

A Data-driven NCTF-PID Controller for Gantry Crane System Based on Adaptive Safe Experimentation Dynamics Algorithm

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Abstract—This paper proposes a parameterized Nominal Characteristic Trajectory Following Proportional-Integral-Derivative (NCTF-PID) controller for nonlinear underactuated Multi-Input Multi-Output (MIMO) systems. Conventional NCTF-based controllers rely on non-parametric nominal characteristic trajectories obtained from open-loop experiments, which makes systematic parameter optimization difficult and limits their application to complex nonlinear MIMO systems. To overcome this limitation, a parameterized NCTF structure is developed and integrated with a PID controller, enabling simultaneous optimization of the trajectory-shaping characteristics and PID gains without requiring an accurate mathematical model. The resulting controller is tuned using the Adaptive Safe Experiment Dynamics (ASED) algorithm based solely on measured input-output data, where the optimization objective balances tracking performance and control effort. The developed NCTF-PID controller is evaluated on a nonlinear gantry crane system and compared with conventional PID and Fuzzy-PID controllers. Simulation results show that it achieves the best overall trade-off among tracking performance, payload swing suppression, and control effort. Compared with the PID and Fuzzy-PID controllers, it reduces the objective function value by approximately 28.7% and 11.0%, respectively, while decreasing the accumulated control effort by 68.1% and 44.2%, with the lowest accumulated tracking error among the three controllers. Additional disturbance-response and repeated optimization experiments further verify its robustness and the repeatability of the optimization results. The NCTF-PID controller provides a parameterized data-driven extension of the conventional NCTF methodology for nonlinear underactuated MIMO systems.

Index Terms—data-driven control, Nominal Characteristic Trajectory Following Proportional-Integral-Derivative (NCTF-PID), adaptive safe experiment dynamics, Multi-Input Multi-Output (MIMO) underactuated systems, trajectory tracking

I. INTRODUCTION

Systems that have fewer control inputs than degrees of freedom are said to be underactuated. Due to their structural simplicity, reduced actuator requirements, and

high energy efficiency, such systems are widely encountered in modern engineering applications, including spacecraft, underwater vehicles, mobile robots, and container crane systems [1, 2]. However, the control of underactuated systems remains a challenging problem because of strong nonlinear dynamics, inherent coupling among multiple subsystems, and limited actuation capability. In particular, for nonlinear Multi-Input Multi-Output (MIMO) underactuated systems, multiple control objectives must be achieved simultaneously under coupled dynamics, which places stringent requirements on controller design [3].

Among various underactuated systems, container crane systems are considered representative nonlinear MIMO plants and have been extensively used as benchmark systems for control research [4]. In practical operation, a crane controller is required to achieve accurate trolley positioning and hoisting while simultaneously suppressing payload swing. These conflicting objectives, together with parameter uncertainties, external disturbances, and unmodeled dynamics, make crane systems a representative platform for evaluating advanced control strategies for nonlinear MIMO underactuated systems [5, 6].

To address these control challenges in underactuated systems, especially crane systems, various control strategies have been proposed. Robust and nonlinear control techniques such as sliding mode control, backstepping control and adaptive control have been extensively investigated for the purpose of suppressing the payload swing and improving tracking performance of crane systems [7–9]. Under some conditions, these methods can provide satisfactory control performance. However, they often require accurate system models or complex controller designs, which may increase the complexity of implementation and limit their applicability in practical scenarios [10].

Proportional-Integral-Derivative (PID) controllers are still widely used in industrial applications because of their simple structure, easy implementation, and practical tuning procedures [11]. PID controllers have been

successfully applied to various engineering systems, including crane systems, where satisfactory control performance can be achieved with relatively low computational requirements [12]. The simple structure of PID controllers also provides a convenient framework for integrating data-driven tuning strategies, making them well-suited for systems with limited modeling information [13].

Despite their popularity, conventional linear PID controllers exhibit inherent limitations when applied to nonlinear and strongly coupled MIMO underactuated systems. First, the fixed linear structure of PID controllers is insufficient to compensate for severe nonlinearities and time-varying dynamics. Second, in MIMO underactuated systems, strong coupling among control channels makes independent PID tuning difficult and often leads to performance degradation or instability [14]. Furthermore, standard PID controllers lack an explicit mechanism to actively shape transient trajectories, which is critical for suppressing payload swing and achieving fast response in crane systems [15].

To overcome the limitations of standard PID controllers, various advanced PID-based schemes have been proposed, including fuzzy PID controllers and neural-network-based PID controllers [16, 17]. These approaches enhance nonlinear handling capability and adaptability; however, they often introduce increased structural complexity [18], require heuristic rule design, or involve training procedures that may compromise transparency and reliability. In recent years, several model-free, nonlinear, and adaptive PID variants have been developed to improve transient performance and robustness while maintaining practical engineering feasibility. These advanced controllers include the Augmented Proportional-Integral-Derivative with Hyperbolic Tangent (APID-T) controller, which integrates a hyperbolic tangent bounded nonlinear term to achieve accurate and steady temperature regulation for highly nonlinear chemical reaction systems [19]; the Sigmoid PID (SPID) controller, which dynamically adjusts control gains according to real-time error signals to balance response speed and regulation smoothness in voltage and motion control applications [20, 21]; the Sigmoid-Based Adaptive Learning Rate Brain Emotional Learning-Based Intelligent Controller-PID (SbLR-BELBIC-PID) intelligent control structure designed for bionic intelligence and emotion-driven control applications [22]; and the Gudermannian PID controller, which adopts a bounded nonlinear activation function to optimize control characteristics and further enhance system disturbance rejection capability and closed-loop stability [23]. Beyond nonlinear PID control, nonlinear activation functions have also been extensively investigated in data-driven intelligent systems. Recent studies have shown that parameterized activation functions in analog artificial neural networks can effectively enhance nonlinear representation capability and learning performance, while dedicated hardware implementations further demonstrate their feasibility for efficient intelligent system design [24–26]. Although

these studies are conducted in different application domains, they highlight the effectiveness of bounded nonlinear mappings in representing complex nonlinear relationships and facilitating performance-oriented optimization. These characteristics provide useful insights for nonlinear controller design, where explicit nonlinear functions can offer a flexible alternative to experimentally constructed nonlinear characteristics. As an alternative data-driven nonlinear tracking framework, the Nonlinear Compensated Tracking Controller (NCTF) has demonstrated promising performance in nonlinear motion control applications. In particular, the Nonlinear Compensated Tracking Controller–Proportional-Integral (NCTF-PI) structure has been successfully applied to Single-Input Single-Output (SISO) systems, where nonlinear compensation is achieved using experimentally obtained tracking characteristics [27].

