur in the torque system, particularly at the reversal point, as illustrated in the simulation results in Figure 5a,c. The research challenge addressed in this study revolves around mitigating the adverse effects caused by the interference of the position system with the torque system, with the aim of achieving precise torque control.

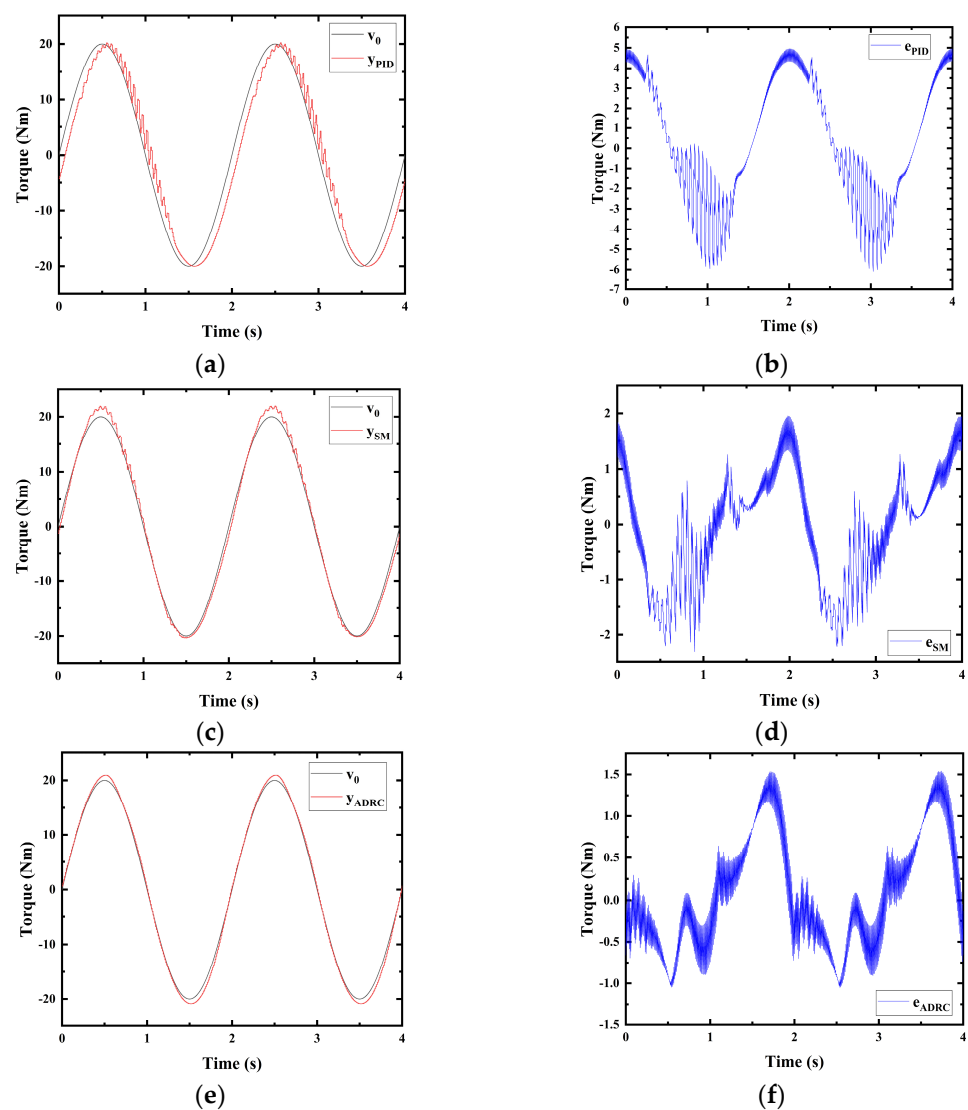


Figure 5. Cont.

