

Adaptive event-triggered backstepping control with disturbance observer and anti-windup compensation for trajectory tracking of electro-hydraulic actuators

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ABSTRACT

Electro-hydraulic actuators are difficult to control accurately because of fast pressure dynamics, valve dead-zone nonlinearity, parameter variations, external disturbances, and input saturation. This study develops an adaptive event-triggered backstepping controller that integrates a disturbance observer and anti-windup compensation within a unified Lyapunov-based framework. The adaptive laws account for uncertain plant parameters and valve-gain variation, while the dead-zone residual is treated as a bounded uncertainty. A strictly positive triggering threshold excludes Zeno behavior under the stated assumptions, and the anti-windup modification preserves uniform ultimate boundedness in the presence of input saturation. The method is assessed through MATLAB/Simulink–Simcenter Amesim co-simulation using six reference trajectories and is compared with proportional–integral–derivative (PID), sliding-mode control, and online self-tuning fuzzy PID control. Across the investigated cases, the proposed controller achieved the lowest RMSE and ARE values; for example, the RMSE was 0.000837 m for the first multi-step test and 0.003778 m for the chirp test. These findings demonstrate improved tracking under the tested co-simulation conditions. Quantitative triggering statistics, observer-error analysis, and saturation behavior are addressed in the revised evaluation, with real-time experimental validation identified as an essential step toward hardware implementation.

Keywords: electro-hydraulic actuator, input saturation compensation, lumped disturbance estimation, uniform ultimate boundedness, MATLAB/Simulink–Simcenter Amesim co-simulation.

INTRODUCTION

Hydraulic systems remain important in robotic, aerospace, and heavy industrial applications because they provide high actuation force and favorable power-to-weight characteristics [1–5]. Most electro-hydraulic platforms use piston–cylinder actuators driven by pressurized fluid, with servo or proportional valves regulating the flow required to achieve the desired displacement, velocity, or force [6,7]. Accurate control is difficult because the plant is strongly nonlinear. Fluid compressibility, valve dead-zone behavior, friction, external disturbances, parameter variations

in inertia and damping, and actuator saturation can all degrade tracking performance [6,8–11]. Among these effects, the valve dead zone is particularly important because spool–sleeve overlap reduces sensitivity around the neutral position and delays the response to small commands [6,11–13]. Its interaction with digital sampling and control delay can also affect closed-loop stability [5].

Dead-zone nonlinearities are generally handled in two ways. One approach treats the dead-zone effect as a bounded uncertainty and relies on robust control to maintain acceptable performance. The other compensates for the nonlinearity more directly by estimating its characteristics

or constructing an adaptive inverse representation [14–16]. Early studies established adaptive dead-zone inverse schemes for unknown dead-zone parameters [14,15], and later work extended the concept to more complex nonlinear systems. Examples include reinforcement-learning-based inverse control combined with sliding-mode action [16], cooperative neural-network control [17], finite-time command-filtered electro-hydraulic position control with dead-zone compensation [18], and adaptive fuzzy output-feedback designs [9]. These methods broaden the range of systems that can be controlled without exact prior knowledge of the nonlinear functions. Their implementation can nevertheless be demanding when internal valve variables must be measured, several parameters are estimated online, or additional learning structures are introduced [6,9,14–18].

Several established controller families have also been applied to hydraulic position control. PID remains widely used because its structure is simple and familiar, while recent electro-hydraulic PID studies have used optimization-based and intelligent tuning to improve tracking over changing operating conditions [19,20]. Fixed-gain PID, however, has limited ability to accommodate strong hydraulic nonlinearities and changing loads because dead-zone behavior, compressibility, leakage, and pressure-dependent flow are not represented explicitly in a standard linear structure [13,19,21]. Sliding-mode control (SMC) offers stronger robustness to parameter variations and external disturbances, and recent fuzzy-rule adaptive SMC designs have been applied to electro-hydraulic position-control systems [22,23]. Boundary-layer or fuzzy modifications can reduce chattering, although some ideal sliding-mode robustness may be lost [22,23]. Fuzzy and adaptive fuzzy controllers provide another way to represent unknown nonlinearities and adjust the control action online [9,24,25]. Their practical performance depends on the selection of membership functions, rule bases, and tuning parameters, which can become difficult to manage as system complexity increases [24,25]. Nonlinear optimal and robust control offer additional disturbance-attenuation strategies, but their implementation may require repeated solution of optimization or Riccati-type equations [21,26].

Adaptive backstepping is more directly suited to the nonlinear strict-feedback structure of electro-hydraulic systems because it provides a recursive Lyapunov-based framework for handling

nonlinear dynamics and parametric uncertainty [2,3,18]. Recent finite-time command-filtered adaptive backstepping has also been verified through comparative simulations and experiments on an electro-hydraulic servo system with a three-stage valve [27]. Prediction-based hydraulic control [28] and model predictive control [29] address the problem differently by using a plant model or learned predictor to anticipate future behavior and account for operating constraints. These approaches can improve adaptability, but their computational requirements depend on the prediction architecture, model complexity, and target processor. Consequently, claims regarding real-time computational advantage should be supported by direct execution-time or hardware measurements rather than inferred from controller structure alone.

Event-triggered control (ETC) and disturbance observers (DOBs) address two further issues that are relevant to practical electro-hydraulic control. ETC updates the control command only when a prescribed state- or error-dependent condition is satisfied, thereby limiting unnecessary command refreshes [30]. In electro-hydraulic systems, event-triggered robust control has been reported to reduce switching activity while preserving tracking performance under disturbances [30]. Recent work has also combined disturbance-observer-based fixed-time event-triggered control with explicit input-saturation treatment in networked electro-hydraulic systems [31]. DOB-based compensation estimates lumped disturbances and feeds the estimate into the control law, which can improve disturbance rejection without requiring a known disturbance profile [10,30,31]. Observer gain selection remains important because faster convergence may increase sensitivity to measurement noise, particularly in hydraulic systems with fast pressure dynamics and fluid compressibility [5,10].

Recent studies have therefore addressed overlapping parts of the present problem through adaptive backstepping and dead-zone compensation [2,3,18,27], disturbance-rejection control under dead-zone and voltage constraints [10], prediction-based hydraulic control [28] and model-predictive control [29], event-triggered robust control [30], and disturbance-observer-based fixed-time event-triggered control with input saturation [31]. These studies provide important building blocks, but they use different plant structures, uncertainty treatments, constraint-handling mechanisms, and stability formulations.

The unresolved issue considered here is not the novelty of each component in isolation, but the coordinated integration of adaptive backstepping parameter adaptation, disturbance estimation, event-triggered held-command updating, and anti-windup compensation for an electro-hydraulic actuator with valve dead-zone nonlinearity within a tractable Lyapunov framework.

The objective of this study is to determine whether adaptive backstepping, event-triggered control, disturbance estimation, and anti-windup compensation can be coordinated to improve trajectory tracking in an electro-hydraulic actuator affected by valve dead-zone nonlinearity, parameter uncertainty, external disturbances, and input saturation. The main contributions are as follows: (1) a unified adaptive backstepping architecture is formulated with a disturbance observer and

event-triggered command update for a symmetric electro-hydraulic actuator with valve dead-zone nonlinearity; (2) projection and leakage are incorporated into the parameter adaptation, while the valve-gain adaptation includes an anti-windup term that acts when the ± 10 V actuator limit is reached; (3) the event-trigger law contains a strictly positive threshold floor, which provides a positive lower bound on inter-event time under the stated boundedness assumptions; (4) the controller is assessed in a coupled MATLAB/Simulink–Simcenter Amesim model against PID, SMC, and online self-tuning fuzzy PID (OTPID) under six reference trajectories. Under the investigated co-simulation conditions, adaptive backstepping with Event-Triggered mechanism (ABIC) achieves the lowest RMSE and ARE for every tested trajectory.

SYSTEM MODELING AND PROBLEM STATEMENT

System modeling

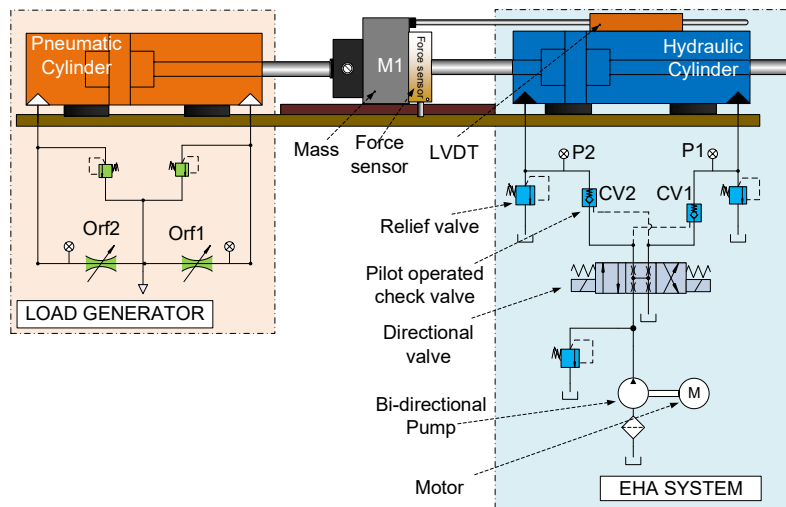


Figure 1. Structure of the evaluation hydraulic system

A symmetric hydraulic cylinder driven by a servo valve is modeled with valve dead zone, external load/disturbance, fluid compressibility, and parametric uncertainty. Newton's law gives the piston dynamics, the continuity equations give chamber-pressure dynamics, and the valve relation defines the nonlinear flow used in the controller design.