However, the direct application of conventional NCTF-PI controllers to nonlinear MIMO underactuated systems remains challenging and largely unexplored. Most existing NCTF-PI studies have mainly focused on SISO systems, where the nominal characteristic trajectory is obtained from open-loop experimental responses of a single control channel. Traditional NCTF construction relies on non-parametric open-loop experimental trajectories, making it difficult to construct independent nonlinear compensation characteristics for multiple coupled control channels. Furthermore, since conventional NCTF is represented by experimentally obtained trajectories rather than explicit mathematical parameters, its nonlinear compensation characteristics cannot be directly incorporated into optimization-based controller tuning. Consequently, previous NCTF-based controllers mainly optimize PID parameters while maintaining a fixed NCTF structure, limiting further performance improvement.

The reformulation of NCTF as a parameterized nonlinear characteristic function converts the controller design problem into a data-driven parameter optimization problem, where both nonlinear compensation parameters and conventional PID gains need to be determined simultaneously. In recent years, various optimization techniques, including swarm intelligence algorithms [28–32], evolutionary optimization methods, and other data-driven optimization approaches, have been widely investigated for solving nonlinear engineering optimization problems due to their derivative-free characteristics and strong search capability [33–37]. Representative algorithms such as Particle Swarm Optimization (PSO), Salp Swarm Algorithm (SSA), Weighted Salp Swarm Algorithm (WSSA), and their improved versions have achieved promising performance in complex parameter optimization tasks [38–42]. These studies show the effectiveness of optimization-based tuning as a method to tune the parameters of a controller without requiring explicit analytical models. In this study, the optimization tool is adopted as the Adaptive Safe Experimentation Dynamics (ASED) algorithm to automatically determine the PID gains and the nonlinear characteristic parameters of the proposed controller [43].

Based on the above observations, a data-driven NCTF-PID control framework is proposed in this paper, where the conventional non-parametric NCTF is modeled using a parameterized nonlinear characteristic function. The proposed parameterized NCTF offers the ability to optimize nonlinear compensation characteristics and PID gains simultaneously in a unified data-driven optimization framework. The ASED algorithm automatically tunes the controller parameters, and the effectiveness of the proposed approach is verified by simulation studies on a nonlinear MIMO underactuated bridge crane system. Therefore, the proposed method extends the applicability of the NCTF methodology from fixed trajectory-based SISO implementations to an optimizable nonlinear compensation framework suitable for coupled MIMO underactuated systems.

The remainder of this paper is organized as follows. Section II presents the control problem for applying the data-driven NCTF-PID controller to a MIMO underactuated system. Section III introduces the ASED algorithm for automatic parameter tuning. Section IV presents simulation studies on a bridge crane system and provides a detailed performance comparison with a conventional PID controller. Finally, Section V concludes the paper and outlines directions for future work.

II. PROBLEM STATEMENT

The proposed underactuated NCTF-PID control configuration for the gantry crane system is shown in Fig. 1. The reference signal, control input vector, and measured output vector are denoted by $\mathbf{r}(t) \in \mathbb{R}^q$, $\mathbf{u}(t) \in \mathbb{R}^p$ and $\mathbf{y}(t) \in \mathbb{R}^q$, respectively, where p and q denote the numbers of control inputs and measured outputs. Owing to the underactuated nature of the gantry crane system, the number of control inputs is smaller than that of measured outputs ($p < q$). The controller operates in discrete time, and the sampling instants are defined as $(t = 0, t_s, 2t_s, 3t_s, \dots, Nt_s)$, where t_s represents the sampling period.

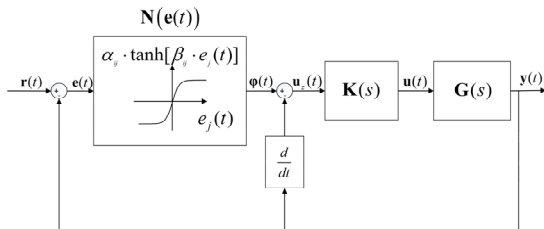


Fig. 1. NCTF-PID control system.

In Fig. 1, after the signal $\phi(t)$ is generated by the nonlinear function $\mathbf{N}(\mathbf{e}(t))$, it is subtracted from the derivative of the output $\mathbf{y}(t)$ to form the $\mathbf{u}_z(t)$.

The controller $\mathbf{K}(s)$ is defined in the following form:

$$\mathbf{K}(s) = \begin{bmatrix} g_{11}(s) & \cdots & g_{1q}(s) \\ \vdots & \ddots & \vdots \\ g_{p1}(s) & \cdots & g_{pq}(s) \end{bmatrix}. \quad (1)$$

For the PID controller, each $g_{ij}(s)$ can be written as:

$$g_{ij}(s) = P_{ij} \left(1 + \frac{1}{I_{ij}s} + \frac{D_{ij}s}{1 + (D_{ij}/N_{ij})s} \right), \quad (2)$$

where g_{ij} represents the transfer function from the j th error channel to the i th control channel. The parameters in the above expression are defined as follows: the proportional gain $P_{ij} \in \mathbb{R}$, the integral time $I_{ij} \in \mathbb{R}$, the derivative time $D_{ij} \in \mathbb{R}$ and the filter coefficient $N_{ij} \in \mathbb{R}$. The output signal $\mathbf{u}(t)$ and input signal of $\mathbf{K}(s)$ are expressed as follows:

$$\mathbf{u}(t) = \left[\sum_{j=1}^q h_{1j}, \sum_{j=1}^q h_{2j}, \dots, \sum_{j=1}^q h_{pj} \right]^T, \quad (3)$$

$$\mathbf{u}_z(t) = \begin{bmatrix} u_{z11}(t) & \cdots & u_{z1q}(t) \\ \vdots & \ddots & \vdots \\ u_{zp1}(t) & \cdots & u_{zpq}(t) \end{bmatrix}, \quad (4)$$

$$u_{zij}(t) = \phi_{ij}(t) - \frac{dy_j}{dt}, \quad (5)$$

where $h_{ij}(t) = g_{ij}(s)u_{zij}(t)$, $i = 1, 2, \dots, p$ and $j = 1, 2, \dots, q$. Here, $u_{zij}(t)$ is the (i, j) -th entries of the matrices $\mathbf{u}_z(t)$. $y_j(t)$ is the j th components of the vectors $\mathbf{y}(t)$ and $\phi_{ij}(t)$ is the (i, j) -th entries of the matrices $\phi(t)$, $t \in \mathbb{R}_+$ is the continuous time.

The above formulation describes a generalized MIMO PID controller structure, in which multiple PID subcontrollers are arranged in a matrix form so as to handle multi-channel coupling effects effectively. While the PID controller is well known for its robustness and steady-state regulation capability, its performance may nevertheless be limited when it comes to dealing with strong nonlinearities and dynamic coupling, especially in underactuated systems where such issues are commonly encountered.

To enhance the transient tracking performance and introduce nonlinear compensation without relying on an explicit system model, a nonlinear compensated tracking mechanism is incorporated into the control framework. Instead of modifying the PID structure itself, the proposed NCTF is introduced as an auxiliary nonlinear signal generator that reshapes the control input according to the system tracking error and output dynamics. The resulting signal is then processed by the PID controller, forming an integrated NCTF-PID control structure.

