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Indirect Adaptive Predictor–Preview Control with Unknown Time-Varying Input Delay and Parameter

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Abstract— **This paper presents an indirect adaptive predictor–preview control architecture for continuous-time systems with *unknown time-varying input delays* and *unknown (slowly varying) parameters*. An adaptive super-twisting algorithm (STA) estimates the unknown delay online using a monotone ramp probe, and an indirect recursive least-squares (RLS) module tracks slow parameter variations; both feed a frozen-parameter predictor and a preview feedforward based on $r(t + \hat{h}(t))$. Nominal exponential tracking is shown under exact prediction, and a practical input-to-state stability (ISS) bound is derived that accounts for delay/parameter estimation errors, disturbances, and numerical approximation. On the DC motor speed servo benchmark, the controller reduces steady-state RMSE/peak error to $0.046/0.074$ (S1) and $0.062/0.099$ (S4), below all compared baselines.**

I. INTRODUCTION

When the input delay of a networked or digitally implemented control loop is *unknown* and *time-varying*, phase margin and tracking performance can degrade rapidly. Predictor feedback (e.g., Artstein reduction) is effective for compensating known input delays [1], [2], but most designs rely on measured or bounded delay information and become fragile under unknown time-varying delays. Since $u(t)$ affects the plant only after the delay elapses, preview control—which uses future reference information available over the delay horizon—is a natural complement to predictor feedback. Yet existing works treat these subproblems separately; no prior design integrates *online delay estimation*, *preview tracking*, and *model adaptation* with a unified stability analysis.

Contributions. We propose a predictor–preview tracking controller in which STA-based delay estimation and indirect RLS model update feed a frozen-parameter predictor and a preview reference feedforward. A practical ISS guarantee is provided that accounts for delay/parameter estimation errors, parameter variation rate, disturbances, and numerical approximations. The approach is validated on the DC motor servo benchmark [3] against recent predictor-based methods [4], [5], [6].

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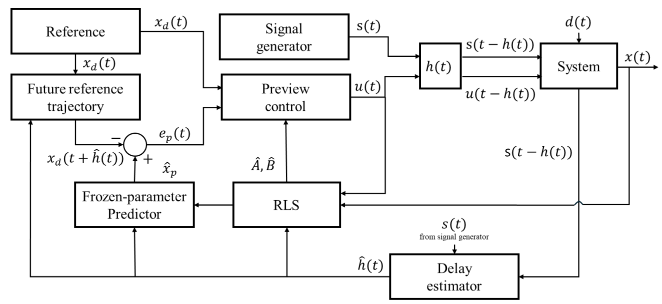

Fig. 1. Proposed Overall Architecture

II. PROBLEM FORMULATION

Consider the uncertain linear parameter-varying plant with an unknown time-varying input delay:

$$\dot{x}(t) = A(\theta(t))x(t) + B(\theta(t))u(t - h(t)) + d(t), \quad (1)$$

$$y(t) = Cx(t), \quad (2)$$

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$, $y \in \mathbb{R}^p$, and $d(t)$ is a bounded disturbance. The delay $h(t) \geq 0$ is unknown and time-varying, and $\theta(t)$ denotes unknown (possibly slowly varying) parameters. We aim to track $y_d(t) = Cx_d(t)$ generated by $\dot{x}_d(t) = A_m x_d(t) + B_m r(t)$, A_m Hurwitz, assuming that $r(t + s)$ is available online for all $s \in [0, h_{\max}]$.

Delay regularity: $0 \leq h(t) \leq h_{\max}$ and $|\dot{h}(t)| \leq \delta < 1$ (so $t \mapsto t - h(t)$ is strictly increasing).

Robust stabilizability: there exists a constant feedback gain K such that $A(\theta) - B(\theta)K$ is uniformly stable over the admissible parameter set.

III. PROPOSED PREDICTOR–PREVIEW CONTROL

A. Architecture

As shown in Fig. 1, an online delay estimator provides $\hat{h}(t)$, an indirect RLS module updates $\hat{\theta}(t)$ (hence $\hat{A}(t), \hat{B}(t)$), a frozen-parameter predictor computes $\hat{x}_p(t)$, and a preview tracking law feeds back the predicted tracking error.

B. Online delay estimation (STA)

A monotone ramp probe $s(t) = s_0 + k_s t$ ($k_s > 0$) is injected through the delay channel. The measured probe is $s_m(t) = s(t - h(t))$. Define

$$\sigma(t) = s(t - \hat{h}(t)) - s_m(t) = -k_s\big(\hat{h}(t) - h(t)\big). \quad (3)$$

Driving $\sigma(t) \to 0$ implies $\tilde{h}(t) := \hat{h}(t) - h(t) \to 0$. We employ an adaptive super-twisting implementation as in [4], [7] to obtain bounded $\hat{h}(t) \in [0, h_{\max}]$ and practical convergence $|\tilde{h}(t)| \leq \varepsilon_h$ after a transient.

C. Frozen-parameter predictor and preview error

Given $(\hat{A}(t), \hat{B}(t))$ and $\hat{h}(t)$, the frozen-parameter predictor is

$$\hat{x}_p(t) = e^{\hat{A}(t)\hat{h}(t)}x(t) + \int_{t-\hat{h}(t)}^{t} e^{\hat{A}(t)(t-\tau)}\hat{B}(t)\,u(\tau)\,d\tau. \quad (4)$$

The predicted tracking error with previewed reference is $e_p(t) = \hat{x}_p(t) - x_d\big(t + \hat{h}(t)\big)$.