$$m \frac{d^2 x_1}{dt^2} = AP_L - kx_1 - c \frac{dx_1}{dt} - F_{ext}(t) \quad (1)$$

where x_1 denotes piston position (m), m represents the load mass, including piston and external load (kg), subject to uncertainty, k is spring constant (N/m), c is damping coefficient (N·s/m), A denotes piston surface area (m^2), equal for both chambers ($A_H = A_R = A$) in a symmetric cylinder, $P_L = P_H - P_R$ pressure difference between the head and rod chambers (Pa), P_H and P_R are the pressures in the head and rod chambers, respectively, $F_{ext}(t)$ represents the external force, assumed bounded. The second derivative of x_1 gives:

$$\frac{dx_2}{dt} = \frac{1}{m}(Ax_3 - kx_1 - cx_2 - F_{ext}(t)) \quad (2)$$

where $x_3 = P_L$ as the third state variable, representing the pressure difference. Since $P_L = P_H - P_R$, the derivative of the pressure difference is:

$$\frac{dP_L}{dt} = \frac{dP_H}{dt} - \frac{dP_R}{dt} = \frac{2\beta_e}{V_t}(Q_H - Q_R - 2Ax_2) \quad (3)$$

where β_e : bulk modulus of the fluid (Pa), V_H, V_R : volumes of the head and rod chambers (m^3), assumed equal for a symmetric cylinder, V_t is the total control volume, Q_H, Q_R : fluid flow rates into/out of the head and rod chambers (m^3/s). The flow rates through the servo valve depend on the valve spool position x_v :

$$Q_H = \begin{cases} C_d w x_v \sqrt{2(P_s - P_H)/\rho}, & x_v \geq 0 \\ C_d w x_v \sqrt{2P_H/\rho}, & x_v < 0 \end{cases}, Q_R = \begin{cases} -C_d w x_v \sqrt{2P_R/\rho}, & x_v \geq 0 \\ -C_d w x_v \sqrt{2(P_s - P_R)/\rho}, & x_v < 0 \end{cases} \quad (4)$$

where C_d : valve discharge coefficient (dimensionless), w : valve port width (m), x_v : valve spool position (m), the system input, P_s : supply pressure (Pa), ρ : fluid density (kg/m^3).

Assuming $P_H + P_R \approx P_s$, the pressure dynamics become:

$$\frac{dx_3}{dt} = \frac{2\beta_e}{V_t} \left(-2Ax_2 + 2C_d w x_v \sqrt{\frac{P_s - \text{sign}(x_v)x_3}{\rho}} \right) + d_e(t) \quad (5)$$

where $d_e(t)$ is a bounded additive lumped disturbance in the pressure-state dynamics, satisfying $|d_e(t)| \leq D_e$. The valve spool position, x_v , is subject to a dead-zone nonlinearity, modeled as:

$$x_v = DI(v) = \begin{cases} m_v(v - b_r), & v > b_r; \\ 0, & b_l < v \leq b_r; \\ m_v(v - b_l), & v \leq b_l \end{cases} \quad (6)$$

Here, $d_e(t)$ is an additive lumped disturbance in the pressure-state derivative dx_3/dt and therefore has SI units of Pa/s. For readability, Figure 16 displays the same quantity in bar/s using $1 \text{ bar} = 10^5 \text{ Pa}$. This pressure-rate disturbance represents unmodeled fluid effects, including leakage, effective-bulk-modulus variation, and residual valve-flow uncertainty. It is distinct from the mechanical external load $F_{ext}(t)$ in Eq. (2), which is expressed in newtons (N); no direct equality or conversion between $d_e(t)$ and $F_{ext}(t)$ is assumed. Where $m_v > 0$ denotes the nominal valve gain, b_l and b_r are the left and right dead-zone thresholds, and $DI(\cdot)$ is the dead-zone mapping. For control design, the mapping may be decomposed as $DI(v) = m_v v + \delta(v)$, where $\delta(v)$ is a bounded nonlinear residual satisfying $|\delta(v)| \leq D\delta$.

Remark 1: The model represents fluid compressibility through the effective bulk modulus and assumes a symmetric cylinder ($A_H = A_R, V_H = V_R$), constant supply pressure P_s , bounded disturbances ($|\delta(v)| \leq D\delta, |F_{ext}(t)| \leq F_{max}$), and a strictly positive lower bound on the load mass $m > m_{min}$. These ensure tractability while capturing uncertainties.

The state-space model is obtained by:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \frac{1}{m}(Ax_3 - kx_1 - cx_2 - F_{ext}(t)) \\ \dot{x}_3 = f_3(x_2) + g_3(x_3, DI(v_T)) + d_e(t) \\ y = x_1 \end{cases} \quad (7)$$

where: $f_3(x_2) = -\frac{4\beta_e}{V_t}Ax_2$; $b = \frac{4\beta_e C_d w}{V_t \sqrt{\rho}}$ and

$$g_3(x_3, DI(v_T)) = b \sqrt{P_s - \text{sign}(DI(v_T))x_3} DI(v_T).$$

Remark 2: The dead-zone in (6) is asymmetric if $|b_l| \neq b_r$. The form $DI(v) = m_v v + \delta(v)$ treats the residual dead-zone effect as a bounded uncertainty, requiring robust compensation to reduce tracking errors.

Controller design

This section presents the detailed design of an adaptive event-triggered backstepping controller for the hydraulic system developed in the preceding section. A disturbance observer (DOB) and an anti-windup

mechanism are incorporated into the control structure. The backstepping procedure constructs the control law recursively, while adaptive laws are introduced to account for uncertain plant parameters. Unnecessary control updates are limited by the event-triggered mechanism. Meanwhile, the DOB estimates lumped disturbances, and the anti-windup component mitigates the effects of control-signal saturation. The resulting framework addresses valve dead-zone effects, parametric uncertainty, external disturbances, load forces, and actuator saturation within a unified control structure. Lyapunov analysis is then employed to establish the uniform ultimate boundedness of the closed-loop errors under the stated boundedness assumptions:

$$\begin{cases} z_1 = x_1 - y_r \\ z_2 = x_2 - \alpha_1 - \dot{y}_r \\ z_3 = x_3 - \alpha_2 \end{cases} \quad (8)$$

From the definition $z_3 = x_3 - \alpha_2$ in Eq. (8), differentiation gives $\dot{z}_3 = \dot{x}_3 - \dot{\alpha}_2$. Substituting the pressure-state dynamics in Eq. (7) gives the third relation in Eq. (9).

$$\begin{cases} \dot{z}_1 = z_2 + \alpha_1 \\ \dot{z}_2 = \theta^T \Phi_2 - \theta_1 F_{ext}(t) - \dot{\alpha}_1 - \ddot{y}_r \\ \dot{z}_3 = f_3(x_2) + g_3(x_3, DI(v_T)) + d_e(t) - \dot{\alpha}_2 \end{cases} \quad (9)$$

where the uncertain parameter vector and regressor are defined as the following:

$$\theta = \left[\frac{1}{m} \quad \frac{k}{m} \quad \frac{c}{m} \right]^T, \quad \Phi_2 = [Ax_3 \quad -x_1 \quad -x_2]^T, \theta_1 = \frac{1}{m}$$

The virtual controls are defined as:

$$\begin{cases} \alpha_1 = -k_1 z_1 - \kappa_1 z_1^3, \\ \alpha_2 = \frac{1}{A\hat{\theta}_1} (-k_2 z_2 - z_1 - \hat{\theta}^T \Phi_2 + \dot{\alpha}_1 + \ddot{y}_r - \kappa_2 z_2^3) \\ \alpha_3 = -z_2 - k_3 z_3 - \kappa_3 z_3^3 - f_3(x_2) + \dot{\alpha}_2 - \hat{d}_e \end{cases} \quad (10)$$

In Eq. (10), $\dot{\alpha}_2$ denotes the total time derivative of the virtual pressure command α_2 . Therefore, reference-trajectory derivative terms are included in $\dot{\alpha}_2$ and no separate third-derivative term appears in the z_3 dynamics.

The DOB compensation is included in α_3 because $d_e(t)$ enters the pressure-state dynamics as a matched additive disturbance.

where $\hat{\theta}_1$ estimates θ_1 , and $\hat{m}_v$ estimates m_v . Choose the Lyapunov function as the following:

$$\begin{cases} V_1 = \frac{1}{2} z_1^2 \\ V_2 = V_1 + \frac{1}{2} z_2^2 + \frac{1}{2} (\theta - \hat{\theta})^T \Gamma^{-1} (\theta - \hat{\theta}) \end{cases} \quad (11)$$

where $\hat{\theta}$ is the estimate of θ , and Γ is a positive definite matrix. Its derivative is:

$$\begin{cases} \dot{V}_1 = z_1 \dot{z}_1 = z_1 (z_2 + \alpha_1) \\ \dot{V}_2 = \dot{V}_1 + z_2 \dot{z}_2 + (\theta - \hat{\theta})^T \Gamma^{-1} (-\dot{\hat{\theta}}) \end{cases} \quad (12)$$

The adaptive law for $\hat{\theta}$ is defined as the following:

$$\dot{\hat{\theta}} = \text{Proj}[\Gamma \Phi_2 z_2 (1 + \mu |z_2|) - \Gamma l_\theta (\hat{\theta} - \theta_0)]_{\hat{\theta}_1 \geq 1/m_{max}} \quad (13)$$

where projection ensures $\hat{\theta}_1 \geq 1/m_{max}, \mu > 0, l_\theta > 0$. To estimate the disturbance $d_e(t)$, define an auxiliary variable p_3 :

$$\dot{p}_3 = -l_{d3} (f_3(x_2) + g_3(x_3, DI(v_T)) + \hat{d}_e - \dot{\alpha}_2) \quad (14)$$

$$\hat{d}_e = p_3 + l_{d3} z_3, \quad l_{d3} > 0 \quad (15)$$

The DOB in Eqs. (14)–(15) estimates only the matched lumped pressure-rate disturbance $d_e(t)$ in the z_3 channel. It does not estimate the mechanical external-load force $F_{\text{ext}}(t)$. Its convergence follows under the boundedness and regularity assumptions below.