The formulas for the NCTF section are as follows:

$$\phi(t) = \mathbf{N}(\mathbf{e}(t)), \quad (6)$$

$$\mathbf{N}(\mathbf{e}(t)) = \begin{bmatrix} N_{11}(e_1(t)) & \cdots & N_{1q}(e_q(t)) \\ \vdots & \ddots & \vdots \\ N_{p1}(e_1(t)) & \cdots & N_{pq}(e_q(t)) \end{bmatrix}, \quad (7)$$

$$N_{ij}(e_j(t)) = \alpha_{ij} \tanh[\beta_{ij} e_j(t)]. \quad (8)$$

The nonlinear compensation matrix is denoted by $\mathbf{N}(\mathbf{e}(t))$, where $N_{ij}(e_j(t))$ represents the nonlinear compensation term associated with the j th error channel. $\tanh(\cdot)$ is the hyperbolic tangent function, α_{ij} and β_{ij} are tunable scalar parameters that adjust the amplitude and slope of the nonlinear function.

Subsequently, the performance indices of the system depicted in Fig. 1 are given by the following two formulas:

$$\hat{e}_j := \int_{t_0}^{t_f} |r_j(t) - y_j(t)|^2 dt, \quad (9)$$

$$\hat{u}_i := \int_{t_0}^{t_f} |u_i(t)|^2 dt, \quad (10)$$

where the notation $u_i(t)$ represents the i th component of the vector $\mathbf{u}(t)$, while $r_j(t)$ represents the j th component of the vector $\mathbf{r}(t)$. In Eq. (9), $\hat{e}_j$ denotes the accumulated squared tracking error of the j th output channel, while in Eq. (10), $\hat{u}_i$ represents the accumulated squared control effort of the i th control input. The initial time $t_0 \in \{0\} \cup \mathbb{R}_+$, and the evaluation horizon are taken as the interval $[t_0, t_f]$. Subsequently, the objective function is expressed as follows:

$$J(\mathbf{P}, \mathbf{I}, \mathbf{D}, \mathbf{N}, \boldsymbol{\alpha}, \boldsymbol{\beta}) = \sum_{j=1}^q w_{1j} \hat{e}_j + \sum_{i=1}^p w_{2i} \hat{u}_i, \quad (11)$$

where $\mathbf{P}$, $\mathbf{I}$, $\mathbf{D}$, $\mathbf{N}$, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are column vectors with the same structure as

$$\mathbf{P} := [P_{11} \ P_{12} \ \cdots \ P_{pq}]^T,$$

$$\mathbf{I} := [I_{11} \ I_{12} \ \cdots \ I_{pq}]^T,$$

$$\mathbf{D} := [D_{11} \ D_{12} \ \cdots \ D_{pq}]^T,$$

$$\mathbf{N} := [N_{11} \ N_{12} \ \cdots \ N_{pq}]^T,$$

$$\boldsymbol{\alpha} := [\alpha_{11} \ \alpha_{12} \ \cdots \ \alpha_{pq}]^T,$$

$$\boldsymbol{\beta} := [\beta_{11} \ \beta_{12} \ \cdots \ \beta_{pq}]^T.$$

Here, $w_{1j} \in \mathbb{R}$ ($j=1, 2, \dots, q$) and $w_{2i} \in \mathbb{R}$ ($i=1, 2, \dots, p$) are weighting coefficients chosen by the designer. The parameters p and q denote the dimensions of $\mathbf{u}(t)$ and $\mathbf{y}(t)$, respectively.

The expression on the right-hand side of Eq. (11), captures the tracking error along with the energy consumed by the control input, both of which reflect the quality of control performance. Consequently, the weights w_{1j} and w_{2i} are chosen according to the conventional Linear Quadratic Regulator (LQR) formulation. Ultimately, the formulation of data-driven

control approaches, along with their corresponding optimization task, can be expressed in the following manner.

Problem 2.1: Given the control architecture depicted in Fig. 1, determine a NCTF-PID controller $\mathbf{K}(s)$ along with $\mathbf{N}(\mathbf{e}(t))$ that minimizes the cost $J(\mathbf{P}, \mathbf{I}, \mathbf{D}, \mathbf{N}, \boldsymbol{\alpha}, \boldsymbol{\beta})$ over the parameters $\mathbf{P}$, $\mathbf{I}$, $\mathbf{D}$, $\mathbf{N}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$. Here, the quantities $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ denote the magnitude and slope, respectively, of the tanh function.

III. DATA DRIVEN NCTF-PID CONTROLLER DESIGN BASED ON ASED

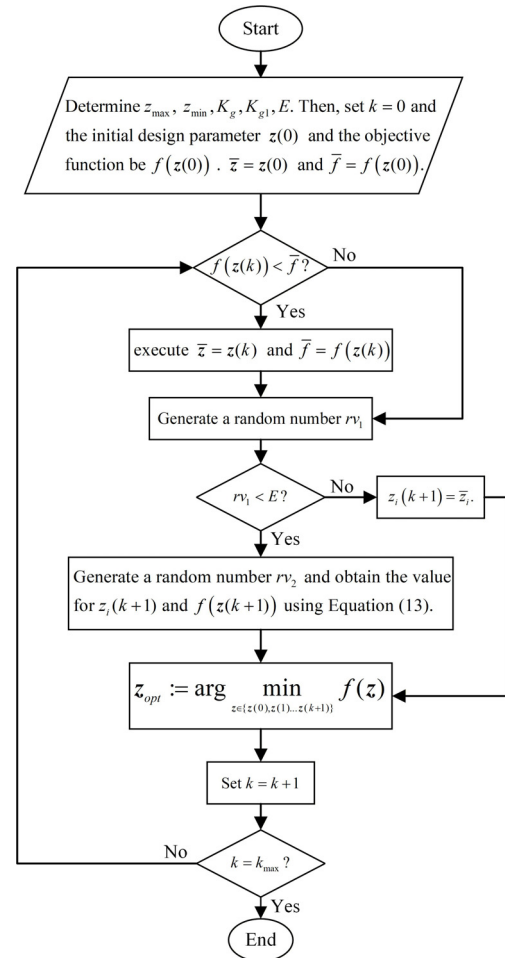


Fig. 2. The flow tuning process of the ASED algorithm.

This section presents the core technique employed to solve Problem 2.1. We begin with a concise overview of the ASED algorithm, which was established as a game-theoretic optimization approach in [44]. The ASED method has demonstrated its applicability in practical control applications. For example, it has been employed to optimize data-driven PID controllers for flexible-joint robotic systems, resulting in improved trajectory tracking and vibration attenuation [45]; to enhance the control precision of Neuroendocrine-PID (NEPID) schemes for MIMO systems [46]; and to optimize Brain Emotional Learning Based Intelligent Controller-PID (BELBIC-PID) controllers for flexible manipulators, achieving

notable reductions in performance indices such as Integral of Time Multiplied by Squared Error (ITSE), Integral of Time Multiplied by Absolute Error (ITAE), Integral of Squared Error (ISE) and Integral of Absolute Error (IAE) [47]. Building upon these successful applications, this work integrates the ASED algorithm into the development of a data-driven NCTF-PID controller. The associated design procedure is presented in the subsequent sections.

