Model-based adaptive controller for fast and restricted swing control in Tower Cranes

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Abstract -
Tower cranes are underactuated, nonlinear systems in which rapid trolley and slew motions inevitably cause payload swing. An effective controller is crucial to ensure operational safety and efficiency, as uncontrolled payload swing can lead to hazardous conditions and reduced productivity. This paper addresses the problem of rapid and restricted swing control for a tower crane comprising two actuated coordinates (jib rotation, trolley travel) and two unactuated sway coordinates (radial and tangential swing). We proposed a model-based adaptive controller that requires only actuated-state measurements and compensates online for various payload and cable parameters. The controller is designed to update its parameters such that the sway motion is effectively damped while maintaining fast tracking of the trolley and hoist positions. The method is implemented and evaluated in a physics-based simulation environment within a real-scale tower crane and compared with a tuned PD controller. Results show that the adaptive controller achieves significantly lower peak swing, faster oscillation decay, and shorter settling times, particularly under parameter variations, demonstrating its potential for safer, faster tower crane operations.

Keywords -

Tower crane; Underactuated systems; Adaptive control; Payload swing suppression; Simulation

1 Introduction

Tower Cranes (TCs) are essential for lifting and transporting heavy payloads on construction sites, where productivity and safety are tightly coupled to the speed and precision of payload handling. However, TCs face significant challenges: varying load weights, payload swing, coupled motions, and site disturbances such as wind can all impact stability and control, which open-loop strategies such as input shaping or command smoothing may not adequately address [1]. In particular, the suspended load behaves like a pendulum, making tower cranes inherently prone to oscillations, as any acceleration of the actuated joints induces pendulum-like swing of the payload. Consequently, excessive swing not only slows operations by requiring operators to wait for oscillations to decay, but also increases the risk of collisions with partially built structures, equipment, and personnel.

Conventional industrial practice largely relies on manual operation supported by simple feedback laws, most commonly PD-type controllers designed around linearized models and small-angle assumptions [2, 3]. Although these controllers are straightforward to tune, their performance degrades when the system operates away from the nominal point, such as during fast maneuvers, large oscillations, or notable parameter changes. Maintaining smooth, robust control actions is important for enhancing performance, safety, and productivity on construction sites, as it mitigates risks associated with sudden changes in control inputs [1]. These limitations have motivated the development of alternative strategies that can better handle the oscillatory behavior and underactuated dynamics of tower cranes.

In this context, open-loop control methods are designed to reduce oscillations and vibrations during crane operations. They work by modifying the input commands to cancel the system's natural oscillatory behavior, thereby minimizing payload sway. Studies [4–8] explore different input-shaping techniques for tower cranes, including adaptive schemes and neural network-based approaches. However, input-shaping controllers have notable limitations. They typically assume that slewing and radial oscillations are uncoupled, an assumption that often fails in real operating environments. They also struggle to manage maneuvers whose duration is shorter than the system's sway period.

Recently, more advanced nonlinear and adaptive controllers have been proposed in other applications. For instance, in [9], a novel algorithm is utilized for parameter linearization for any dynamics that use the Denavit-Hartenberg approach, and this algorithm is implemented for 4-DOF robot. Elbadawy et al. [10] investigated an inverse dynamics controller for a marine tower crane mounted on a Stewart platform subject to continuous disturbances. Experiments showed it outperformed closed-loop PID input shaping, achieving greater oscillation reduction. Furthermore, several studies have refined Sliding Mode Control (SMC) for tower cranes by adding nonlinear dynamics and integral terms [11–13], incorporating fault tolerance validated on real cranes [14], and using finite-time disturbance observers for improved tracking [15]. However, SMC requires rapid switching between input limits, which can cause mechanical wear and instability, and its reliance on precise system models makes it sensitive to modeling errors and difficult for implementation.