Theorem 1: The disturbance observer (14)–(15) ensures that the estimation error $e_d = d_e - \hat{d}_e$ converges exponentially to a bounded set, provided $l_{d3} > \frac{1}{2}$ and $|\dot{d}_e| \leq \bar{D}$.

Proof: From (14)–(15):

$$\dot{\hat{d}}_e = \dot{p}_3 + l_{d3}\dot{z}_3 = -l_{d3}(f_3 + g_3 + \hat{d}_e - \dot{\alpha}_2) + l_{d3}(f_3 + g_3 + d_e - \dot{\alpha}_2) = l_{d3}(d_e - \hat{d}_e)$$

Thus, $\dot{e}_d = \dot{d}_e - l_{d3}e_d$. Lyapunov function $V_d = \frac{1}{2}e_d^2$:

$$\dot{V}_d = e_d(\dot{d}_e - l_{d3}e_d) \leq \frac{1}{2}e_d^2 + \frac{1}{2}\dot{d}_e^2 - l_{d3}e_d^2 = -(l_{d3} - \frac{1}{2})e_d^2 + \frac{1}{2}\bar{D}^2$$

Let $\gamma = 2(l_{d3} - \frac{1}{2})$ then $\dot{V}_d \leq -\gamma V_d + \frac{1}{2}\bar{D}^2$, so:

$$|e_d(t)| \leq \sqrt{2V_d(0)}e^{-\gamma t/2} + \sqrt{\frac{\bar{D}^2}{\gamma}}$$

The control signal is held constant between triggering events:

$$v_T(t) = v(t_k), t \in [t_k, t_{k+1}) \quad (16)$$

The triggering condition is defined as the following:

$$t_{k+1} = \inf\{t > t_k : |v_e(t)| \geq \sigma(t)\}, \quad v_e(t) = v(t) - v_T(t) \quad (17)$$

The adaptive threshold is defined as below:

$$\sigma(t) = \sigma_{\min} + \sigma_0[1 - \exp(-\lambda|z_1(t)|)], \quad \sigma_{\min} > 0, \sigma_0 > 0, \lambda > 0 \quad (18)$$

Remark 3: The positive floor $\sigma_{\min}$ prevents the triggering threshold from approaching zero as the tracking error vanishes. The state-dependent term increases the threshold away from the origin and can reduce unnecessary updates. In practice, $\sigma_{\min}$ may be selected by considering the sampling resolution, valve bandwidth, and allowable tracking error.

Theorem 2: Suppose that all closed-loop signals are bounded and that there exists a finite constant $M > 0$ such that $|\dot{v}_e(t)| \leq M$. Then, the event-triggering mechanism (16)–(18), with $\sigma_{\min} > 0$, excludes Zeno behavior, and the inter-event times satisfy $t_{k+1} - t_k \geq \frac{\sigma_{\min}}{M} > 0$.

Proof: At each triggering instant t_k , $v_e(t_k) = 0$. Between two successive events, $|v_e(t)| \leq \int_{t_k}^t |\dot{v}_e(\tau)| d\tau \leq M(t - t_k)$. A new event cannot occur before $|v_e|$ reaches the triggering threshold, which satisfies $\sigma(t) \geq \sigma_{\min} > 0$. Hence, $t_{k+1} - t_k \geq \frac{\sigma_{\min}}{M}$.

Since this lower bound is strictly positive, infinitely many events cannot occur within a finite time interval. Therefore, Zeno behavior is excluded.

The unconstrained control signal is defined as

$$v_{uc} = \frac{\alpha_3}{b\hat{m}_v\sqrt{P_s - \text{sign}(\alpha_3)x_3}} \quad (19)$$

where $\hat{m}_v$ denotes the estimate of the valve gain m_v . The sign of the desired virtual control signal α_3 is used to determine the valve-flow direction, thereby avoiding an implicit dependence on the dead-zone output $DI(v)$. The physically admissible pressure condition $P_s - \text{sign}(\alpha_3)x_3 > 0$ ensures that the square-root term is well defined. In particular, this condition is satisfied when $|x_3| < P_s$. The saturated control signal is expressed as

$$v = \text{sat}(v_{uc}) = \begin{cases} v_{\max}, & v_{uc} > v_{\max}, \\ v_{uc}, & v_{\min} \leq v_{uc} \leq v_{\max}, \\ v_{\min}, & v_{uc} < v_{\min}. \end{cases} \quad (20)$$

The implemented signal path is $v_{uc}(t) \rightarrow v(t) = \text{sat}(v_{uc}(t)) \rightarrow v_T(t)$, where v_T is updated at triggering instants and held between events.

The physical valve therefore receives $v_T(t)$, so the applied dead-zone term is $DI(v_T)$. The hold error $v_e(t) = v(t) - v_T(t)$ is bounded by $\sigma(t)$ and enters the closed-loop analysis as a bounded term.

The adaptation law for $\hat{m}_v$ is defined using a projection operator as

$$\dot{\hat{m}}_v = \text{Proj} [m_{v,\min}, m_{v,\max}] \{-\eta_m \alpha_3 z_3 (1 + \mu_m |z_3|) - \eta_m l_m (\hat{m}_v - \hat{m}_{v0}) - \eta_m \Delta_v z_3 \text{sgn}(\hat{m}_v)\} \quad (21)$$

where

$$\Delta v = v_{uc} - \text{sat}(v_{uc}),$$

$$\eta_m > 0, l_m > 0, \mu_m \geq 0,$$

and

$$0 < m_{v,\min} < m_{v,\max}, \hat{m}_{v0} \in [m_{v,\min}, m_{v,\max}]$$

The projection operator constrains the valve-gain estimate to the admissible interval

$$m_{v,\min} \leq \hat{m}_v(t) \leq m_{v,\max}$$

Therefore, $\hat{m}_v$ remains strictly positive, and the denominator of the control law in (19) does not become singular. The leakage term in (21) limits parameter drift, whereas the final term modifies the adaptation process when input saturation occurs.

Theorem 3: Consider the closed-loop system governed by the adaptive event-triggered backstepping controller, the disturbance observer, and the projected valve-gain adaptation law in (21). Suppose that the reference trajectory and its required derivatives are bounded, the disturbance and observer residuals are bounded, and the hydraulic gain satisfies

$$0 < \underline{g} \leq b m_v \sqrt{P_s - \text{sign}(\alpha_3) x_3} \leq \bar{g}$$

Assume further that

$$|\Delta_v| \leq \bar{\Delta}_v, 0 < m_{v,\min} \leq \hat{m}_v(t) \leq m_{v,\max}$$

where

$$\Delta_v = v_{uc} - \text{sat}(v_{uc})$$

Then, the anti-windup modification and the leakage term in (21) preserve the uniform ultimate boundedness of the closed-loop tracking, parameter-estimation, and disturbance-estimation errors in the presence of input saturation.

Proof: Define the saturation mismatch as

$$\Delta_v = v_{uc} - \text{sat}(v_{uc})$$

Therefore, $\Delta_v = 0$ when the actuator operates within its admissible input range, whereas $\Delta_v \neq 0$ only when the unconstrained control input exceeds the saturation limits.

Consider the composite Lyapunov function

$$V = \frac{1}{2} z_1^2 + \frac{1}{2} z_2^2 + \frac{1}{2} z_3^2 + \frac{1}{2} \tilde{\theta}^T \Gamma^{-1} \tilde{\theta} + \frac{1}{2\eta_m} \tilde{m}_v^2 + \frac{1}{2} e_d^2$$

where $\tilde{\theta} = \theta - \hat{\theta}$, $\tilde{m}_v = m_v - \hat{m}_v$, and $e_d = d_e - \hat{d}_e$

In the absence of input saturation, the adaptive backstepping design and the disturbance observer yield negative-definite terms associated with the tracking and estimation errors, together with bounded residual terms. When saturation occurs, the difference between v_{uc} and the applied input introduces the additional term $z_3 b m_v \Delta_v \sqrt{P_s - \text{sign}(\alpha_3) x_3}$ into the Lyapunov derivative. Using the assumed bounds on the hydraulic gain and the saturation mismatch gives $|z_3 b m_v \Delta_v \sqrt{P_s - \text{sign}(\alpha_3) x_3}| \leq \bar{g} \bar{\Delta}_v |z_3|$

By Young's inequality, for any $\varepsilon > 0$,

$$\bar{g} \bar{\Delta}_v |z_3| \leq \frac{\varepsilon}{2} z_3^2 + \frac{\bar{g}^2 \bar{\Delta}_v^2}{2\varepsilon}$$

The anti-windup term in (21) modifies the valve-gain adaptation whenever $\Delta_v \neq 0$, while the leakage term limits parameter drift. The projection operator ensures that $\hat{m}_v$ remains within the admissible interval

$m_{v,\min} \leq \hat{m}_v(t) \leq m_{v,\max}$ and therefore remains strictly positive. After substituting the adaptive laws and applying the preceding bounds, the derivative of the composite Lyapunov function can be written as

$$\dot{V} \leq -c_1 z_1^2 - c_2 z_2^2 - \left(c_3 - \frac{\varepsilon}{2}\right) z_3^2 - c_4 \|\tilde{\theta}\|^2 - c_5 \tilde{m}_v^2 - c_6 e_d^2 + C$$

where $c_i > 0$ are determined by the controller, adaptation, observer, and leakage gains, while $C > 0$ collects the bounded disturbance, triggering, observer, approximation, and saturation residuals. Selecting $0 < \varepsilon < 2c_3$ ensures that $c_3 - \frac{\varepsilon}{2} > 0$. Hence, there exist positive constants k and c such that $\dot{V} \leq -kV + c$. It follows that $V(t) \leq V(0)e^{-kt} + \frac{c}{k}(1 - e^{-kt})$. Consequently, $\limsup_{t \rightarrow \infty} V(t) \leq \frac{c}{k}$, and all closed-loop tracking and estimation errors remain uniformly ultimately bounded. Therefore, the proposed anti-windup adaptive controller preserves closed-loop boundedness in the presence of input saturation.