Fig. 2 presents the procedure used to implement the ASED method.

A. Mathematical Background of the ASED Algorithm

Let us consider

$$\min_{\mathbf{z} \in \mathbb{R}^n} f(\mathbf{z}). \quad (12)$$

This constitutes an optimization problem aimed at adjusting the design variable $\mathbf{z} \in \mathbb{R}^n$ (where n denotes its dimensionality) so as to subsequently minimize the cost function f . Subsequently, ASED was applied to determine the best solution through iterative adjustment of the design variables. At each iteration, the algorithm uses game-theoretic rules to generate safe candidates, balances exploration/exploitation under constraints, evaluates the cost, and retains the best individuals. Accordingly, the update rule for the ASED algorithm is presented below:

$$z_i(k+1) = \begin{cases} h(\bar{z}_i - K_g r_{v_2}) + K_{g1} \left(\frac{f(\mathbf{z}(k)) - \bar{f}}{f(\mathbf{z}(k))} \right), & \text{if } r_{v_1} \leq E, \\ \bar{z}_i + K_{g1} \left(\frac{f(\mathbf{z}(k)) - \bar{f}}{f(\mathbf{z}(k))} \right), & \text{if } r_{v_1} > E. \end{cases} \quad (13)$$

In this formulation, the iteration count is denoted by $k = 1, 2, \dots, k_{\max}$ and $z_i \in \mathbb{R}$ stands for the i th component of the design vector $\mathbf{z} \in \mathbb{R}^n$. The symbol $\bar{z}$ represents the best value stored so far among the design parameters. The total number of iterations, $k_{\max}$ is preset by the controller designer. Meanwhile, the parameters K_g and K_{g1} specify the step-size ranges used in the random search for each z_i and in the adaptive mechanism, respectively. The probability of accepting a newly generated random configuration for $\mathbf{z}$ is denoted by E . Two types of random numbers are distinguished: $r_{v_1} \in \mathbb{R}$ is uniformly drawn from the interval $[0, 1]$, whereas $r_{v_2} \in \mathbb{R}$ is uniformly sampled between the lower and upper bounds of the design variables $z_{\min}$ and $z_{\max}$. Based on the above, the function appearing in Eq. (13), is now described as follows:

$$h(\cdot) = \begin{cases} z_{\max}, & \text{if } \bar{z}_i - K_g r_{v_2} < z_{\max}, \\ \bar{z}_i - K_g r_{v_2}, & \text{if } z_{\min} \leq \bar{z}_i - K_g r_{v_2} \leq z_{\max}, \\ z_{\min}, & \text{if } \bar{z}_i - K_g r_{v_2} < z_{\min}. \end{cases} \quad (14)$$

Remark 3.1: It can be seen that $z_{\max}$ and $z_{\min}$ specify the upper and lower limits of the feasible range for the design parameters, which define the allowable search domain for the optimization process.

Several preliminary optimization trials were conducted to determine the bounds $z_{\max}$ and $z_{\min}$. Recommendations

for choosing K_g and E can be found in [48]. Specifically, for any probability value $E < 1$, if the exploration coefficient K_g is set sufficiently low, then the optimal parameter z_{opt} can be attained provided a sufficiently high iteration count k is used. Consequently, a large maximum iteration number $k_{\max}$ was selected to ensure convergence to z_{opt} . In practice, $k_{\max}$ may be determined once the convergence curve shows near-saturation.

B. Data-driven NCTF-PID Controller Design

A logarithmic scaling was employed to accelerate the convergence toward the design variable $\mathbf{z}$. Given this approach, the NCTF-PID parameters are expressed as follows:

$$\boldsymbol{\psi} = [\mathbf{P}, \mathbf{I}, \mathbf{D}, \mathbf{N}, \boldsymbol{\alpha}, \boldsymbol{\beta}] \in \mathbb{R}^n. \quad (15)$$

Each element of $\boldsymbol{\psi}$ is represented in logarithmic form as $\psi_i = 10^{z_i}$ ($i = 1, 2, \dots, n$). Accordingly, the objective function can be reformulated in terms of the transformed variables as $f(10^{z_1}, 10^{z_2}, \dots, 10^{z_n})$. The procedure of the data-driven NCTF-PID is outlined as follows:

Step 1: The objective function is formulated as $f(\mathbf{z}) = J(\mathbf{P}, \mathbf{I}, \mathbf{D}, \mathbf{N}, \boldsymbol{\alpha}, \boldsymbol{\beta})$, with the relationship between the optimization variables and the actual controller parameters defined by $z_i = \log \psi_i$. The maximum number of ASED iterations is specified as $k_{\max}$.

Step 2: The ASED algorithm is performed to evaluate the current solution and obtain the corresponding objective function value according to Eq. (11).

Step 3: Once the optimization process reaches the prescribed iteration limit, the final solution is selected as $\mathbf{z}_{\text{opt}} = \bar{\mathbf{z}}(k_{\max})$. The corresponding controller parameters are then recovered through the inverse logarithmic transformation, $\boldsymbol{\psi}_{\text{opt}} = [10^{z_{1\text{opt}}}, 10^{z_{2\text{opt}}}, \dots, 10^{z_{n\text{opt}}}]^T$ and subsequently assigned to $\mathbf{K}(s)$ and $\mathbf{N}(e(t))$ in the NCTF-PID controller, as illustrated in Fig. 1.

Remark 3.2: The controller parameters are obtained by data driven optimization approach using input-output data without explicit mathematical model of the controlled system in the tuning procedure. Therefore, this work does not provide a formal analytical proof of stability of the resulting closed-loop system. Additional simulations are performed to further evaluate the performance of the optimized controller. An external disturbance is introduced to examine the disturbance rejection capability, and ten independent optimization runs are conducted under the same simulation conditions to assess the repeatability of the obtained results. These additional simulations demonstrate the controller response under disturbed conditions and the repeatability of the optimization results.

IV. SIMULATION RESULT

This section presents a performance evaluation of the underactuated container gantry crane system using a data-driven NCTF-PID controller optimized through the

ASED algorithm. The evaluation is structured to first develop the dynamic model representing the nonlinear and underactuated characteristics of the system under investigation, and then to conduct numerical simulations to assess the control performance of the proposed controller. Then, the robustness and repeatability of the proposed control framework are investigated through disturbance rejection tests and repeated independent optimization experiments.

A. Dynamic Model Describing the Underactuated Container Gantry Crane

The underactuated crane system of the gantry variety features two actuators and three output variables. As depicted in Fig. 3, the generalized coordinates encompass three key variables, namely the trolley's displacement $x(t)$, the length of the rope $l(t)$, and the angular sway $\theta(t)$. The two actuator-generated inputs are the force applied to the trolley, F_x , and the force produced by the hoist motor, F_l .