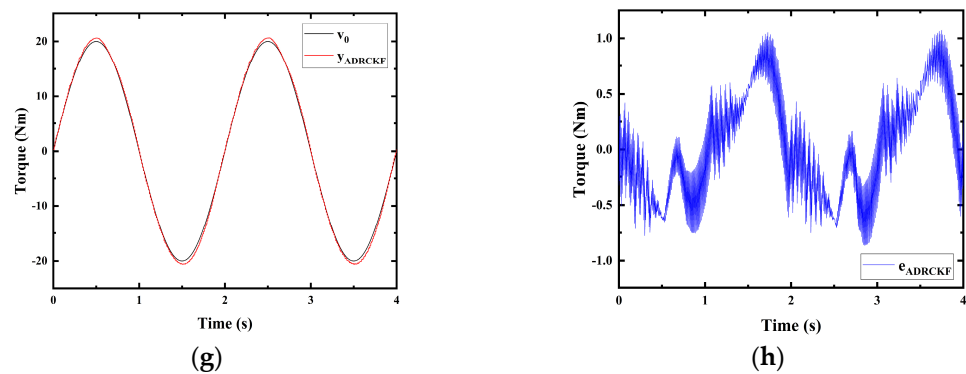


Figure 5. Simulation results of torque control under position disturbance were obtained using a PID, an SM, an ADRC, and an ADRCCKF at a frequency of 0.5 Hz. (a) Torque trajectory tracking of the PID. (b) Torque trajectory—tracking error of the PID. (c) Torque trajectory tracking of the SM. (d) Torque trajectory—tracking error of the SM. (e) Torque trajectory tracking of the ADRC. (f) Torque trajectory—tracking error of the ADRC. (g) Torque trajectory tracking of the ADRCCKF. (h) Torque trajectory-tracking error of the ADRCCKF.

The paper presents a simulation comparison of a PID, an SM, an ADRC, and an ADRCCKF controller with an amplitude of 20 Nm and a frequency of 0.5 Hz, as depicted in Figure 5. Figure 5a depicts the simulation results of PID torque trajectory tracking, which shows evident oscillations. The PID controller lacks disturbance-rejection capability, leading to significant oscillations at the reversal point of the torque signal due to interference from the position system. Figure 5b represents the torque trajectory-tracking error for PID, with a maximum error of 6 Nm. Figure 5c illustrates the simulation results of SM torque trajectory tracking, displaying slight oscillations. The disturbance-rejection capability of the sliding-mode controller is slightly superior to that of PID, consequently leading to a reduced magnitude of oscillations compared with PID. Figure 5d shows the torque trajectory-tracking error for SM, with a maximum error of 2.3 Nm. Figure 5e displays the simulation results of ADRC torque trajectory tracking, without oscillations. Owing to the strong disturbance-rejection capability and robustness of the active disturbance-rejection controller, oscillations are virtually eliminated. Figure 5f presents the torque trajectory tracking error for the ADRC, with a maximum error of 1.6 Nm. Figure 5g shows the simulation results of the ADRCCKF torque trajectory tracking. The ADRCCKF exhibits superior disturbance-rejection capability and robustness; oscillations are completely eliminated, and the output signal closely adheres to the desired signal. Figure 5h represents the torque trajectory-tracking error for the ADRCCKF, with a maximum error of 1.1 Nm. Note that $1.1 \text{ Nm} < 1.6 \text{ Nm} < 2.3 \text{ Nm} < 6 \text{ Nm}$. The simulation results validate the effectiveness and superiority of the ADRCCKF control strategy.

The maximum errors of PID, SM, ADRC, and ADRCCKF controllers in simulating sinusoidal-torque trajectory tracking with an amplitude of 20 Nm and a frequency of 0.5 Hz are presented in Table 2.

Table 2. Simulation results at 0.5 Hz.

Control Strategy	Maximum Error
PID	6 Nm
SM	2.3 Nm
ADRC	1.6 Nm
ADRCCKF	1.1 Nm

3.2. Experimental Results

The experimental setup examined in this research is a pneumatic-torque system that is based on position disturbance, and it is illustrated in Figure 6.