System setup

The co-simulation was conducted using MATLAB/Simulink R2022b and Simcenter Amesim 2021.1. The hydraulic plant and passive pneumatic load are modeled in Amesim, whereas the controller, adaptive laws, event-trigger logic, disturbance observer, and post-processing are implemented in MATLAB/Simulink. A common communication/sampling interval of $T_s = 0.001$ s is used for all controllers. The source simulation configuration uses a Runge–Kutta integration scheme in Simulink and the regular Forward Euler integrator for the Amesim plant. Signals are exchanged through the Amesim–Simulink co-simulation interface at each communication instant.

Table 1. Hydraulic system parameter settings

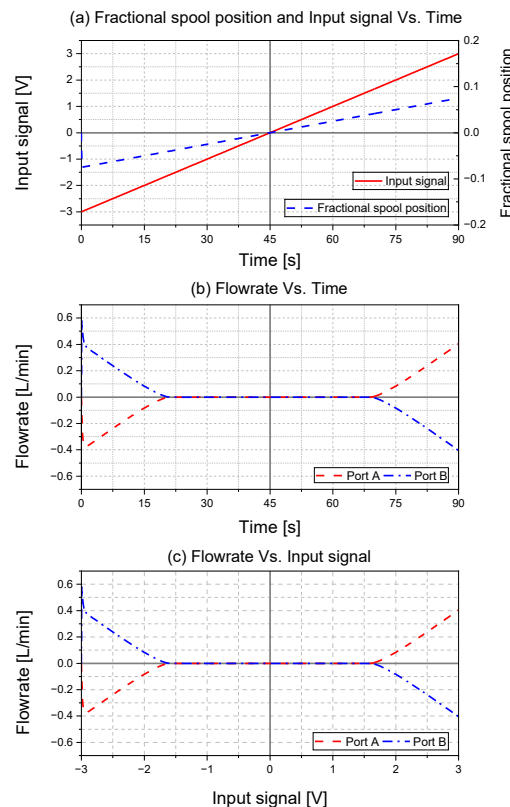
Component	Parameter	Value	Unit
Hydraulic pump	Pump displacement	100	cc/rev
	Motor speed	1500	rev/min
Load	Mass	3	kg
Pneumatic cylinder	Displacement of piston	0.3	m
	Piston, rod diameter	25, 12	mm
	Length of stroke	0.5	m
	Dead volume at port 1, 2 end	50, 50	cm ³
Pneumatic relief valve	Relief valve cracking pressure	2	bar
Pneumatic orifices	Flow coefficient (C_q)	0.72	-
Hydraulic cylinder	Piston diameter	25	mm
	Rod diameter at port 1, 2 end	12, 12	mm
	Length of stroke	0.3	m
	Dead volume at port 1, 2 end	50, 50	cm ³
Hydraulic relief valve	Relief valve cracking pressure	150	bar
Hydraulic directional valve	Deadband	0.04	-

The Amesim proportional directional valve was configured with a deadband of ± 0.04 . A ramp input from -3 to $+5$ V produces the zero-flow region shown in Figure 2, representing the dead-zone characteristic embedded in the plant model; the corresponding parameters are listed in Table 1. All four controllers were evaluated using the same plant model, reference trajectories, load/disturbance conditions, sampling interval, and ± 10 V actuator limits.

The passive pneumatic load was initialized at approximately 10^5 Pa (1 bar), and the pneumatic-orifice flow coefficient was set to $C_q = 0.72$. The actual plant mass was 3.0 kg, whereas the controller load-mass estimate was initialized at 1.0 kg to introduce parameter uncertainty. The coupled pneumatic subsystem generates the trajectory-dependent mechanical load $F_{\text{ext}}(t)$ in the piston dynamics. This mechanical force is recorded separately and is not the quantity estimated by the DOB. For the observer evaluation in Figure 16, a bounded lumped pressure-rate disturbance $d_e(t)$ was introduced in the pressure-state channel of the Simulink controller model, and the same signal was used as the reference for assessing $\hat{d}_e(t)$. No direct conversion between $d_e(t)$ and $F_{\text{ext}}(t)$ was used.

Table 2. Controller parameters, projection bounds, and initial conditions

Category	Parameter	Symbol	Value
Controller gains	Linear feedback gains	k_1, k_2, k_3	100, 50, 200
	Nonlinear feedback gains	$\kappa_1, \kappa_2, \kappa_3$	0.13, 0.22, 0.09
Adaptive law parameters	Adaptation gain matrix	Γ	diag(10, 10, 10)
	Leakage & robust gains	l_0, μ	0.05, 0.1
	Valve gain adaptation	η_m, l_m, μ_m	50, 0.01, 0.1
Disturbance observer	Pressure-disturbance observer gain	l_{d3}	100
Event-Trigger	Minimum threshold	$\sigma_{\min}$	0.005
	Adaptive threshold terms	σ_0, λ	0.05, 10
Saturation & projection	Control input limits	$v_{\min}, v_{\max}$	-10, 10 V
	Valve gain bounds	$m_{v,\min}, m_{v,\max}$	0.1, 5.0
	Load mass projection	$m_{\min}, m_{\max}$	1.0, 10.0 kg
Initial conditions	System states	$x_1(0), x_2(0), x_3(0)$	0, 0, 0
	Valve gain estimate	$\hat{m}_v(0)$	1.0
Benchmark SMC	Sliding-surface coefficient	c_1, c_2	100, 2500
Benchmark SMC	Switching gain	K_{sw}	1000
Benchmark SMC	Boundary-layer thickness	Φ	0.05


Figure 2. Relationship between the control signal and the flow rate

The conventional PID gains are $K_p = 98.752$, $K_i = 43.814$, and $K_d = 22.326$. The initial tuning followed a Ziegler–Nichols-type heuristic procedure and was subsequently fine-tuned to reduce RMSE while avoiding excessive oscillation or instability under the nominal operating condition. SMC controller [22]: The tracking error is $e = y_r - y$ and the sliding surface is $s = \ddot{e} + c_1 \dot{e} + c_2 e$. A saturation function $\text{sat}(s/\Phi)$ replaces the ideal sign function to reduce chattering. The implemented sliding-surface coefficient $c_1 = 100$, $c_2 = 2500$, switching gain $K_{sw} = 1000$, and boundary-layer thickness $\Phi = 0.05$. The sliding-surface coefficient c sets the nominal error convergence on $s = 0$; the switching gain K_{sw} must be large enough to dominate the matched uncertainty/disturbance term in the implemented SMC dynamics, while Φ defines the boundary-layer width used to trade chattering against local tracking

accuracy. The online self-tuning fuzzy PID controller [32] uses the tracking error and change in error to adjust ΔK_p , ΔK_i , and ΔK_d around the same baseline PID gains. Five linguistic sets with Gaussian and sigmoid membership functions over the normalized universe $[0, 1]$ of absolute error and absolute derivative of error. In this study, the fuzzy inference output is obtained by aggregating the fuzzy input sets according to the designed fuzzy rules. The max-product method is employed for the aggregation process, while the centroid method is used for defuzzification.

The sinusoidal reference is $y_r(t) = 0.1 \sin(2\pi f t)m$ with $f = 0.05\text{Hz}$. The chirp reference is $y_r(t) = 0.1 \sin(2\pi(f_0 + \frac{f_1 - f_0}{2T_{\text{sim}}} t)t)m$, where $f_0 = 0.05\text{ Hz}$, $f_1 = 0.25\text{ Hz}$, and $T_{\text{sim}} = 40\text{ s}$.

Trapezoidal 1: A periodic piece-wise linear signal with a maximum amplitude of $\pm 0.1m$, a gentle velocity limit of $\dot{y}_{r,\text{max}} = 0.01m/s$. The command includes a 10 s hold at $+0.1\text{ m}$ and is defined over the full 50 s interval as:

$$y_r(t) = \begin{cases} 0.01t, 0 \leq t < 10 \\ 0.1, 10 \leq t < 20 \\ 0.1 - 0.01(t - 20), 20 \leq t < 40 \\ -0.1, 40 \leq t < 50 \end{cases}$$

Trapezoidal 2: A more aggressive periodic piece-wise linear signal with a maximum amplitude of $\pm 0.1m$, a steeper velocity limit of $\dot{y}_{r,\text{max}} = 0.02\text{ m/s}$. The current definition is:

$$y_r(t) = \begin{cases} 0.02t, 0 \leq t < 5 \\ 0.1, 5 \leq t < 10 \\ 0.1 - 0.02(t - 10), 10 \leq t < 20 \\ -0.1, 20 \leq t < 25 \\ -0.1 + 0.02(t - 25), 25 \leq t < 30 \end{cases}$$

Multi-step 1:

$$y_r(t) = \begin{cases} -0.05, 0 \leq t < 20 \\ 0.10, 20 \leq t < 40 \\ -0.075, 40 \leq t < 60 \\ 0.05, 60 \leq t < 80 \\ -0.05, t \geq 80 \end{cases}$$

Multi-step 2:

$$y_r(t) = \begin{cases} -0.05, 0 \leq t < 20 \\ -0.10, 20 \leq t < 40 \\ -0.075, 40 \leq t < 60 \\ -0.025, 60 \leq t < 80 \\ -0.05, t \geq 80 \end{cases}$$

Let N denote the number of samples in the evaluation interval, $y(i)$ the actuator position, $y_r(i)$ the reference position, and $\bar{y}_r$ the mean reference value. With $T_s = 0.001s$, the nominal sample counts are 100,000 for each 100 s test, 50,000 for each 50s test, and 40,000 for the 40s chirp test.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_r(i) - y(i))^2}; R^2 = 1 - \frac{\sum_{i=1}^N (y_r(i) - y(i))^2}{\sum_{i=1}^N (y_r(i) - \bar{y}_r)^2}; ARE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_r(i) - y(i)}{|y_r(i)| + \delta} \right|$$

with $\delta = 10^{-5}\text{ m}$. The ARE denominator is explicitly $|y_r(i)| + \delta$; hence $|y_r(i)| + \delta \geq \delta > 0$ for every sample, including zero crossings. The regularization constant has the same unit as the displacement reference and corresponds to 0.01% of the 0.1m nominal trajectory amplitude. This regularized pointwise relative-error definition is the one used for all reported ARE calculations.