In contrast, Bock et al. [16] applied Model Predictive Control (MPC) for tower crane path-following using a nonlinear model and a zero-error manifold for stability. While MPC offers significant advantages, it also comes with challenges such as complex modeling requirements, high computational load, and sensitivity to modeling inaccuracies, which can limit its practicality for real-world applications. To address this limitation, research has focused on nonlinear, adaptive, and robust strategies. Le and Lee [17] proposed a control strategy that integrates sliding mode control with model reference adaptive control to address system uncertainties and external disturbances, resulting in effective load swing suppression. Chen et al. [18] developed an adaptive tracking controller for a 4-DOF crane system, demonstrating stable and robust performance through experimental validation. Furthermore, Zhang et al. [19] introduced a neural-network-based adaptive control framework combined with barrier Lyapunov functions for double-pendulum cranes. Their approach accounts for input dead zones and modeling uncertainties, and ensures bounded tracking errors.

In a related contribution, Guo et al. [20] presented an adaptive control approach for tower cranes that simultaneously estimates unknown payload masses and friction-related parameters. Furthermore, Zhang et al. [21] employ an adaptive output-feedback control method with online gravity compensation to address key challenges in real tower-crane systems, including noise amplification caused by numerical differentiation, and steady-state cable errors. It assumes no uncertainties in the tower crane's components, such as jib inertia or unmodeled dynamics, which can introduce parameter variations and affect the overall system behavior. Despite these advances, most existing studies validate control strategies using simplified analytical models with idealized dynamics. Although such models are useful for theoretical analysis, they often fail to capture key physical effects such as realistic inertial distributions, friction forces, and geometric constraints. In contrast, this paper addresses this limitation by implementing our proposed controller in a physics-based simulation environment that closely replicates the physical system behaviour and captures these effects, thereby bridging the gap between purely mathematical validation and real-world deployment.

In this paper, we developed a model-based adaptive control scheme for rapid and restricted swing control of a 4-DOF tower crane system. It is validated not by an idealized mathematical model, but by a physics-based simulator that closely resembles real-world tests. This approach can improve safety problems in the field of crane control. Our approach is based on a nonlinear dynamic model that captures the underactuated joints and the coupling between trolley, jib, and payload sway. The controller uses only actuated-state measurements and an adaptive mechanism to account for uncertain parameters such as payload mass and cable-related terms. By appropriately shaping the closed-loop dynamics, the controller applies effective damping motion with jib and trolley actuators into the sway motion, enabling fast point-to-point maneuvers while keeping the swing angles small and driving residual oscillations to negligible levels. Furthermore, we utilized Robot Operating System (ROS) [22] to connect our controller to a physics engine. ROS is an open-source middleware framework that provides tools and libraries for building complex robot applications, enabling real-time communication between modules and efficient message parsing. It supports scalability through its modular architecture, enabling the addition of new functionalities or modifications to existing modules without disrupting the overall system's integrity. It is not an Operating System but a layer that simplifies development by connecting different components (nodes) via different communication types (topics, services, actions). Using ROS functionalities, we were able to connect our controller to the simulation and send control commands and receive feedback signals.

The main contributions of this work are:

(1) A nonlinear 4-DOF model of an underactuated tower crane, comprising two actuated and two unactuated coordinates, implemented in a physics-based simulation environment and tailored for swing-control design.

(2) An adaptive controller that relies only on actuated-state measurements and compensates for parameter uncertainties while damping swing.

(3) A comparative evaluation against PD control in a physics-based simulation environment, demonstrating superior swing attenuation and improved transient behavior for realistic crane operation.

The remainder of the paper is organized as follows. Section 2 presents the nonlinear model of the 4-DOF tower crane. Section 3 details the adaptive control design and stability properties. Section 4 describes the simulation setup. Section 5 discusses the results and implications for construction practice, and the conclusion of the paper is presented in Section 6.

