Enhanced Temperature Control of Continuous Stirred Tank Reactors Using QIO-based 2-DoF PID Controller

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Abstract—**Accurate temperature control of continuous stirred tank reactors (CSTRs) remains a major challenge due to the nonlinear dynamics and inherent time delay of the system. Conventional proportional-integral-derivative (PID) controllers often struggle to maintain optimal performance under such complexities, highlighting the need for more advanced control strategies. In this study, a two-degree-of-freedom (2-DOF) PID controller is designed and optimized using the quadratic interpolation optimization (QIO) to enhance temperature regulation in CSTRs. The proposed approach aims to minimize steady-state error, settling time, and overshoot. To implement this method, the nonlinear model of the CSTR is linearized around a stable operating point, and the controller parameters are tuned by minimizing a composite cost function consisting of normalized overshoot and instantaneous error. Simulation results demonstrate that the QIO-based 2-DOF PID controller significantly outperforms other metaheuristic approaches such as differential evolution, particle swarm optimization, slime mould algorithm, and greater cane rat algorithm. Furthermore, comparisons with recent works reveal substantial improvements in rise time, settling time, and steady-state accuracy.**

Keywords—Two-Degree-of-Freedom (2-DOF) PID Controller; Quadratic Interpolation Optimization; Metaheuristics; Continuous Stirred Tank Reactor; Temperature Control.

I. INTRODUCTION

Maintaining accurate temperature control in continuous stirred tank reactors (CSTRs) is a well-known challenge in process industries due to their inherent nonlinearities, time delays, and susceptibility to disturbances [1]. These dynamic complexities often render conventional control methods ineffective, leading to significant steady-state errors, long settling times, and suboptimal disturbance rejection [2]. To overcome these issues, this study proposes a two-degree-of-freedom (2-DOF) proportional-integral-derivative (PID) control framework enhanced by the quadratic interpolation optimization (QIO) algorithm, which aims to achieve precise regulation through intelligent parameter tuning.

The effectiveness of such an approach largely depends on the underlying control structure. Among various strategies, PID controllers particularly the 2-DOF PID have been widely applied due to their simplicity and practical utility [3]. Unlike traditional PID controllers, which apply the same tuning across all control objectives [4], the 2-DOF configuration separates the tracking and disturbance rejection paths, providing better adaptability to nonlinear processes like CSTRs [5]. However, the performance of these controllers is heavily influenced by their parameter settings, which are often difficult to optimize manually or through traditional tuning rules. To address this, several recent studies have explored hybrid or intelligent optimization methods integrated with advanced PID structures [6]–[8]. For example, Jabari, et al. [7] proposed a novel TDn(1+PIDn) controller combined with a DCSA algorithm to efficiently regulate pressure in nonlinear condensers. Similarly, a multistage FOPD(1+PI) controller optimized via the Pelican algorithm has shown significant improvements in DC motor control [6]. Another contribution involved PIDn(1+PD) tuning for DC-DC converters using the GEO algorithm, demonstrating enhanced tracking accuracy [8].

To address the challenge of PID tuning in nonlinear systems, various metaheuristic algorithms have been employed. Differential evolution (DE) [9] and particle swarm optimization (PSO) [10] are among the most widely used, valued for their simplicity and convergence behavior. More recent methods like the slime mould algorithm (SMA) [11] and greater cane rat algorithm (GCRA) [12] offer improved exploration in complex search spaces. The quadratic interpolation optimization (QIO) [13] algorithm further enhances search efficiency through interpolation-based updates, making it suitable for high-dimensional control problems.

Several recent studies have explored the integration of quadratic interpolation-based optimization algorithms into complex engineering control and prediction tasks [14]–[16]. Dao, et al. [17] proposed a fault diagnosis framework for hydro-turbine systems using a deep learning model optimized by a chaotic QIO (CQIO) algorithm, which improved diagnostic accuracy through diverse initial population generation and fine-tuned CNN-LSTM hyperparameters. In another application, Bayoumi, et al. [18] applied QIO to the parameter estimation of photovoltaic (PV) systems under varying irradiance conditions, outperforming conventional algorithms like GWO, PSO, and SSA in accuracy and convergence speed. Ekinci, et al. [15] employed QIO in combination with a real PID plus second-order derivative ($RPIDD^2$) controller for electric furnace temperature control and showed that QIO-$RPIDD^2$ achieved faster settling time and reduced overshoot compared to FLA, RSA, and DE-based counterparts. Similarly, Izci, et al. [16] introduced a hybrid simulated annealing-QIO (hSA-QIO) algorithm for dynamic load frequency control (LFC) in power systems, demonstrating superior control precision and robustness against fluctuations in hybrid photovoltaic-thermal systems. To overcome the limitations of conventional QIO in high-dimensional and nonlinear problems, Khan, et al. [19] proposed an improved QIO (IQIO) integrating Weibull flight motion, chaotic mutation, and prairie dog optimization (PDO). This enhanced variant significantly reduced costs and emissions in stochastic short-term hydrothermal scheduling, particularly under uncertainty from solar and wind energy sources. These studies collectively highlight the effectiveness and adaptability of QIO and its enhanced variants in a variety of industrial and energy control applications.