For the extended transient and control-effort assessment, the following indices are also considered: maximum absolute tracking error $e_{\text{max}} = \max_i |y_r(i) - y(i)|$; integral absolute error $IAE = \int_0^{T_{\text{sim}}} |y_r(t) - y(t)| dt \approx \sum_{i=1}^N |e_i| \Delta t$; peak control effort $v_p = \max |v(t)|$; RMS control effort $v_{\text{RMS}} = \sqrt{\frac{1}{T_{\text{sim}}} \int_0^{T_{\text{sim}}} v(t)^2 dt} \approx \sqrt{\frac{1}{N} \sum_{i=1}^N v_i^2}$; overshoot $OS = \frac{y_{\text{max}} - y_r}{y_r} \times 100\%$ relative to the commanded step amplitude; and settling time based on a $\pm 2\%$ error band around the commanded level.

CO-SIMULATION RESULTS AND DISCUSSION

PID under the identical conditions in Table 3 and six reference trajectories. Tracking responses are shown in Figures 4, 6, 8, 10, 12, and 14, with quantitative performance summarized in Tables 4–7.

Tracking accuracy under reference trajectories

The benchmark controllers show different limitations. Fixed-gain PID follows the references but gives the largest chirp RMSE (0.0109) and ARE (0.113). SMC improves nonlinear robustness but retains transition errors; for Multi-Step 1 it gives RMSE = 0.0024 and ARE = 0.263. OTPID performs better overall, reducing the Multi-Step 1 RMSE to 0.0017, although its chirp RMSE and ARE rise to 0.0076 and 0.085. These

trends indicate increasing difficulty during abrupt or frequency-varying motion.

ABIC gives the smallest RMSE and ARE in all six tests (Table 4). For Multi-Step 1, RMSE is 0.000837, about half the OTPID value and substantially below SMC. R^2 approaches unity, including 0.999986 for Trapezoidal 1. Under the chirp input, ABIC maintains RMSE = 0.0038 and ARE = 0.037, compared with 0.0109 for PID and 0.0091 for SMC. The trigger plots show intermittent command updates, while the external-force traces indicate small tracking deviations under the trajectory-dependent load.

Figures 4–15 summarize the tracking and control responses under the six reference trajectories. Figures 4, 6, 8, 10, 12, and 14 show tracking performance and external load forces, whereas Figures 5, 7, 9, 11, 13, and 15 present the corresponding ABIC control and triggering responses. The held valve command is updated intermittently without a noticeable loss of tracking accuracy under the investigated co-simulation conditions.

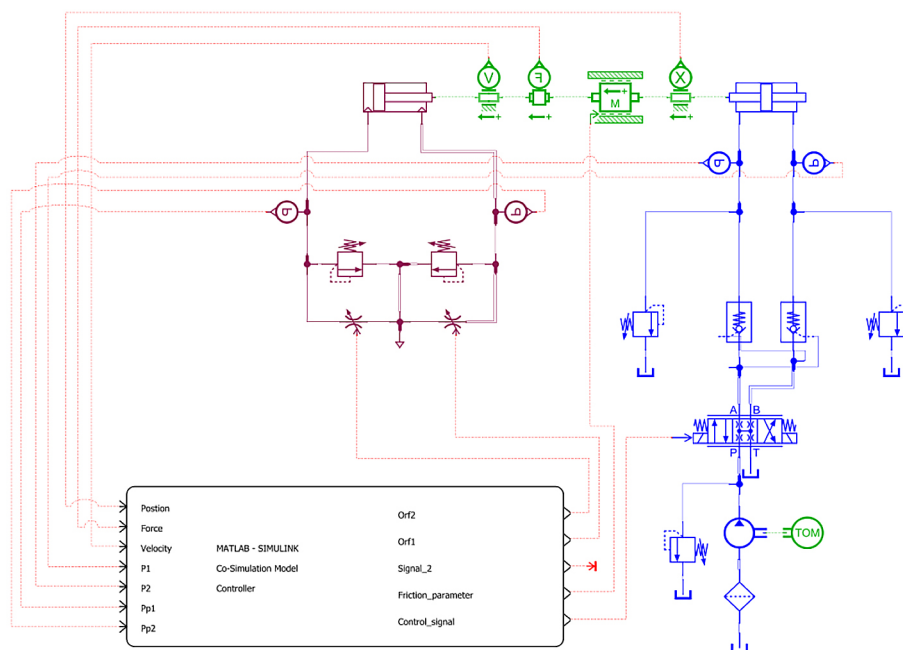


Figure 3. Schematic diagram of the hydraulic system in the co-simulation platform

Table 3. Case studies of the investigation

Profile	Amplitude/Frequency	Time
Multi-Step 1	-0.075 → 0.1[m]	100 sec.
Multi-Step 2	-0.10 → -0.025 [m]	100 sec.
Trapezoidal 1	-0.10 → 0.10[m]	50 sec.
Trapezoidal 2	-0.10 → 0.10[m]	50 sec.
Sinusoidal	0.1[m]/0.05 [Hz]	50 sec.

Table 4. Performance evaluation using three criteria

Ref.	Criteria	Controller			
		ABIC	OTPID	SMC	PID
Multi-Step 1	RMSE	0.000837	0.001732	0.002394	0.002136
	R ²	0.999826	0.999313	0.998481	0.999088
	ARE	0.064382	0.126235	0.262977	0.100618
Multi-Step 2	RMSE	0.000389	0.000533	0.000758	0.000811
	R ²	0.999783	0.999604	0.999134	0.999018
	ARE	0.005848	0.008789	0.010265	0.012788
Trapezoidal 1	RMSE	0.000324	0.00056	0.001173	0.00071
	R ²	0.999986	0.999967	0.999805	0.999939
	ARE	0.009334	0.014674	0.021183	0.020342
Trapezoidal 2	RMSE	0.000588	0.00154	0.002672	0.001817
	R ²	0.99997	0.999757	0.998778	0.999705
	ARE	0.0197	0.056788	0.170028	0.039748
Sinusoidal	RMSE	0.001175	0.002598	0.003785	0.003058
	R ²	0.999903	0.999238	0.997328	0.999431
	ARE	0.009363	0.030708	0.050326	0.034511
Chirp	RMSE	0.003778	0.007637	0.009069	0.010934
	R ²	0.99751	0.988875	0.983185	0.976619
	ARE	0.036656	0.08485	0.107293	0.112987