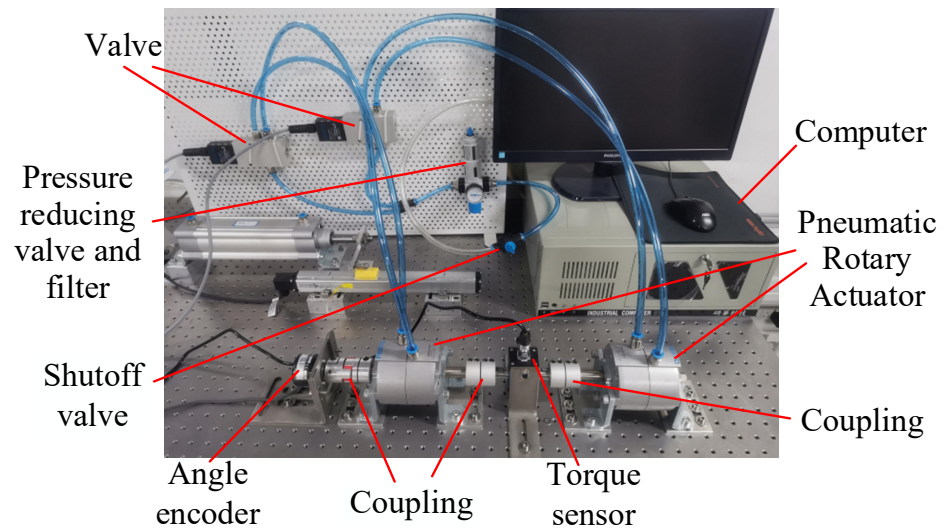


Figure 6. Experimental setup with two pneumatic rotary actuators.

Using an experimental air-pressure condition of 0.7 MPa, an experiment was conducted to measure the dead zone of the proportional valve, which was found to be between 4.9 V and 5.1 V. The following parameters were used to design the ADRCKF:

$$\begin{cases} v_1(n+1) = v_1(n) + 0.1v_2(n) \\ v_2(n+1) = v_2(n) + 0.1f_{hst}(\gamma(n), v_2, 50, 0.15) \\ z_1(n+1) = z_1(n) + 0.1(z_2(n) - 10e_1(n)) \\ z_2(n+1) = 0.1(z_3(n) - 20fal(e_1(n), 0.6, 0.1)) + b_0u(n) \\ \quad + z_2(n) \\ z_3(n+1) = z_3(n) + 0.1(-30fal(e_1(n), 0.4, 0.1)) \\ u(n) = \alpha_1fal(d_1(n), 0.4, 0.01) + \alpha_2fal(d_2(n), 0.6, 0.01) \\ \quad - z_3(n)/b_1 \end{cases} \quad (42)$$

For different experiments, the parameters were set differently. For the sinusoidal-torque trajectory tracking at a frequency of 0.5 Hz, $\alpha_1 = 2.5$, $\alpha_2 = 2.5$ and $b_1 = 13$. For the 1 Hz sinusoidal-torque trajectory tracking, $\alpha_1 = 3.5$, $\alpha_2 = 2.5$ and $b_1 = 13$.

In the presence of position disturbance with a frequency of 0.5 Hz and an amplitude of 85° , the PID controller conducted a sinusoidal-torque trajectory tracking experiment with a frequency of 0.5 Hz and an amplitude of 20 Nm, as illustrated in Figure 7. The active disturbance-rejection controller (ADRC), the active disturbance-rejection controller integrated with a Kalman filter (ADRCKF), and the sliding-mode controller (SM) performed a sinusoidal-torque trajectory-tracking experiment with a frequency of 0.5 Hz and an amplitude of 20 Nm, as shown in Figure 8. Under the conditions of position disturbance with a frequency of 1 Hz and an amplitude of 85° , the ADRC, ADRCKF, and SM conducted sinusoidal-torque tracking experiments with a frequency of 1 Hz and an amplitude of 20 Nm, as presented in Figure 9.