2 Tower crane dynamic

A tower crane transports payloads using three primary actuated motions: jib rotation (slewing), trolley displacement along the jib (radial movement), and hook hoisting (vertical motion). These motions are strongly coupled: jib rotation induces tangential sway, while variations in trolley acceleration can excite radial sway and amplify oscillations if not properly controlled. In this work, rope length variations are treated as disturbances; therefore, the cable length is assumed constant during operation. The constant-length assumption is a common approach in the literature [2, 23] to focus on swing dynamics induced by horizontal accelerations, which are the dominant source of payload oscillation. The suspended load, connected to the trolley via a steel cable, exhibits two additional unactuated motions – radial and tangential sway – as illustrated in Figure 1. This configuration results in a 4-DOF underactuated system with significant nonlinear coupling between base rotation, trolley movement, and pendular dynamics. The model is formulated using Lagrangian mechanics, adopting a single-pendulum representation with state coordinates defined as:

$$q = \left[\gamma(t),\, x(t),\; \theta_1(t),\, \theta_2(t)\right]^\top \tag{1}$$

Where $\gamma(t)$ jib rotation, $x(t)$ trolley movement along the jib, and sway angles $\theta_1(t), \theta_2(t)$ as shown in Figure 1.

In this case, q is a 4×1 vector, and the parameter ℓ cable length is constant and is not in q state coordinates but instead appears as a dynamic parameter.

The equations of motion for general coordinations can be written as:

$$\mathbf{M}(q)\,\ddot{q} + \mathbf{C}(q,\dot{q})\,\dot{q} + \mathbf{G}(q) = \mathbf{F}(q,\dot{q}) + \mathbf{U} \tag{2}$$

Here, q denotes the state vector containing the generalized coordinates; $\mathbf{M}(q)$ is the inertia (mass) matrix; $\mathbf{C}(q, \dot{q}_s)$ is the Centripetal–Coriolis matrix; $\mathbf{G}(q)$ is the gravity vector; $\mathbf{F}(q, \dot{q}_s)$ collects joint frictions, damping, dead-zone nonlinearities (or any combination); and $\mathbf{U}$ is the input vector. When $q \in \mathbb{R}^{4\times1}$, then $\mathbf{M}$ and $\mathbf{C} \in \mathbb{R}^{4\times4}$, and $\mathbf{G}, \mathbf{U}, \mathbf{F} \in \mathbb{R}^{4\times1}$. Detailed expressions of a 4-DOF tower crane for each matrix and vector are provided in reference [1].

3 Adaptive control algorithm

The proposed controller is organized into three interconnected modules: a first-level controller, an adaptation law, and a torque-level control law. The reference trajectories and measured outputs are first processed by the first-level controller, which computes the auxiliary signals r, v, and a. These signals are then supplied to the adaptation block, where they are used to update the estimates of the uncertain system parameters. Finally, the signals r, v, and a, together with the estimated parameters, are passed to the control law, which computes the corresponding control torques applied to the actuated joints. These signals can be calculated with:

Table 1. System parameters and variables.

Symbol	Description	Units
$\gamma(t)$	Jib slew angle	deg
$x(t)$	Trolley displacement	m
$\theta_1,\ \theta_2$	Tangential/Radial swings	deg
m	Payload mass	Kg
m_t	Trolley mass	Kg
l	Cable length	m
J	Jib rotational inertia	kg m^2
g	Gravitational acceleration	m/s^2
P	Parameter vector	-
q	State vector	-
q_{ref}	Desired state (reference trajectory)	-
$\tilde{q}$	State vector	-
Λ	Positive definite gain matrix	-
r, s, v	Auxiliary signals	-

$$\tilde{q} = q_{ref} - q, \qquad r = \dot{\tilde{q}} + \Lambda\tilde{q}, \tag{3}$$

where q_{ref} represent the internal reference and Λ is a positive definite matrix. The time derivatives $\dot{\tilde{q}}$ and $\dot{q}_{ref}$ are computed numerically using backward differences at the controller's sampling period. The first-level outputs provided to the regressor and adaptation are

$$v = \dot{q}_{ref} + \Lambda\tilde{q}, \qquad a = \dot{v}. \tag{4}$$

Now, for developing adaptive control, first need to express the dynamics while the state variables are separated from unknown parameters like:

$$\mathbf{M}(q)\,a + \mathbf{C}(q,\dot{q})\,v + \mathbf{G}(q) = W(a, v, \dot{q}, q)\,P \tag{5}$$

The regressor matrix W depends on the measurable state variables. The parameter vector P collects the effective inertias, coupling terms, and viscous-like coefficients, which are either unknown or only approximately known. This linear representation in (5) enables online parameter identification without requiring a fully specified rigid-body model.