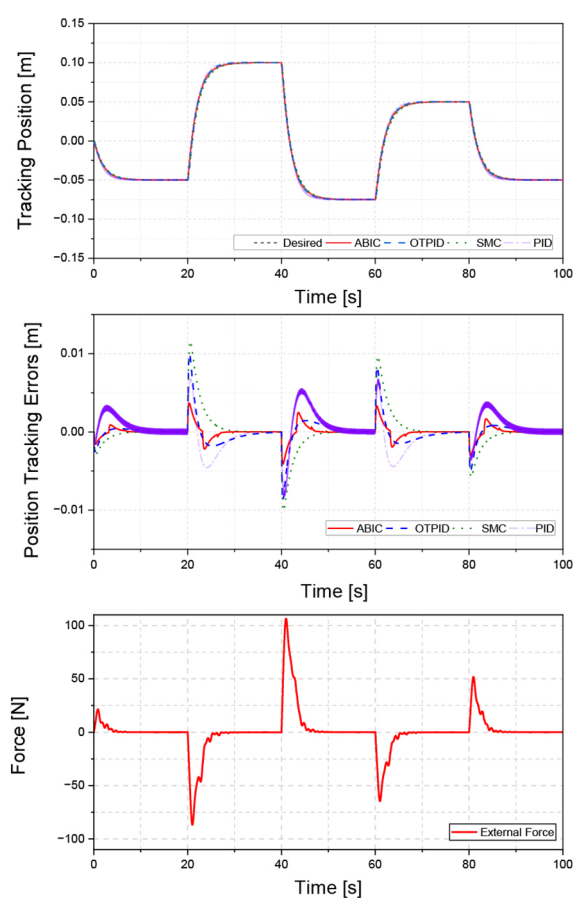
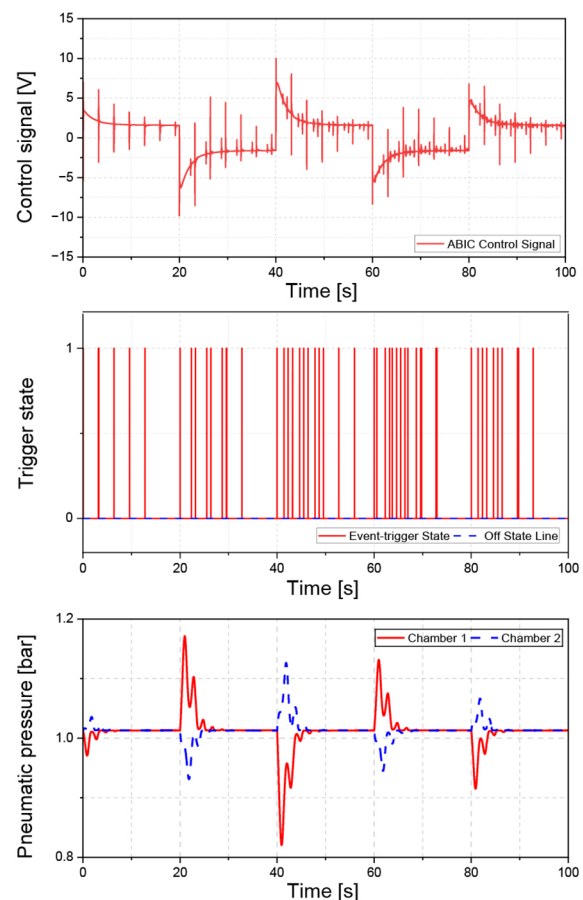
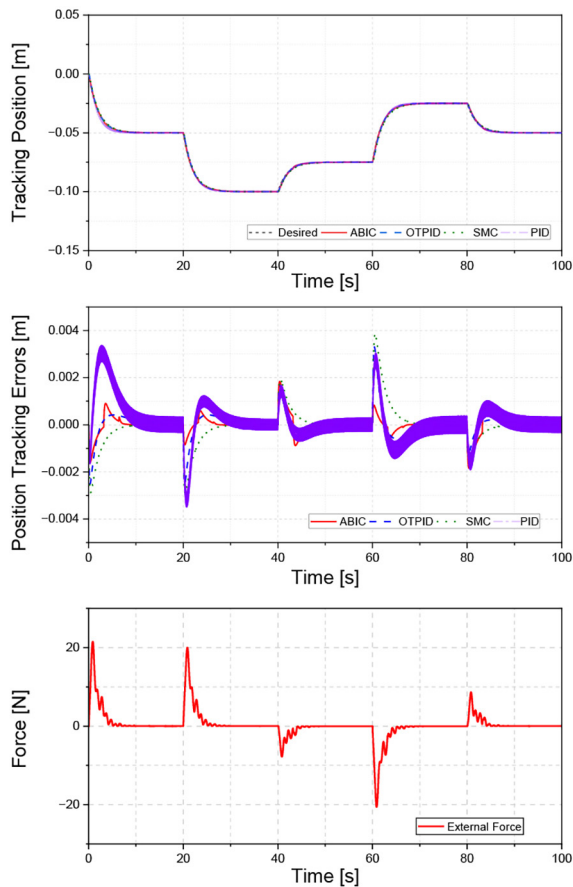
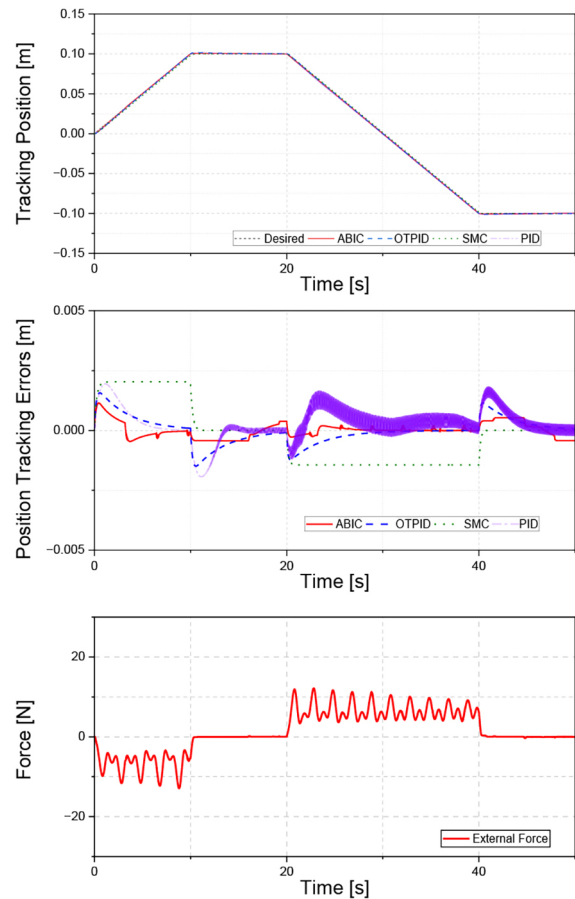

Figure 4. Tracking control performance under the first multi-step trajectory: position response, tracking error, and applied external-load response

Figure 5. ABIC control activity under the first multi-step trajectory, including the control command, trigger state, and pneumatic chamber pressures

Table 5. Extended performance comparison under the Multi-Step 2 trajectory

Metric	ABIC (Proposed)	OTPID	SMC	PID
Maximum tracking error (m)	0.001839	0.003298	0.0038432	0.003497
Overshoot (%)	0.003	0.12	0.38	0.49
Settling time (s)	7.775	7.191	7.926	7.266
IAE (m·s)	0.01999	0.03080	0.03940	0.05864
Peak control effort (V)	7.01	7.18	8.60	7.20
RMS control effort (V)	1.86	1.97	1.93	1.89


Figure 6. Tracking control performance under the second multi-step trajectory: position response, tracking error, and applied external-load response

Figure 8. Tracking control performance under the first trapezoidal trajectory: position response, tracking error, and applied external-load response

Disturbance estimation and parameter adaptation

Figure 16 demonstrates the performance of the disturbance observer (DOB). In the pressure dynamics, the matched lumped disturbance $d_e(t)$ represents unmodeled fluid effects such as leakage, effective-bulk-modulus variation, and residual valve-flow uncertainty. The DOB tracks this injected pressure-rate disturbance, with the estimate $\hat{d}_e(t)$, displayed in bar/s, converging rapidly

to $d_e(t)$. The observer error $d_e(t) - \hat{d}_e(t)$ remains bounded, consistent with Theorem 1. The signals in Figure 16 are pressure-rate disturbances and are distinct from the pneumatic external-load force $F_{ext}(t)$ plotted in the trajectory-response figures.

The valve-gain estimate remains within its projection bounds and the parameter estimates approach bounded values. Exact physical-parameter convergence is not claimed because the analysis establishes boundedness rather than persistent-excitation-based identification.

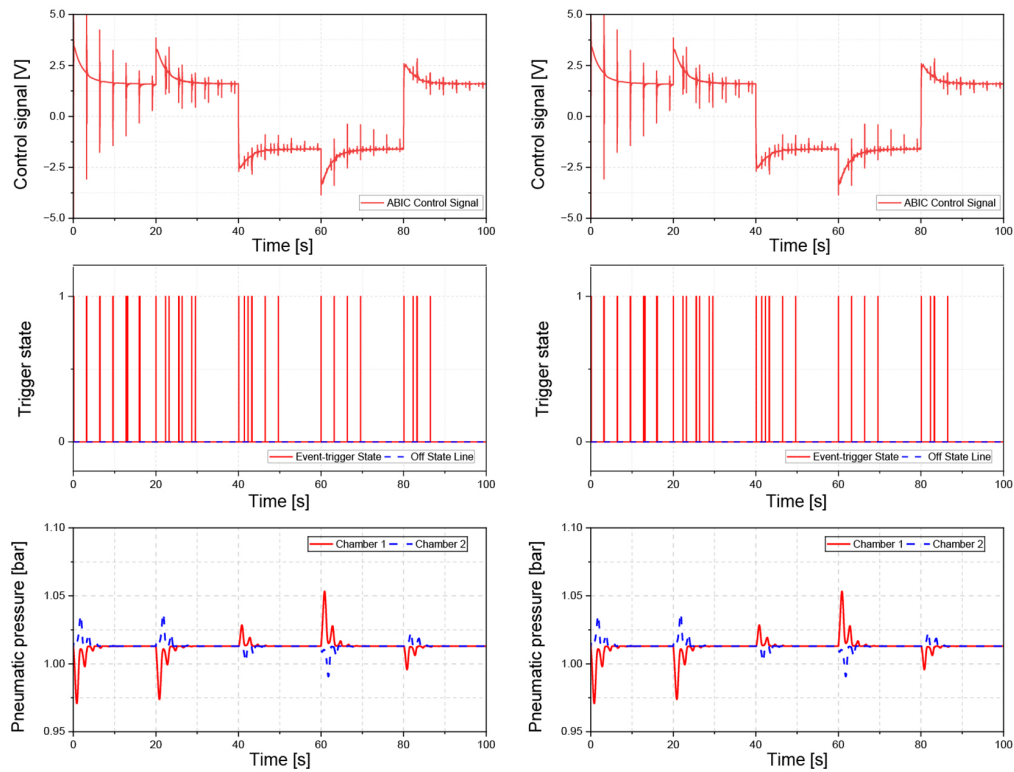


Figure 7. ABIC control activity under the second multi-step trajectory, including the control command, trigger state, and pneumatic chamber pressures

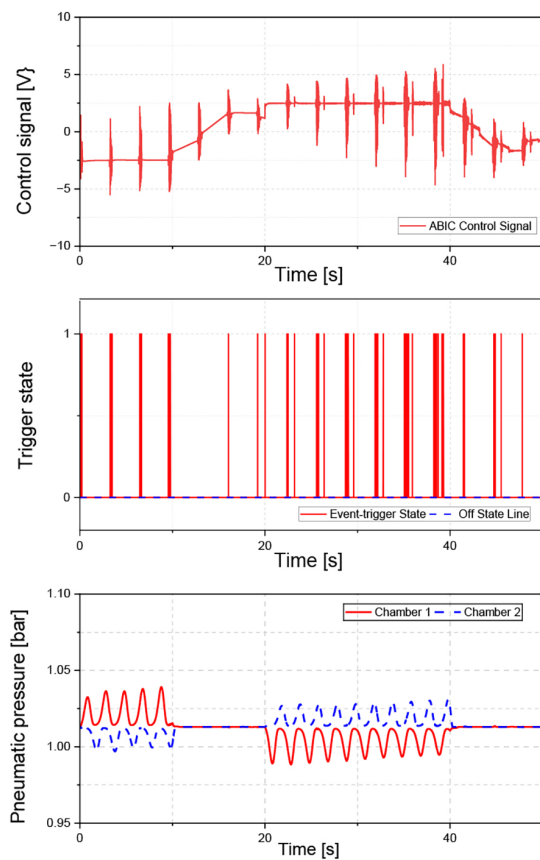


Figure 9. ABIC control activity under the first trapezoidal trajectory, including the control command, trigger state, and pneumatic chamber pressures