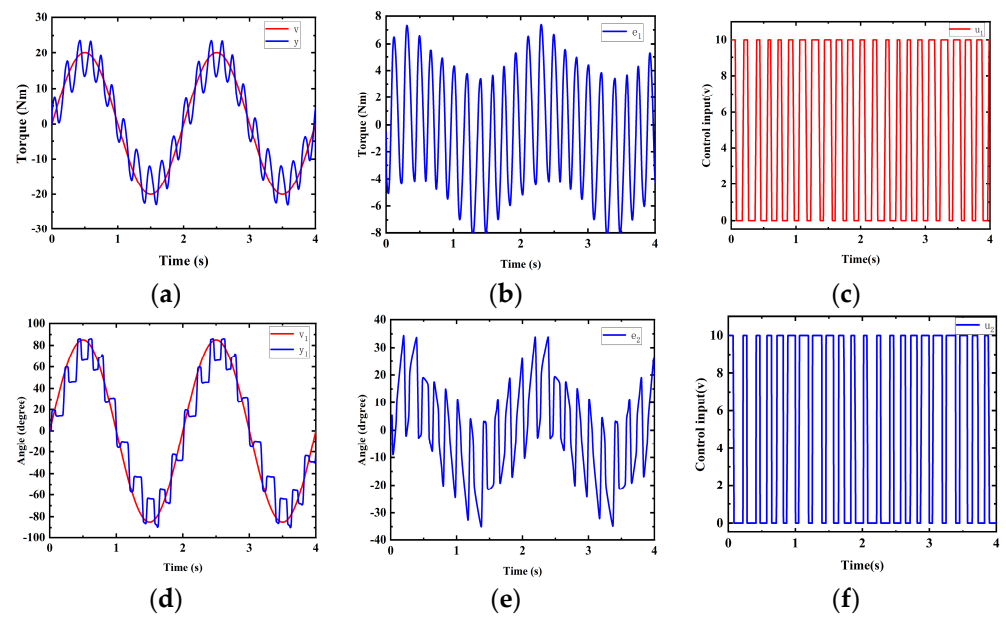


Figure 7. Experimental results of a torque control based on position disturbance, controlled by a PID controller at a frequency of 0.5 Hz. (a) Torque. (b) Torque error. (c) Control input of the torque system. (d) Angle. (e) Angle error. (f) Control input of the position system.

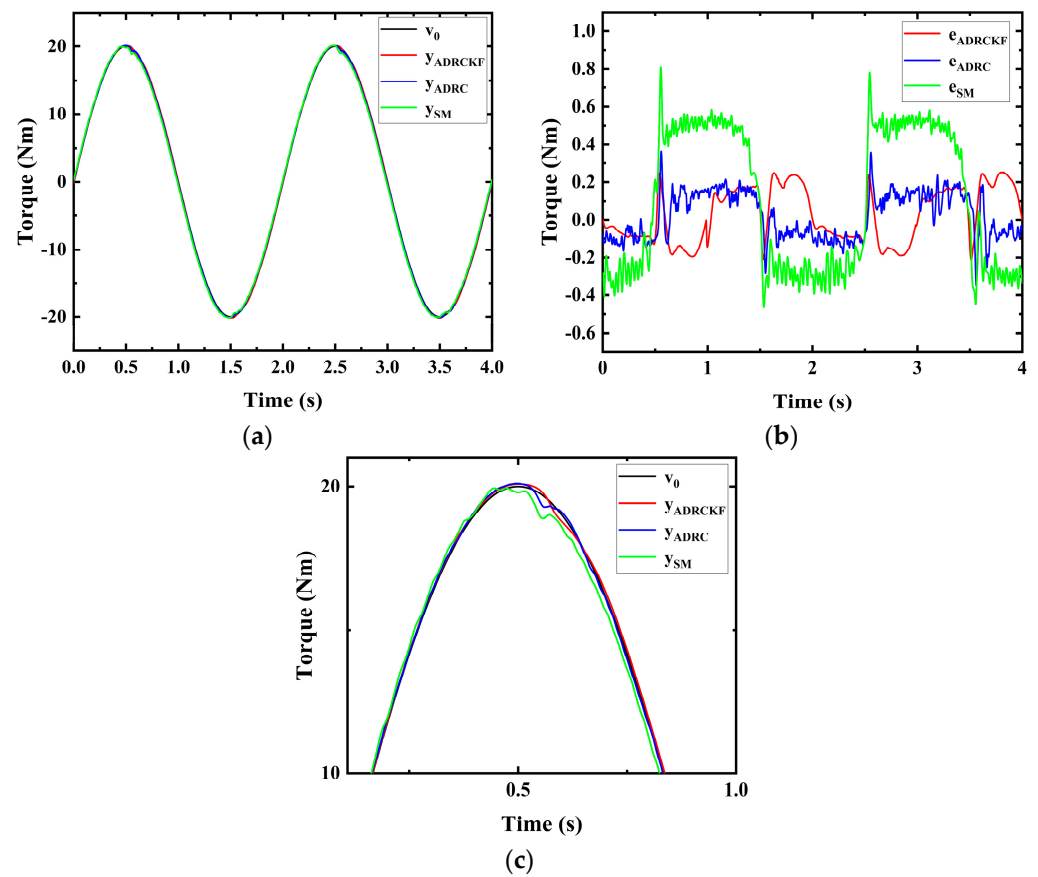


Figure 8. Experimental results of torque control under position disturbance were obtained using an ADRCKF, an ADRC, and an SM at a frequency of 0.5 Hz. (a) Torque trajectory tracking. (b) Torque trajectory-tracking error. (c) Partial enlarged drawing of the ADRCKF, ADRC, and SM.