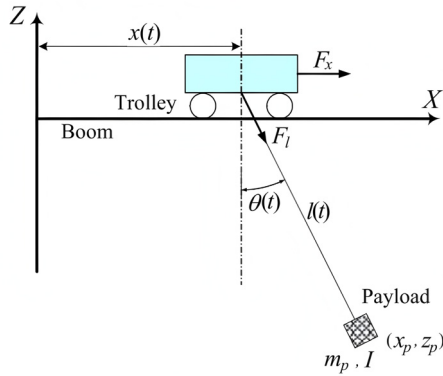


Fig. 3. Underactuated container crane in gantry type [49].

The dynamic model of the container crane is expressed as follows:

$$(m_t + m_p)\ddot{x} + m_p \sin \theta \ddot{l} + m_p l \cos(\theta) \ddot{\theta} + 2m_p \cos(\theta) \dot{l} \dot{\theta} - m_p l \sin \theta \dot{\theta}^2 = F_x, \quad (16)$$

$$m_p \sin(\theta) \ddot{x} + (m_t + m_p) \ddot{l} - m_p l \dot{\theta}^2 - m_p g \cos(\theta) = F_l, \quad (17)$$

$$m_p l \cos(\theta) \ddot{x} + (m_p l^2 + I) \ddot{\theta} + 2m_p l \dot{l} \dot{\theta} + m_p g l \sin(\theta) = 0. \quad (18)$$

here, m_p represents the payload mass. The parameter m_t refers to the equivalent mass of the trolley–hoist assembly, which moves as a single rigid unit during horizontal motion. In addition, I represents the payload's mass moment of inertia, and g denotes the gravitational acceleration.

B. Verification via Numerical Simulations

The parameter settings of the underactuated container crane, as illustrated in Section IV-A and Fig. 3, are specified in Table I.

TABLE I: SYSTEM PARAMETERS OF THE UNDERACTUATED CONTAINER CRANE

Symbol	Parameter Description	Value	Unit
m_p	Payload mass	0.73	kg
m_t	Equivalent trolley-related mass	1.06	kg
I	Mass moment of inertia	0.005	kgm ²

The values of all parameters mentioned above are taken from reference [50], which documents an experimental gantry crane system. For the system model, the input and output quantities are specified as follows: the horizontal force F_x corresponds to the first control input $u_1(t)$, the rope tension F_l is defined as the second control input $u_2(t)$, while the trolley displacement $x(t)$, rope length $l(t)$, and sway angle $\theta(t)$ serve as the three measured outputs $y_1(t)$, $y_2(t)$, and $y_3(t)$, respectively. A sampling period of 0.01 s was used. Initially, both the trolley displacement and the rope length were 1 m. In contrast, the reference values were defined as 0 m and 0.2 m, respectively. The sway angle of the payload started from zero and was required to settle at zero as well. The NCTF-PID controller is then defined as follows:

$$\mathbf{K}(s) = \begin{bmatrix} h_{11} & 0 & h_{13} \\ 0 & h_{22} & 0 \end{bmatrix} \quad (19)$$

and

$$\mathbf{N}(\mathbf{e}(t)) = \begin{bmatrix} N_{11} & 0 & N_{13} \\ 0 & N_{22} & 0 \end{bmatrix}. \quad (20)$$

Based on the derived equations, the dimension n of the NCTF-PID in Eq. (19) and Eq. (20) is 18. For comparison, the conventional PID controller contains 12 optimization parameters, whereas the NCTF-PID controller contains 18 parameters due to the additional parameters introduced by the NCTF mechanism. The Fuzzy-PID controller considered in this study contains 21 optimization parameters, including the parameters associated with the fuzzy inference system and the PID gains. The maximum optimization iterations are set to 1000, 1500, and 1750 for the PID, NCTF-PID, and Fuzzy-PID controllers, respectively.

The ASED algorithm parameters were assigned as $Z_{\max}=3.0$, $Z_{\min}=-2.5$, $E=0.66$, $K_g=0.022$ and $K_{g1}=0.0008$. The weighting coefficients for tracking errors were specified as $w_{11}=200$, $w_{12}=400$ and $w_{13}=200$, while those corresponding to the control inputs were $w_{21}=1$ and $w_{22}=1$. The total simulation duration was selected to be $t_f=20$ s. Note that these coefficient values in the ASED algorithm are defined by running several trials, and the coefficients that obtain the best results are selected [43].

Fig. 4 shows the objective function $J(\mathbf{P}, \mathbf{I}, \mathbf{D}, \mathbf{N}, \boldsymbol{\alpha}, \boldsymbol{\beta})$ as a function of iteration number k over 1500 iterations. The cost value starts at a relatively high level, decreases sharply during the initial iterations, and gradually converges to a stable minimum. This evolution demonstrates the effectiveness of the ASED method in minimizing J . The exact final value is omitted here as further iterations or parameter variations may be considered in subsequent analyses.

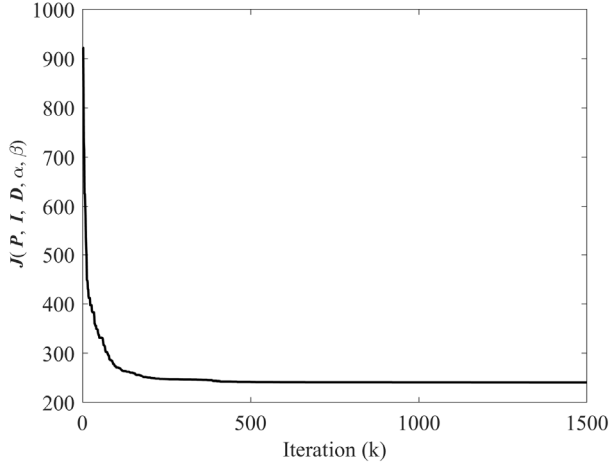


Fig. 4. ASED control performance of NCTF-PID.

From the equations given above, the NCTF-PID controller contains 18 design variables, as defined in Eq. (19) and Eq. (20). The corresponding parameter vector, $\psi = [P, I, D, N, \alpha, \beta] \in \mathbb{R}^{18}$, is summarized in Table II. The optimization process searches for the parameter vector $\psi \in \mathbb{R}^{18}$ that minimizes the objective function J in Eq. (11).