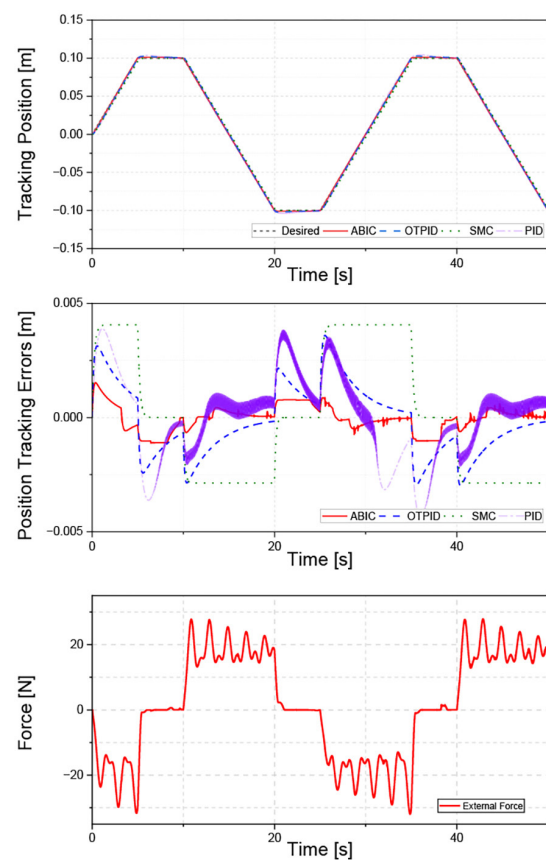


Figure 10. Tracking control performance under the second trapezoidal trajectory: position response, tracking error, and applied external-load response

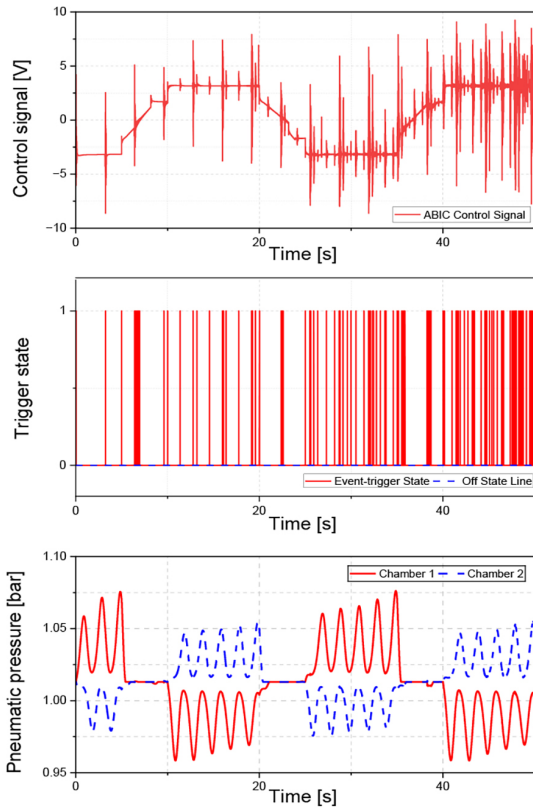


Figure 11. ABIC control activity under the second trapezoidal trajectory, including the control command, trigger state, and pneumatic chamber pressures

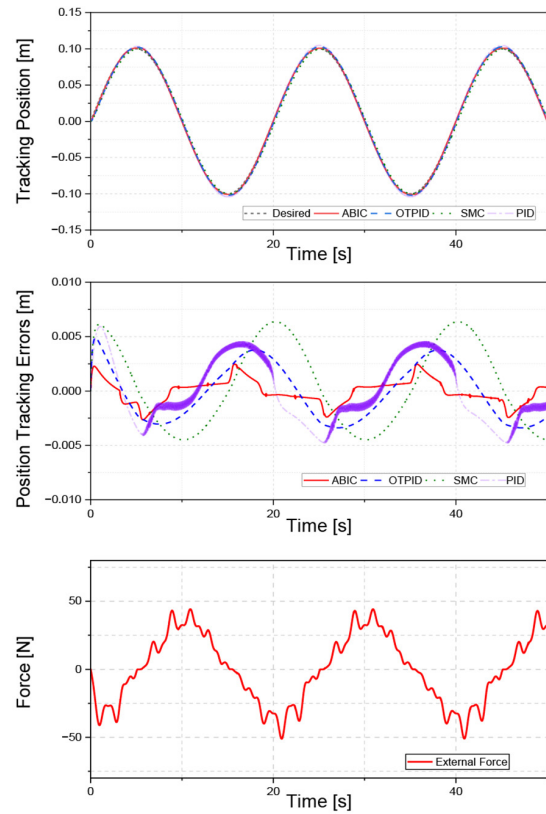


Figure 12. Tracking control performance under the sinusoidal trajectory: position response, tracking error, and applied external-load response

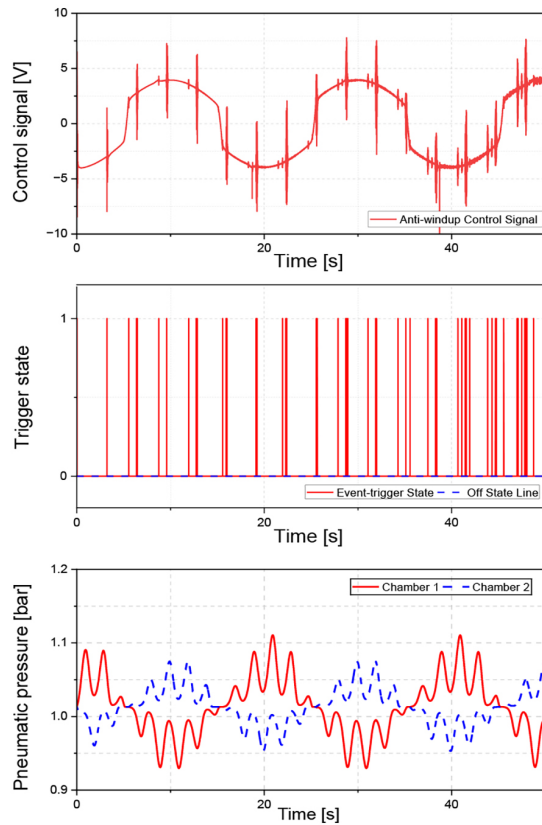


Figure 13. ABIC control activity under the sinusoidal trajectory, including the control command, trigger state, and pneumatic chamber pressures

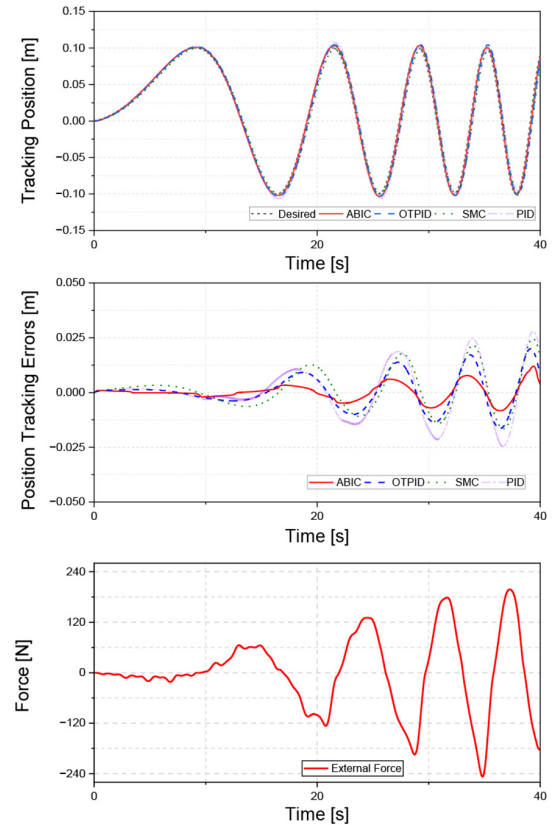


Figure 14. Tracking control performance under the chirp trajectory: position response, tracking error, and applied external-load response

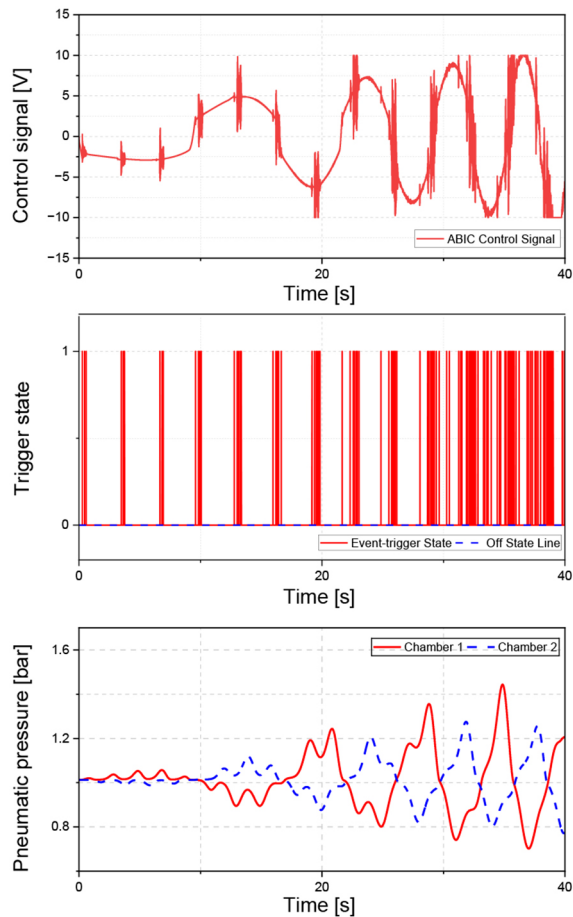


Figure 15. ABIC control activity under the chirp trajectory, including the control command, trigger state, and pneumatic chamber pressures

Event-triggering performance and update reduction

At $T_s = 0.001$ s, periodic update counts are 100,000 for the 100 s tests, 50,000 for the 50 s tests, and 40,000 for the 40 s chirp. The corresponding event-trigger counts are 22,444, 25,753, 14,231, 13,786, 15,124, and 13,507 (Table 6).