To enable adaptive control, the system dynamics must be expressed in a form that is linear with respect to the unknown parameters, a process commonly referred to as parameter linearization. Several approaches exist for this purpose. In this study, we adopt the parameter linearization algorithm proposed in [9] to construct the regressor matrix. The procedure begins by temporarily assigning nominal numerical values to the unknown physical parameters only for identifying their structural contribution to the system dynamics. Each entry of the inertia matrix

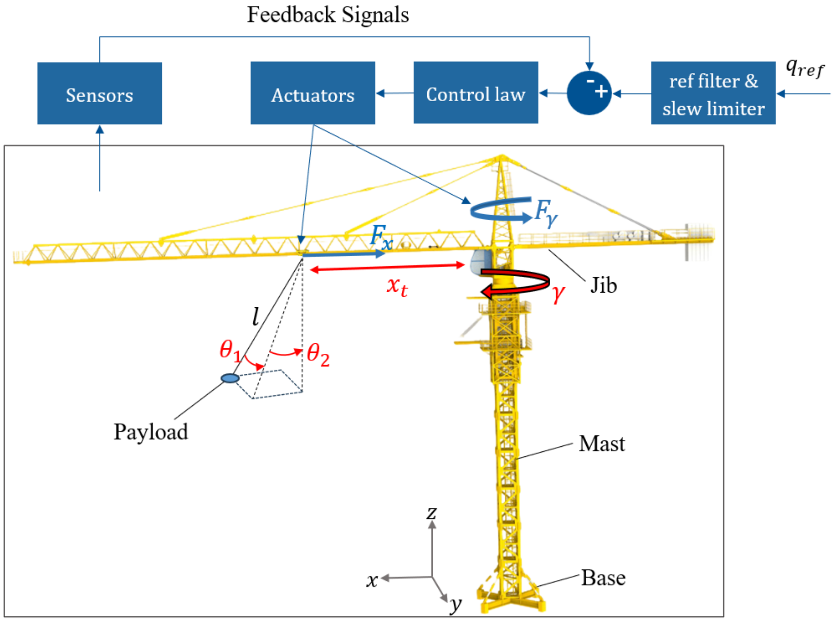

Figure 1. Single-pendulum tower crane model and overall control architecture

M is then examined individually to determine whether it can be decomposed into a sum of distinct terms. These terms, which depend on measurable state variables, are identified and stored. An identical decomposition procedure is subsequently applied to the gravity matrix **G**. In the next stage, the kinetic and potential energy contributions associated with each identified term are computed, and the corresponding dynamics are derived using the Lagrangian formulation. This decomposition allows the system dynamics to be reorganized into a linear-in-parameters form, yielding the regressor matrix **W** and the associated parameter vector **P**. Based on the resulting parameter-linearized dynamics of the 4-DOF model, the parameter vector is defined as follows:

$$P = [m_p \ell, m_p \ell^2, (m_t + m_p)/2, J]^T \tag{6}$$

Using the resulting regressor matrix W and the auxiliary signals r, v, a, the adaptive control torque law is given by:

$$U = W(q, \dot{q}, a, v)\,\hat{P} \;+\; K\,r \tag{7}$$

Where $\hat{P}$ denotes the estimate of the unknown parameter vector P and K is a positive definite gain matrix. The first term compensates the estimated system dynamics, while the second term provides stabilizing feedback based on the filtered tracking error. The parameter estimates are updated using a gradient-based adaptation law, which minimizes the squared prediction error with respect to the unknown parameters,

$$\dot{\hat{P}} = \Gamma W^\top r \tag{8}$$

Under this adaptive control scheme, the closed-loop system drives the tracking errors of the 4-DOF tower crane model toward zero. The controller is particularly suitable for tower crane applications, as it compensates for uncertainties in payload-related parameters and inertia terms without requiring exact prior knowledge of the system dynamics.