TABLE II: PARAMETER CONFIGURATION FOR THE NCTF-PID CONTROLLER

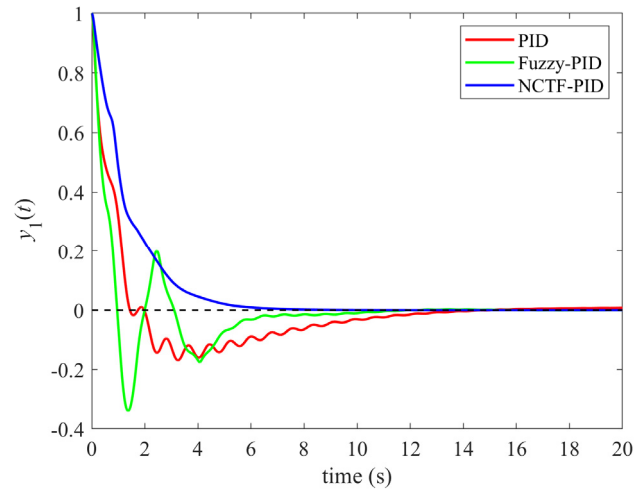
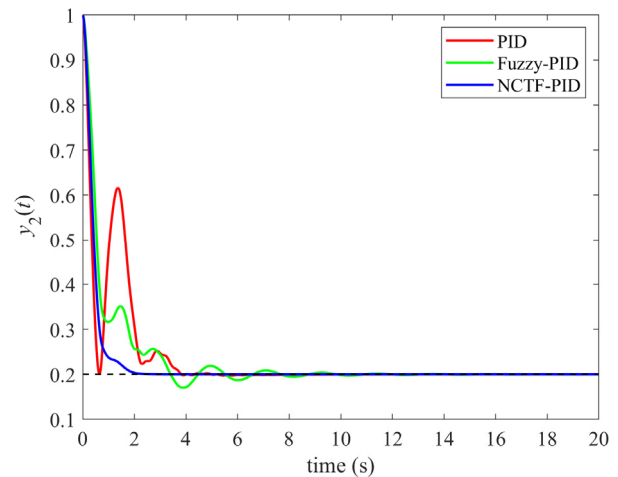
ψ	NCTF-PID Gain	$z(0)$	$10^{z(0)}$	z_{opt}	$10^{z_{opt}}$
ψ_1	P_{11}	0.5	3.1623	0.3825	2.4127
ψ_2	I_{11}	0.1	1.2589	-1.1892	0.0647
ψ_3	D_{11}	0	1	0.1424	1.3880
ψ_4	N_{11}	1	10	0.6740	4.7206
ψ_5	α_{11}	0.3979	2.5	-0.0767	0.8381
ψ_6	β_{11}	0.3010	2	0.9581	9.0803
ψ_7	P_{13}	-1	0.1	-0.6820	0.2080
ψ_8	I_{13}	0.1	1.2589	-0.1852	0.6528
ψ_9	D_{13}	0	1	0.0273	1.0649
ψ_{10}	N_{13}	1	10	1.4495	28.1514
ψ_{11}	α_{13}	0.3617	2.3	0.3410	2.1928
ψ_{12}	β_{13}	0.2041	1.6	-0.2977	0.5038
ψ_{13}	P_{22}	0.8	6.3096	0.7850	6.0954
ψ_{14}	I_{22}	0.5	3.1623	-0.6679	0.2148
ψ_{15}	D_{22}	0	1	-0.7247	0.1885
ψ_{16}	N_{22}	1	10	-0.1861	0.6515
ψ_{17}	α_{22}	0.4150	2.6	-0.5770	0.2649
ψ_{18}	β_{22}	0.2041	1.6	-0.7400	0.1820

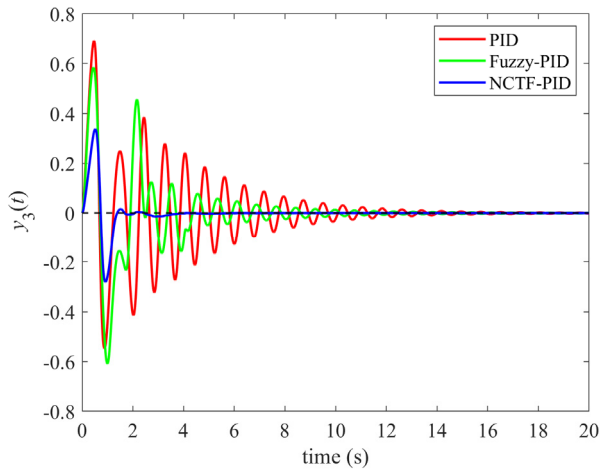
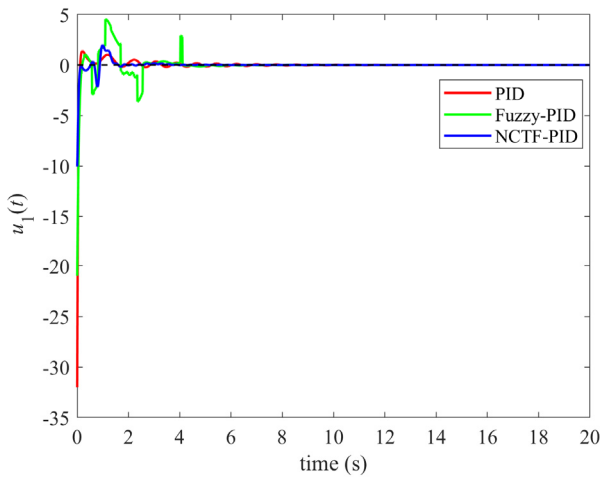
The controller parameters before and after optimization are summarized in Table II, including the PID gains and NCTF parameters. The PID gains mainly determine the feedback regulation characteristics, while the NCTF parameters govern the nonlinear compensation behavior. Since these parameters are optimized simultaneously, their effects should therefore be considered collectively as the effect of the overall

controller configuration rather than as isolated individual parameter effects. A comparison of the initial and optimized parameter values demonstrates that the ASED algorithm effectively adjusts the complete NCTF-PID parameter set to improve the overall control performance.

Together with the convergence characteristics shown in Fig. 4, the parameter comparison in Table II confirms that the proposed ASED approach can effectively reduce the objective function while simultaneously identifying a suitable set of controller parameters. These results demonstrate the effectiveness of the optimization process and provide the optimized NCTF-PID controller configuration for the subsequent control performance evaluation.

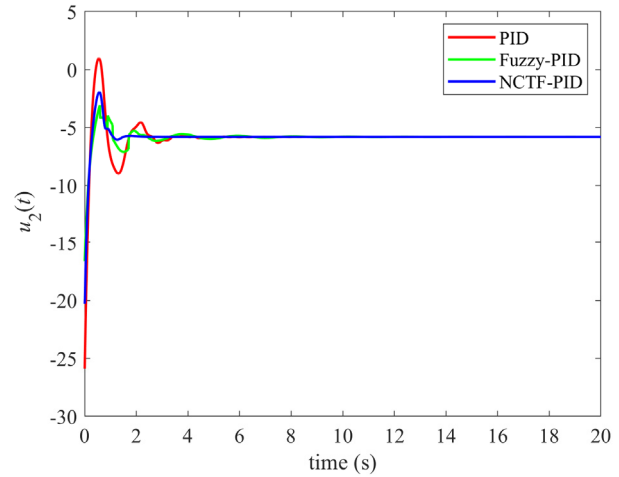
To assess the optimized NCTF-PID controller, comparative simulations are performed on the overhead crane system using conventional PID and Fuzzy-PID controllers as benchmarks. The time-domain responses of the trolley position, cable length, payload swing angle, trolley driving force, and hoisting tension are presented in Figs. 5–9, respectively. These results enable a direct comparison of the tracking performance, transient response, swing suppression, and control effort of the three controllers.


 Fig. 5. The trolley displacement response, $y_1(t)$.

 Fig. 6. The rope length position response, $y_2(t)$.


Fig. 7. The sway angle response, $y_3(t)$.