D. Control law with feedforward

The predictor–preview tracking law is

$$u(t) = u_{\text{ff}}\big(t + \hat{h}(t)\big) - Ke_p(t), \quad (5)$$

where K is a constant stabilizing gain and $u_{\text{ff}}(t) = \hat{B}^{\dagger}(t)\big(\dot{x}_d(t) - \hat{A}(t)x_d(t)\big)$.

E. Indirect RLS model update

Parameter mismatch and slow variations are compensated by updating $\hat{\theta}$ via forgetting-factor RLS with projection [8]; the resulting $(\hat{A}, \hat{B})$ enter (4) and (5). Gating near saturation and mild low-pass filtering improve numerical robustness.

IV. STABILITY GUARANTEE (SUMMARY)

Nominal case. If $h(t) \equiv h$, $\theta(t) \equiv \theta$, $\hat{h} \equiv h$, $(\hat{A}, \hat{B}) \equiv (A, B)$, and (4) is exact so that $\hat{x}_p(t) = x(t+h)$, then (5) recovers delay-free error dynamics and yields exponential tracking (for $d \equiv 0$) under a Hurwitz $A(\theta) - B(\theta)K$ [1], [2].

Practical case (ISS). Under bounded estimation errors and disturbances, the tracking error $e(t) = x(t) - x_d(t)$ satisfies

$$\limsup_{t\to\infty} \|e(t)\| \le \kappa_h\,\bar{\tilde{h}} + \kappa_\theta\,\bar{\tilde{\theta}} + \kappa_{\dot{\theta}}\,\bar{\dot{\theta}} + \kappa_d\,\bar{d} + \kappa_n, \quad (6)$$

where $\bar{\tilde{h}}, \bar{\tilde{\theta}}, \bar{\dot{\theta}}, \bar{d}$ bound the delay/parameter estimation errors, parameter variation rate, and disturbance, and κ_n captures residual numerical approximation effects. The $\kappa_h\bar{\tilde{h}}$ term makes explicit that tighter delay estimation reduces the achievable steady-state error.

V. EXPERIMENTS: DC MOTOR SERVO BENCHMARK

We evaluate on the DC motor speed servo benchmark [3]:

$$\dot{\omega}(t) = -\tfrac{b}{J}\omega(t) + \tfrac{K_t}{J}i(t) - \tfrac{1}{J}\tau_L(t), \quad (7)$$

$$\dot{i}(t) = -\tfrac{K_e}{L}\omega(t) - \tfrac{R}{L}i(t) + \tfrac{1}{L}u(t - h(t)). \quad (8)$$

Four scenarios use $h(t) = 0.06 + 0.02\sin(2\pi \cdot 0.2\,t)$ s: S1) time-varying delay; S2) + load-step disturbance; S3) + parameter mismatch; S4) + time-varying parameters. We compare against Deng 2021 [4], Lee 2022 [5] (fixed delay), and Lee 2025 [6].

As Table I shows, the proposed controller records the lowest RMSE and peak error among all methods in every scenario. Preview tracking with online delay estimation eliminates phase lag in S1–S2, and the indirect RLS update preserves prediction accuracy under mismatch and parameter drift in S3–S4.

TABLE I
QUANTITATIVE COMPARISON ON DC MOTOR BENCHMARK.

Method	S1: TV delay		S2: + load step		S3: + mismatch		S4: + TV params	
	RMSE	Peak	RMSE	Peak	RMSE	Peak	RMSE	Peak
Proposed	0.046	0.074	0.301	0.341	0.056	0.089	0.062	0.099
Deng 2021 (STA)	3.216	4.812	3.213	4.931	5.290	8.067	7.752	12.797
Lee 2022 (PPC)	0.363	0.531	0.419	0.722	1.736	2.809	3.377	5.641
Lee 2025 (RPC)	2.023	3.159	2.003	2.862	2.840	4.723	5.150	8.844

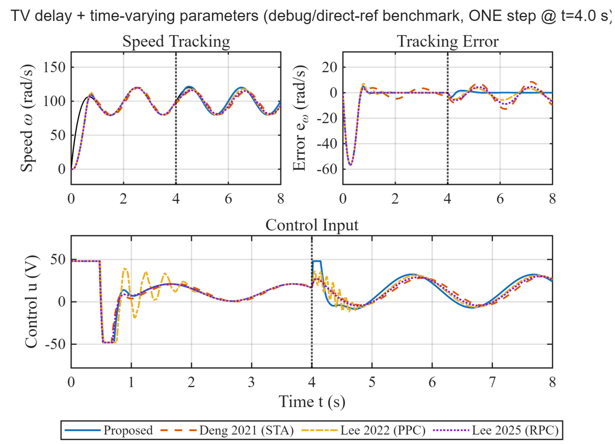

Fig. 2. S4: time-varying parameters under time-varying delay.

VI. CONCLUSION

We presented an indirect adaptive predictor–preview controller for systems with unknown time-varying input delays and parameters. The design couples STA-based delay estimation with frozen-parameter prediction, preview tracking, and indirect RLS updates, and is backed by a practical ISS bound. On the DC motor servo benchmark, the controller reduced RMSE and peak error relative to the three compared baselines in all four scenarios.

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