4 Case study and simulation setup

To validate the proposed controller, we simulate tower crane operations within the Gazebo, a physics-based simulator. This simulation platform incorporates a physics engine that accurately replicates real-world crane dynamics, including geometry, mass and inertia, contact interactions, and damping effects. Such a detailed representation is important to minimize the sim-to-real gap and ensure that the controller performs reliably under realistic conditions. By leveraging this advanced simulation framework, the study enables repeatable, virtual experiments that expose the controller to realistic operational scenarios prior to on-site deployment, thereby reducing risk and improving robustness.

We modeled the 4-DOF tower crane system using the state coordinates as described in equation (1).

In the Gazebo simulation, there is an offset between the trolley's position and the prismatic joint feedback. So we define x_{model} as:

$$x_{\text{model}} \;=\; x + x_{\text{offset}}, \tag{9}$$

where this value will be used in the controller. In Figure

2, the tower crane in the Gazebo physics engine is shown, and in Table 1, the parameters and variables of the system are described.

Simulation environment

The initial CAD model of the tower crane was converted into the simulation-supported description files, and then the Unified Robotics Description Format (URDF) was created by providing the visual and collision tags. These description files define not only the crane geometry but also its kinematic and dynamic properties, such as mass, inertia, joint limits, and connections, as detailed in our previous work [24]. Furthermore, various objects of interest with different mass and inertia were inserted into the simulation environment.

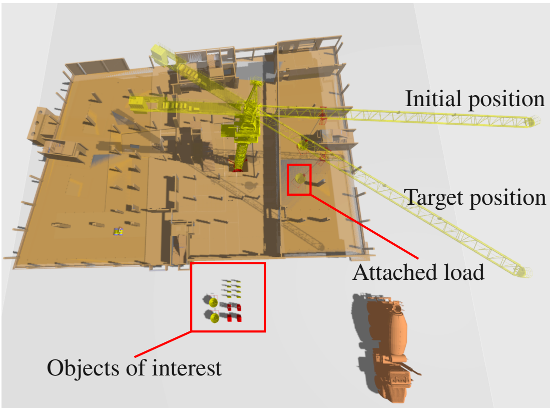

Figure 2. The simulation environment with the objects of interest

5 Results

To assess the effectiveness of the proposed model-based adaptive control, an established approach, a PD controller is used as a benchmark, as it represents an established baseline in crane control research. The corresponding PD gains, summarized in Table 2, are from previously published literature [3] to maintain consistency with prior studies and to ensure a meaningful comparison. The resulting experimental comparisons are shown in Figure 3, which shows the relative performance of both controllers in terms of motion tracking and payload sway suppression under test conditions.

Tracking performance and swing suppression

Figure 3 compares the closed-loop response of the proposed adaptive controller with a baseline PD controller for a combined slewing and trolley motion. The first two subplots show the jib angle γ and trolley position x. The adaptive controller (red) tracks the desired references (black dashed) with small overshoot and short settling time, whereas the PD controller (blue) exhibits large oscillations around the reference in both coordinates over the entire crane's motion.

The lower subplots in Figure 3 report the double-pendulum swing angles θ_1 and θ_2. Under PD control, both angles remain significantly excited, with persistent oscillations. In contrast, the adaptive controller limits the sway to small amplitudes and damps it out rapidly, keeping θ_2 at zero after the initial transient. This demonstrates that the proposed adaptive scheme achieves accurate payload positioning while effectively suppressing both radial and tangential swing.

Control effort comparison

The corresponding control efforts are shown in Figure 4. For the slewing joint (upper plot), the PD controller requires a highly oscillatory torque, varying roughly between ± 100 N m, which is consistent with the oscillatory behaviour of γ. The adaptive controller, by contrast, produces a short transient followed by a nearly constant torque with markedly reduced variations.