Fig. 8. Trolley force response, $u_1(t)$.

The output responses and corresponding control inputs of the gantry crane system under the conventional PID controller, the Fuzzy-PID controller, and the proposed NCTF-PID controller are presented in Figs. 5–9. The trolley position, rope length and sway angle responses are shown in Figs. 5–7, respectively and the trolley and hoist control inputs are shown in Figs. 8–9, respectively. It can be observed that all three controllers are capable of stabilizing the gantry crane system, but their transient responses are significantly different. Compared with the conventional PID and Fuzzy-PID controllers, the proposed NCTF-PID controller generally exhibits reduced oscillations and superior payload swing suppression, particularly in the sway-angle response. Although the transient rise time varies among the three controllers, the proposed controller achieves improved settling characteristics and steady-state tracking accuracy for the main output variables. Meanwhile, the generated control inputs remain bounded throughout the control process and become smoother after the initial transient period, indicating that the improved overall control performance is achieved without excessive control effort. These qualitative observations suggest that the proposed controller provides a favorable compromise between transient response, tracking accuracy, payload swing

suppression, and control-input smoothness. A quantitative comparison of these characteristics is therefore required to further clarify the performance differences among the three controllers.


Fig. 9. The hoist force response, $u_2(t)$.

To quantitatively assess these observations, the main time-domain performance indices obtained from the output responses are summarized in Table III.

TABLE III: COMPARISON OF TIME-DOMAIN PERFORMANCE INDICES OF DIFFERENT CONTROLLERS

Output Channel	Performance Indicator	PID	Fuzzy-PID	NCTF-PID
Trolley position y_1	$T_r(s)$	1.1700	0.7800	2.8100
	$T_s(s)$	11.2600	6.9800	5.0200
	$OS(\%)$	16.91	33.97	0.00
	$e_{ss}(m)$	7.40×10^{-3}	2.00×10^{-4}	0.0000
Rope length y_2	$T_r(s)$	0.4000	1.6900	0.5700
	$T_s(s)$	3.5000	5.1400	1.6000
	$OS(\%)$	0.31	3.67	0.00
	$e_{ss}(m)$	0.0000	0.0000	0.0000
Sway angle y_3	$P(rad)$	0.6916	0.6088	0.3373
	$T_s(s)$	13.4600	10.8000	3.2700
	$e_{ss}(rad)$	2.00×10^{-4}	1.00×10^{-4}	0.0000

As summarized in Table III, the proposed NCTF-PID controller achieves the most favorable overall time-domain performance among the three controllers. For the trolley-position response $y_1(t)$, the proposed controller eliminates overshoot while maintaining zero steady-state error. Although its rise time (2.81 s) is longer than those of the PID and Fuzzy-PID controllers, it achieves the shortest settling time (5.02 s), corresponding to reductions of approximately 55.4% and 28.1%, respectively. This suggests that the proposed controller trades a slower initial response for a smoother transient process and faster overall stabilization.

For the rope-length response $y_2(t)$, the proposed controller achieves the shortest settling time of 1.60 s, representing reductions of approximately 54.3% and

68.9% compared with the PID and Fuzzy-PID controllers, respectively. Moreover, both the overshoot and steady-state error are eliminated, demonstrating excellent regulation capability for the hoisting subsystem.

Regarding the sway-angle response $y_3(t)$, the proposed controller produces the smallest peak swing angle (0.3373 rad), corresponding to reductions of approximately 51.2% and 44.6% compared with the PID and Fuzzy-PID controllers, respectively. In addition, the settling time is reduced to 3.27 s, which is approximately 75.7% shorter than that of the PID controller and 69.7% shorter than that of the Fuzzy-PID controller. These results demonstrate that the proposed controller provides superior payload swing suppression and faster attenuation of the swing response.

Overall, the quantitative results presented in Table III are consistent with the response curves shown in Figs. 5–9, confirming that the proposed NCTF-PID controller achieves a more favorable balance among tracking accuracy, transient response, settling performance, and payload swing suppression. Although the proposed controller does not minimize every individual performance index, it provides the most favorable overall combination of these competing control objectives among the three controllers.

Besides the conventional time-domain performance indices listed in Table III, the overall performances of the three controllers are measured by the optimization objective value, accumulated tracking error, and accumulated control effort. The corresponding results are summarized in Table IV.

TABLE IV: PARAMETER INDEX COMPARISON

Controller	PID	Fuzzy-PID	NCTF-PID
J	337.5020	270.2562	240.6117
$\sum_{j=1}^3 \hat{e}_j$	1.1089	0.9306	0.9294
$\sum_{i=1}^2 \hat{u}_i$	65.5079	37.3985	20.8748

The proposed NCTF-PID controller achieves the lowest objective function value of 240.6117, as shown in Table IV, which corresponds to improvements of approximately 28.7% and 11.0% over the PID and Fuzzy-PID controllers, respectively. The accumulated tracking error is reduced to 0.9294, slightly less than the PID controllers (1.1089) and Fuzzy-PID controllers (0.9306). More importantly, the total control effort decreases from 65.5079 for the PID controller and 37.3985 for the Fuzzy-PID controller to only 20.8748, which is about 68.1% and 44.2% reductions, respectively. The results indicate that the proposed controller can obtain a more favorable overall control performance by maintaining a similar level of accumulated tracking accuracy, while effectively decreasing the overall objective value and control effort.

The proposed controller shows better overall control performance, but the computational cost of optimizing its parameters should be taken into account. To be able to compare the optimization complexity fairly, the number of optimized parameters, maximum iteration number, and

total optimization time for the three controllers are summarized in Table V.

TABLE V: COMPARISON OF OPTIMIZATION COMPLEXITY AMONG DIFFERENT CONTROLLERS

Controller	PID	Fuzzy-PID	NCTF-PID
No. of optimized parameters	12	21	18
Maximum iterations	1000	1750	1500
Total optimization time (s)	410.3449	832.8192	646.5836

As shown in Table V, the proposed NCTF-PID controller optimizes 18 parameters, which are higher than the 12 parameters of the conventional PID controller but lower than the 21 parameters of the Fuzzy-PID controller. The corresponding total optimization time is 646.5836 s, which lies between those of the PID and Fuzzy-PID controllers. This result is consistent with the relative optimization complexity associated with the number of parameters and maximum iteration numbers. Although the proposed controller requires additional computational resources compared with the conventional PID controller, the associated optimization cost is justified by its improved overall control performance, particularly its reduced objective function value, substantially lower control effort, and enhanced payload swing suppression capability.

C. Robustness and Repeatability Analysis

The robustness and repeatability of the proposed controller are further tested by two additional tests. First, an external disturbance is applied to the sway angle channel to test the response of the controller to a sudden change in the working condition. This is then followed by ten independent optimization runs to check the reliability of the results obtained from the optimization. The disturbance is defined as

$$d_{y_3}(t) = \begin{cases} 0.2, & 10 \leq t \leq 12, \\ 0, & \text{otherwise,} \end{cases} \quad (21)$$

where the disturbance amplitude is set to 0.2 and applied during the time interval $10 \leq t \leq 12$ s. The corresponding disturbed responses of the trolley position, rope length, and payload sway angle are presented in Figs. 10–12, respectively.