Update reduction is 66.23–77.56%. This measures command-refresh reduction, not CPU-time or processor-load reduction, which also depends on solver, I/O, communication, and hardware overhead.

For consistency with the reported event counts, the mean update interval in Table 6 is defined as T/N_e , where T is the test duration and N_e is the number of triggered updates. This gives mean update intervals of 4.456, 3.883, 3.513, 3.627, 3.306, and 2.961 ms for Multi-Step 1, Multi-Step 2, Trapezoidal 1, Trapezoidal 2, Sinusoidal, and Chirp, respectively. The minimum and

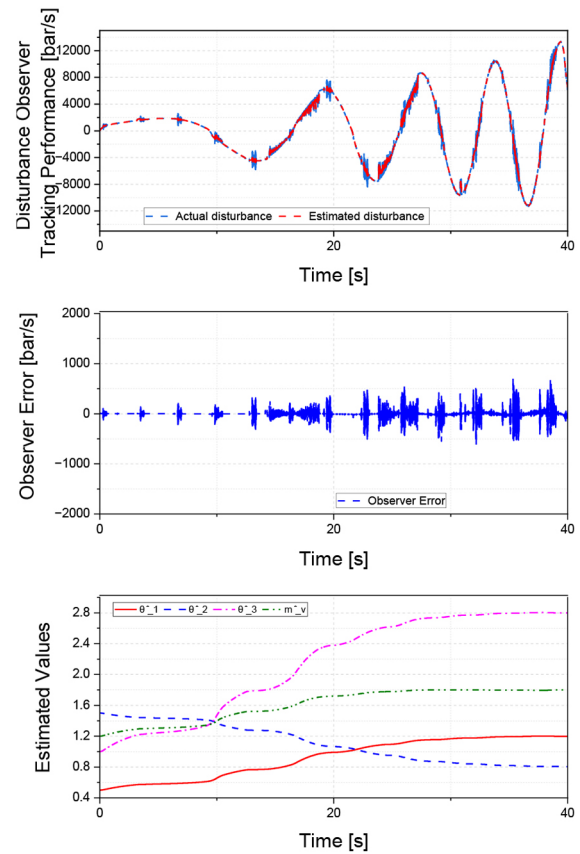


Figure 16. Disturbance-observer and parameter-adaptation responses: (a) actual lumped pressure-rate disturbance $d_e(t)$ and its observer estimate $\hat{d}_e(t)$; (b) disturbance-estimation error $d_e(t) - \hat{d}_e(t)$; (c) estimated plant parameters and valve-gain estimate

maximum intervals are retained from the recorded event-log statistics.

Input saturation and anti-windup compensation

The actuator command is limited to $\pm 10V$. The anti-windup modification is activated through the saturation mismatch $\Delta v = v_{uc} - \text{sat}(v_{uc})$, with $v = \text{sat}(v_{uc})$. Hence $\Delta v = 0$, within the admissible range and becomes nonzero only when the unconstrained command exceeds the actuator limit. The valve-gain adaptation is modified during these intervals so that it does not continue to respond to an unattainable valve command. Figure 17 presents the additional component-level simulation used to examine the anti-windup and ablation effects. The control-signal comparison illustrates the effect of the anti-windup modification during demanding transients, while the position-tracking and tracking-error responses show the behavior of the complete and degraded

Table 6. Event-triggering statistics across the six reference trajectories

Trajectory	Periodic steps	Triggered events	Update rate (%)	Update reduction (%)	Min Δt (s)	Mean update interval (s)	Max Δt (s)
Multi-Step 1	100,000	22,444	22.44	77.56	0.001	0.004456	6.882
Multi-Step 2	100,000	25,753	25.75	74.25	0.001	0.003883	3.625
Trapezoidal 1	50,000	14,231	28.46	71.54	0.001	0.003513	3.160
Trapezoidal 2	50,000	13,786	27.57	72.43	0.001	0.003627	3.029
Sinusoidal	50,000	15,124	30.25	69.75	0.001	0.003306	3.084
Chirp	40,000	13,507	33.77	66.23	0.001	0.002961	2.912

Table 7. Ablation-study metrics for the complete and degraded ABIC configurations

Controller variant	RMSE	R ²	ARE	Update rate (%)
Complete ABIC	0.003778	0.99751	0.036656	33.77%
ABIC without DOB	0.005745	0.99012	0.057246	42.36%
ABIC without anti-windup	0.006781	0.98813	0.059842	45.28%
ABIC without ETC	0.003555	0.99789	0.035428	100%

controller configurations. The total saturation duration is calculated as $T_{sat} = T_s \sum_i I(|v_{uc}(i)| > 10)$, where $I(\cdot)$ is the indicator function.

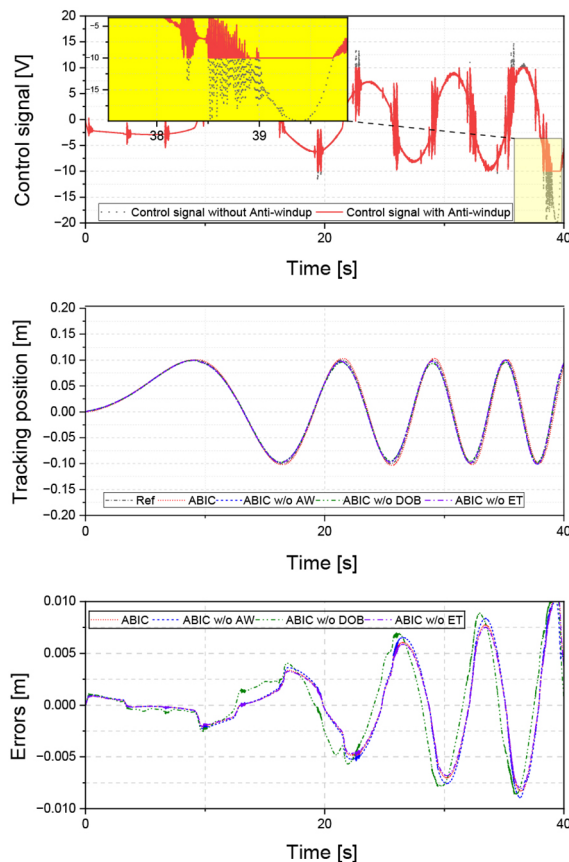


Figure 17. Component-level responses for the anti-windup and ablation assessment under the chirp trajectory: (a) control-signal responses of the complete ABIC and degraded variants; (b) position-tracking responses; (c) tracking-error responses

Ablation study

The ablation study is evaluated under the Chirp trajectory and compares the complete ABIC with variants without DOB, without anti-windup, and without ETC; the last variant refreshes the saturated command at every sampling instant.

Figure 17 shows the component-level response differences, while Table 7 provides the RMSE, R², ARE, and update-rate results used for quantitative attribution.

Comparison with previous studies

Comparison with prior work focuses on assumptions, controller structure, and validation conditions because trajectories, disturbances, and metric definitions differ across studies. Adaptive and command-filtered backstepping/dead-zone studies [2, 3, 18] establish Lyapunov-based recursive control under electro-hydraulic nonlinearity and uncertainty. The present design adds disturbance estimation, event-triggered held-command updating, and anti-windup compensation within the same electro-hydraulic framework.

Prior disturbance-rejection work addresses dead zones and voltage limits [10], while recent work combines fixed-time DOB, ETC, and input saturation in networked electro-hydraulic systems [31]. The present study differs by integrating these functions with adaptive backstepping, plant-parameter adaptation, and valve dead-zone residual treatment. Direct numerical comparison is avoided because the plant and test conditions differ.

Prediction-based hydraulic control [28] and model-predictive control [29] rely on prediction or online optimization, whereas ABIC uses adaptive uncertainty and disturbance compensation. Event-triggered hydraulic control [30] similarly supports reduced command updating; here the comparison covers six trajectories with an explicit ± 10 V input constraint.

Study limitations

The present evidence is limited to MATLAB/Simulink–Simcenter Amesim co-simulation of a symmetric-cylinder model and therefore does not replace physical test-bench validation. Sensor noise and bias, communication delay, sampling-frequency variation, supply-pressure changes, dead-zone asymmetry, and high-frequency valve dynamics were not systematically evaluated; consequently, the observer results do not establish noise robustness, and the reduction in update counts should not be interpreted as a direct measure of processor load. Experimental and HIL/real-time validation are therefore required before making claims regarding industrial robustness, embedded execution time, or long-term actuator performance.

CONCLUSIONS

This study integrated adaptive backstepping, ETC, disturbance estimation, and anti-windup compensation for an electro-hydraulic actuator with valve dead zone, uncertainty, disturbances, and saturation. The resulting ABIC forms a unified Lyapunov-based architecture for which uniform ultimate boundedness is established under the stated assumptions.

Across six co-simulation trajectories, ABIC produced the lowest RMSE and ARE among PID, SMC, OTPID, and ABIC. RMSE was 0.000837 for Multi-Step 1 and 0.003778 for the chirp test; the event-triggered mechanism reduced command-update frequency while preserving tracking under the investigated conditions.

The current evidence remains co-simulation based. Future work will therefore focus on hydraulic-bench and HIL/real-time validation, including processor-load measurement and robustness tests under sensor noise, communication delay, supply-pressure variation, and changing dead-zone characteristics.

Acknowledgments

We acknowledge Ho Chi Minh City University of Industry and Trade, Ho Chi Minh City, Vietnam and Nguyen Tat Thanh University, Ho Chi Minh City, Vietnam for supporting this study.

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