A similar trend appears for the trolley force in the lower plot of Figure 4. The PD controller generates large, persistent oscillations of up to about ± 20 N, whereas the adaptive controller converges to a smooth input with much smaller amplitude. Overall, the adaptive scheme delivers better tracking and swing suppression with substantially lower and less aggressive control effort, which is beneficial for actuator service life and energy consumption.

Parameter adaptation

Figure 5 illustrates the time evolution of the estimated parameters P_1–P_4 in the regressor-based model. All parameters remain bounded and exhibit a clear adaptation phase during the maneuvers, after which they converge to nearly constant values.

The smooth convergence and absence of oscillatory or divergent behavior in these trajectories indicate that the online identification is numerically well behaved and captures an effective approximation of the crane dynamics over the considered operating range. Together with the tracking and effort plots, these results show that the proposed adaptive model-based controller can be implemented in the physics-based simulation to provide improved performance over a conventional PD strategy while continuously tuning its internal model.

Table 2. Gain of the PD controller

Control methods	Control gains
PD control method	$k_{p\phi} = 15,\ k_{d\phi} = 20,\ k_{px} = 8,$ $k_{dx} = 10,\ k_{pl} = 20,\ k_{dl} = 5$

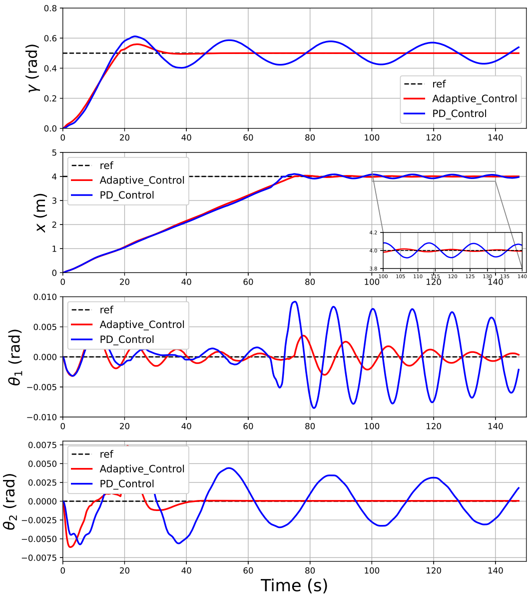

Figure 3. Results of the PD control and proposed control method for formwork with 50 kg weight and the cable length of 30 meter

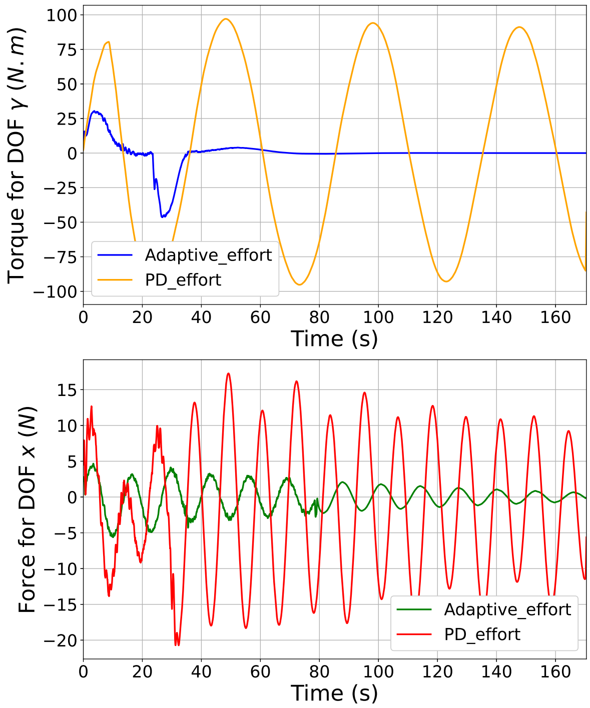

Figure 4. Respected torque for proposed control method for formwork with 50 kg weight and the cable length of 30 meters

6 Discussion

The results of this study underscore the advantages of employing adaptive control for tower crane systems. Compared to conventional PD controllers, the proposed adaptive approach demonstrated superior performance in minimizing payload sway, reducing settling times, and maintaining robustness under significant parameter variations. These improvements are critical for construction environments where operational safety and efficiency are important.