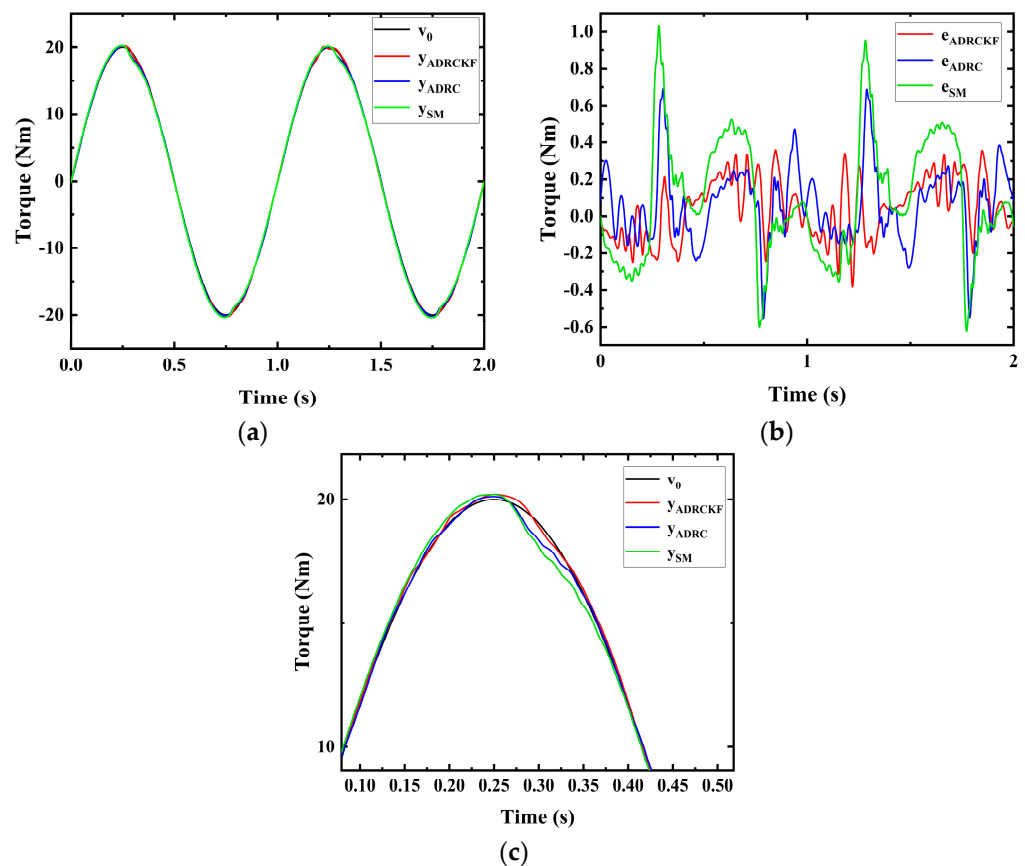


Figure 9. Experimental results of torque control under position disturbance were obtained using an ADRCKF, an ADRC, and an SM at a frequency of 1 Hz. (a) Torque trajectory tracking. (b) Torque trajectory-tracking error. (c) Partial enlarged drawing of the ADRCKF, ADRC, and SM.

Figure 7 illustrates experiments of a pneumatic-torque servo control controlled by a PID controller that is based on position disturbance. The position disturbance signal is a sinusoidal signal with an amplitude of 85° and a frequency of 0.5 Hz. The torque signal to be controlled is a sinusoidal signal with an amplitude of 20 Nm and a frequency of 0.5 Hz. Figure 7a,d, respectively, show the output y of torque trajectory tracking and the angle output y_1 of the position-disturbance part. Figure 7b,e show the corresponding tracking errors e_1 and e_2 , which are 8 Nm and 35 degrees, respectively. Figure 7a,d exhibit significant oscillations. This is attributed to the poor robustness of the PID controller and the series connection of the position output terminal and the torque output terminal, leading to mutual interference. Figure 7c,f display the control voltage u_1 and u_2 of the valve in the torque and position systems, respectively. It can be observed that the voltage of both valves reached the limit, indicating that the valves are operating at their optimal performance. This results in the system control accuracy being at its highest level.