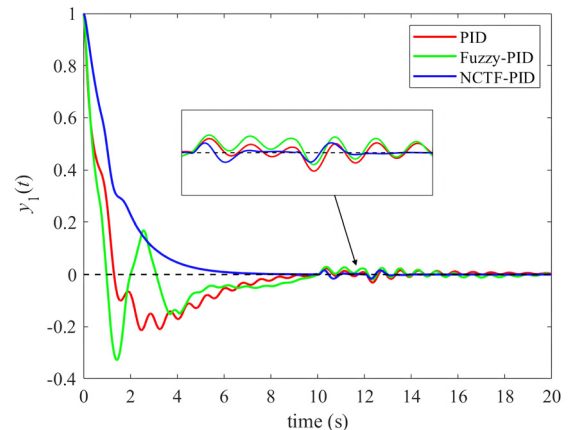


Fig. 10. The trolley displacement $y_1(t)$ with disturbance.

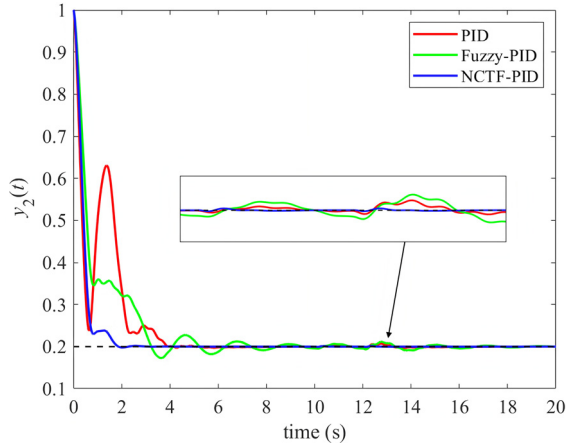


Fig. 11. The rope length $y_2(t)$ with disturbance.

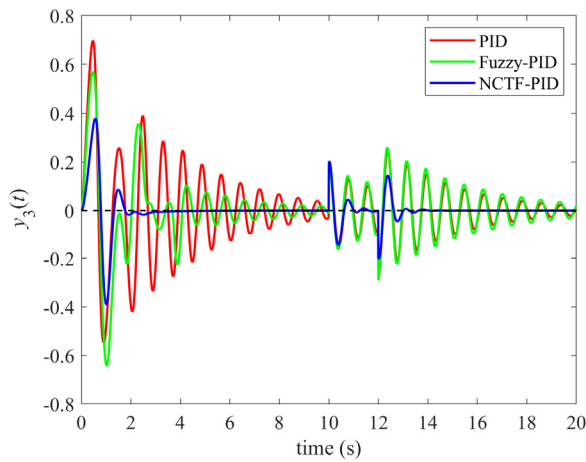


Fig. 12. The sway angle $y_3(t)$ with disturbance.

Figs. 10–12 illustrate the system responses under the applied disturbance. It can be observed that all output variables remain bounded throughout the simulation. Relative to the PID and Fuzzy-PID controllers, the proposed NCTF-PID controller exhibits smaller sway-angle oscillations and faster recovery after the disturbance is removed.

To further evaluate the repeatability of the proposed optimization framework, ten independent optimization runs were conducted. The corresponding statistical results are summarized in Table VI.

TABLE VI: STATISTICAL RESULTS OF TEN INDEPENDENT OPTIMIZATION RUNS

Performance Index	Statistical Metric	PID	Fuzzy-PID	NCTF-PID
J	Best	337.5020	253.984	223.7266
	Worst	353.0283	318.7155	248.9357
	Mean	342.9012	288.4617	239.1476
	Std.	4.6637	22.8817	6.4642
$\sum_{j=1}^3 \hat{e}_j$	Best	1.0928	0.8897	0.8307
	Worst	1.1713	1.0198	0.9836
	Mean	1.1313	0.9596	0.9193
	Std.	0.0228	0.0473	0.0380
$\sum_{i=1}^2 \hat{u}_i$	Best	63.6449	27.9984	18.3287
	Worst	72.9498	62.992	24.4515
	Mean	66.5862	45.4964	22.0173
	Std.	2.6281	12.3297	1.6633

As shown in Table VI, the proposed NCTF-PID controller achieves the lowest best, worst, and mean values for all three performance indices among the three controllers. The corresponding mean values of J , $\sum_{j=1}^3 \hat{e}_j$, and $\sum_{i=1}^2 \hat{u}_i$ are 239.1476, 0.9193, and 22.0173, respectively, demonstrating a favorable overall control performance with reduced control effort over the ten independent optimization runs. The standard deviations of the three performance indices are also compared to evaluate the repeatability of the optimization results. In particular, the Fuzzy-PID controller shows higher standard deviations for J and $\sum_{i=1}^2 \hat{u}_i$, with values of 22.8817 and 12.3297, respectively. Compared with the Fuzzy-PID controller, the proposed NCTF-PID controller has lower standard deviations for both indices, namely 6.4642 for J and 1.6633 for $\sum_{i=1}^2 \hat{u}_i$. The proposed controller also achieves the smallest standard deviation for $\sum_{i=1}^2 \hat{u}_i$ among the three controllers.

V. CONCLUSION

This paper proposed an ASO-optimized NCTF-PID controller for a nonlinear gantry crane system. The PID gains and NCTF parameters were simultaneously optimized in a data-driven manner, and the proposed controller was comprehensively compared with conventional PID and Fuzzy-PID controllers. The results demonstrated that the proposed NCTF-PID controller achieved the most favorable overall control performance among the three controllers. Although it did not minimize every individual performance index, it provided a better balance among tracking accuracy, transient response, payload swing suppression, and control effort. In particular, the proposed controller achieved the lowest objective function value and substantially reduced the accumulated control effort while maintaining a comparable level of accumulated tracking error. The disturbance-response results also verified its ability to generate stable output responses under external disturbances. Moreover, the repeatability of the obtained optimization results was verified by ten independent optimization runs.

However, the current structure of the NCTF-PID has some limitations. The nonlinear compensation function is derived from a hyperbolic tangent function, the shape of which is primarily determined by two adjustable parameters. Although this structure provides effective nonlinear compensation, its flexibility in representing diverse nonlinear characteristics is limited. Future work will therefore focus on developing more flexible parameterized nonlinear compensation functions, such as piecewise structures, to provide greater freedom in shaping the compensation characteristics while maintaining a manageable optimization complexity.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Fengtao Zhang and Mohd Riduwan Ghazali designed the research. Mohd Riduwan Ghazali supervised the experiments and manuscript writing. Fengtao Zhang performed the experiments, simulations, and wrote the manuscript. Mohd Riduwan Ghazali and Mohd Ashraf Ahmad analyzed the data. Mohd Ashraf Ahmad carefully reviewed the manuscript. Mohd Zaidi Mohd Tumari contributed to the results discussion and revised the manuscript. All authors approved the final version.

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