A key contribution of this work is the effective suppression of load swing in a real-scale tower crane implemented in a physics-based simulation environment that captures realistic crane behavior, including inertial effects, payload oscillations, and gravitational forces. By leveraging online parameter estimation, the controller dynamically compensates for uncertainties in payload-related inertial parameters, ensuring consistent performance even under non-ideal conditions. This adaptability addresses a major limitation of traditional fixed-gain controllers, which often fail when subjected to deviations from nominal operating points.

The use of a physics-based simulation environment further strengthens the validity of the results. Unlike idealized models commonly used in prior research, the high-fidelity simulation employed here captures realistic dynamics, including geometric constraints, mass, and inertia. This approach reduces the sim-to-real gap and provides greater confidence in the applicability of the proposed method to real-world crane operations. Furthermore, we plan to deploy our framework to a scaled-down version of a tower crane in the future. Experimental validation on physical crane systems can confirm the scalability and reliability of the approach under practical conditions. It will also provide insights into real-world implementation issues, such as sensor noise, actuator limitations, and communication delays.

Despite these promising outcomes, certain limitations remain. The current implementation assumes constant cable length and does not explicitly account for external disturbances such as wind or dynamic rope effects. Future work should extend the controller to handle variable rope lengths and integrate disturbance observers for enhanced robustness. Additionally, future work will broaden

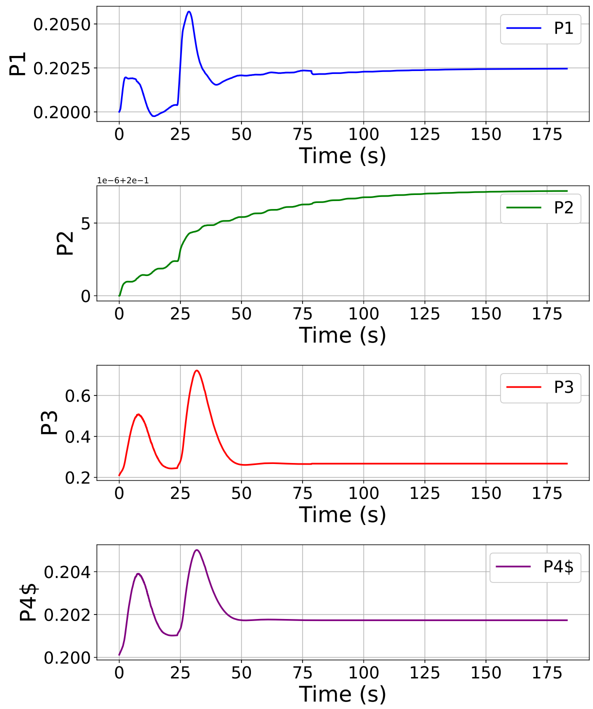

Figure 5. Estimated parameters obtained using the adaptive algorithm

the comparative study to include additional control approaches. We will also investigate the implementation of these controllers in a physics-based simulation framework to enable more realistic and fair benchmarking.

7 Conclusion

This research presents an adaptive controller for a tower crane by suppressing oscillatory dynamics and payload oscillations. In this work, we conduct a comparative study against a PD controller tuned for the same positioning tasks. The two controllers are implemented on a physics-based simulation. The comparison considers construction-relevant metrics, including maximum swing angle, residual swing, and payload settling time. The results show that the proposed adaptive controller consistently outperforms the PD controller, especially when payload and cable parameters deviate from their nominal values, by damping the swings much more effectively while maintaining rapid motion. Overall, the results suggest that the proposed adaptive control offers a viable and effective solution for improving the safety and productivity of tower crane operations. Its ability to combine rapid maneuvering with restricted swing makes it particularly suitable for modern construction sites where time efficiency and risk mitigation are critical.

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