Figure 8 depicts the experiments of sinusoidal-torque trajectory tracking based on position disturbances. The controlled torque signal is a sinusoidal signal with an amplitude of 20 Nm and a frequency of 0.5 Hz, while the position disturbance signal is a sinusoidal signal with an amplitude of 85° and a frequency of 0.5 Hz. Figure 8a illustrates the sinusoidal-torque trajectory-tracking experiment controlled by an ADRCKF, an ADRC, and an SM, where the output signals $y_{ADRCCKF}$, y_{ADRC} , and y_{SM} rapidly track the desired torque signal v_0 . Figure 8b represents the tracking errors in the sinusoidal-torque trajectory controlled by the ADRC, ADRCKF, and SM, with maximum tracking errors of 0.25 Nm, 0.38 Nm, and 0.8 Nm for $e_{ADRCCKF}$, e_{ADRC} , and e_{SM} , respectively. Note that $0.25 \text{ Nm} < 0.38 \text{ Nm} < 0.8 \text{ Nm} < 8 \text{ Nm}$. Figure 8c shows a comparatively enlarged view of the ADRCKF, ADRC, and SM under position disturbances during the sinusoidal-torque

trajectory-tracking experiment. At the commutation point, the outputs y_{ADRCKF} , y_{ADRC} , and y_{SM} of the three controllers both oscillated, but the ADRCKF was less affected by oscillations, resulting in higher control accuracy. This indicates that the Kalman filter effectively enhances system robustness and suppresses system oscillations.

Figure 9 depicts experiments of a pneumatic-torque servo control based on position disturbance, controlled by an ADRCKF, an ADRC, and an SM. The controlled torque signal is a sinusoidal signal with an amplitude of 20 Nm and a frequency of 1 Hz, while the position disturbance signal is a sinusoidal signal with an amplitude of 85° and a frequency of 1 Hz. In Figure 9a, the sinusoidal-torque tracking experiment controlled by an ADRCKF, an ADRC, and an SM is depicted, with the output signals y_{ADRCKF} , y_{ADRC} , and y_{SM} rapidly tracking the desired torque signals. In Figure 9b, the sinusoidal-torque trajectory-tracking errors controlled by the ADRCKF, ADRC, and SM are shown, with maximum tracking errors of 0.4 Nm, 0.7 Nm, and 1.0 Nm for e_{ADRCKF} , e_{ADRC} , and e_{SM} , respectively. Note that $0.4 \text{ Nm} < 0.7 \text{ Nm} < 1.0 \text{ Nm}$. The experiment once again demonstrates the superior performance of the ADRCKF.

This paper, under the condition of position disturbance with a frequency of 0.5 Hz and an amplitude of 85° , designed three sets of experiments for tracking sinusoidal-torque trajectories with a frequency of 0.5 Hz and an amplitude of 20 Nm for comparison. The four controllers used were the PID, ADRCKF, ADRC, and SM. The tracking errors for the four sets of experiments are shown in Figures 7b and 8b, which are 8 Nm, 0.25 Nm, 0.36 Nm, and 0.8 Nm, respectively. Additionally, it explored the tracking of a sinusoidal torque with a frequency of 1 Hz and an amplitude of 20 Nm using an ADRCKF, an ADRC and an SM under the condition of position disturbance with a frequency of 1 Hz and an amplitude of 85° , as illustrated in Figure 9a. The tracking errors are 0.4 Nm, 0.7 Nm, and 1.0 Nm respectively, as shown in Figure 9b.

The maximum errors in the results of the 0.5 Hz sinusoidal-torque tracking experiments under different control strategies are shown in Table 3, while the maximum errors in the results of the 1 Hz sinusoidal-torque tracking experiments under different control strategies are presented in Table 4.

Table 3. 0.5 Hz experimental results.

Control Strategy	Maximum Error
PID	8 Nm
SM	0.8 Nm
ADRC	0.38 Nm
ADRCKF	0.25 Nm

Table 4. 1 Hz experimental results.

Control Strategy	Maximum Error
SM	1.0 Nm
ADRC	0.7 Nm
ADRCKF	0.4 Nm

In addition to utilizing the maximum-error metric, the integral absolute-error metric (IAE) is also employed. Over a specified time period, the absolute values of errors for various controllers are integrated to derive the IAE metrics. The IAE metrics for the 0.5 Hz sine experiment are presented in Table 5, while the IAE metrics for the 1 Hz sine experiment are detailed in Table 6.

Table 5. 0.5 Hz experimental results.

Control Strategy	Integral Absolute Error
PID	14,794.439 Nm
SM	1449.426 Nm
ADRC	534.191 Nm
ADRCKF	448.347 Nm

Table 6. 1 Hz experimental results.

Control Strategy	Integral Absolute Error
SM	544.884 Nm
ADRC	337.312 Nm
ADRCKF	286.561 Nm

Remark 2. *Sinusoidal-torque trajectory tracking based on position disturbance shows the poor performance of the PID controller. This is because the position output and torque output interfere with each other, and the PID controller lacks robustness, making the torque-control part unable to resist interference from the position side. In contrast, the SM, the ADRC, and the ADRCKF controllers demonstrate strong robustness and high disturbance-rejection capabilities, leading to more satisfactory torque trajectory-tracking control. However, integrating the Kalman filter into the ADRC controller improves the purity of the feedback signal, increases the robustness of the controller, reduces oscillations, and enhances control precision.*

4. Discussion

This paper employs an active disturbance-rejection controller integrated with a Kalman filter to suppress system oscillations, achieving precise torque control. In comparison with the four data-driven control methods mentioned in the introduction, it exhibits superior disturbance-rejection capabilities and higher real-time performance. This is attributed to the real-time estimation and compensation of internal nonlinearity and external disturbances by the nonlinear extended observer, thereby offsetting both internal nonlinearity and external disturbances. Additionally, the Kalman filter performs state estimation on the system and filters the feedback signals, enhancing the robustness of the system. In the context of data-driven methodologies, the present application of the ADRCKF entails feedback control that relies on real-time input, output, and estimated disturbance value.

The primary challenge in the control methodology presented in this paper lies in the mutual interference and coupling between the torque and position systems. As depicted in Figures 8b and 9b, the maximum error manifests after the reversal point. Both the torque signal and the position signal are sinusoidal signals with identical frequencies. When the torque signal reverses, the position signal also reverses simultaneously. At this juncture, the acceleration of the position system is maximal, resulting in the most substantial torque disturbance to the torque system. Consequently, the largest error in the torque system emerges after the reversal point.

In Figure 7, the experimental setup employed a PID controller, resulting in pronounced system oscillations. This is attributed to the limited robustness of the PID controller, which hinders its ability to effectively counteract external position disturbances. Experiment 8 utilized a sliding-mode controller based on the extended observer from the literature [11], an ADRC, and an ADRCKF. At the reversal point, the ADRCKF experienced the least impact, resulting in the smallest maximum error. As shown in Table 3, the minimum error for the ADRCKF was 0.25 Nm. Similarly, in Experiment 9, the ADRCKF encountered minimal influence at the reversal point, leading to the smallest maximum error. As indicated in Table 4, the minimum error for the ADRCKF was 0.4 Nm. Furthermore, the IAE results in Tables 5 and 6 confirm that the ADRCKF exhibits stronger disturbance-rejection capabilities compared with the ADRC and SM. The experimental results indicate that the improvement of the active disturbance-rejection controller through the integration of a Kalman filter

is effective. It successfully suppressed system oscillations, enhancing the resistance to disturbances of the system and overall robustness. In the future, it is anticipated to achieve better application performance in systems with strong disturbances.

5. Conclusions

This paper presented an ADRCKF for the pneumatic-torque servo control system based on positional interference. This approach has proven to be an effective means of mitigating nonlinearity and disturbances in pneumatic-torque servo systems. The Kalman filter enhances the purity of the feedback signal in real-time, effectively reduces oscillation, and improves control accuracy. The total nonlinearity in the pneumatic servo system is estimated and compensated for in real time by the ESO, which then feeds back all observed values to the nonlinear error-state feedback controller (NLEF). The Lyapunov stability theory is utilized to demonstrate the validity of the ESO and the convergence of the NLEF. Experimental results confirm the excellent performance of the ADRCKF. For sinusoidal signal tracking with a 0.5 Hz amplitude of 20 Nm, the torque error is within 0.25 Nm. Similarly, at a corresponding frequency of 1 Hz, the torque error is within 0.4 Nm. However, there is still room for improvement, particularly regarding the precision of high-frequency control.

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