To address these gaps, this study integrates the QIO algorithm [14], a recent interpolation-based metaheuristic, with a 2-DOF PID controller [20]–[22] for the CSTR process. The proposed QIO-based approach is benchmarked against state-of-the-art methods, showing significant improvements in rise time, settling time, overshoot, and steady-state error. These results confirm the novelty and practical impact of our method and underscore its potential for broader use in advanced industrial control systems.

This paper is organized as follows. Section 2 presents the mathematical modeling of the continuous stirred tank reactor (CSTR), including its nonlinear dynamics and the linearized transfer function used for control design. Section 3 introduces the quadratic interpolation optimization (QIO) algorithm, describing its generalized interpolation mechanism and suitability for control parameter tuning. Section 4 outlines the proposed QIO-based 2-DOF PID control strategy, including the controller structure, objective function formulation, and parameter optimization methodology. Section 5 reports and analyzes the comparative simulation results, evaluating the proposed method against existing metaheuristic algorithms and recent literature in terms of performance metrics such as rise time, overshoot, settling time, steady-state error, and integral absolute error (IAE). Finally, Section 6 concludes the study by summarizing the findings and suggesting directions for future research and real-time implementation.

II. Mathematical Model of Continuous Stirred Tank Reactor

The continuous flow chemical reaction process in process industries relies heavily on continuous stirred tank reactors (CSTRs) as crucial components [23][24]. The ability of these reactors to deliver uniform mixing and consistent product quality makes them a crucial element in multiple chemical manufacturing processes. The nonlinear behavior of CSTRs becomes especially problematic when handling exothermic reactions which makes maintaining precise temperature control highly challenging. To achieve effective control strategies, it is necessary to have a precise mathematical model that accurately represents the reactor behavior when operating conditions change. The behavior of a CSTR that experiences an exothermic reaction responds to nonlinear differential equations which originate from both material and energy balance principles. The governing equations represent ideal reactor conditions including perfect mixing and uniform physical characteristics throughout the system with constant volume. The governing equations are expressed as follows:

- Material Balance

$$\frac{dC_A}{dt} = \frac{Q}{V}(C_{Ain} - C_A) - r \quad (1)$$

- Energy Balance

$$\frac{dT}{dt} = \frac{Q}{V}(T_{in} - T) - \left(\frac{\Delta H}{\delta c_p}\right) r + \frac{UA}{V\delta c_p}(T_j - T) \quad (2)$$

- Reaction Rate Expression

$$r = k_0 \times \exp\left(-\frac{E_a}{RT}\right) \times C_A \quad (3)$$

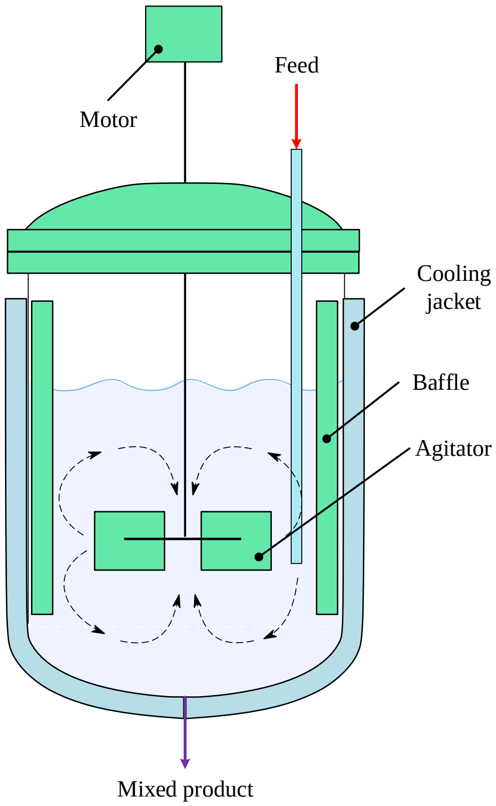

Fig. 1. Cross-sectional diagram of a continuous stirred tank reactor

These equations describe how the concentration of the reactant C_A and the temperature inside the reactor T evolve over time. The variable r indicates the chemical reaction rate which relies on both temperature and concentration levels. The reaction rate exhibits exponential temperature dependence according to the Arrhenius equation while being multiplied by concentration which causes significant nonlinear behavior in the system.

An effective control system design usually involves linearizing a nonlinear model at a steady-state operating point. The operating point selection happens under reactor conditions that guarantee safety and stability. The definition of the operating point for this scenario is as follows:

$$C_A = 0.98\ mol/m^3,\ T = 304.2\ K,\ and\ T_j = 280\ K \quad (4)$$

The process transfer function which relates the reactor and jacket temperature is approximated as stable first-order plus time delay model (SFOPTD) using Sundaresan and Krishnaswamy method [25] for a step change of 10 K in jacket temperature, and the model is given as follows [26]:

$$G_{cstr}(s) = \frac{0.85}{0.4355s + 1} e^{-0.0135s} \quad (5)$$

This transfer function serves as a simplified linear representation of the CSTR system and is used as the basis for controller design, particularly for tuning parameters in model-based or optimization-driven control strategies. Fig. 1 shows the cross-sectional diagram of a continuous stirred tank reactor. The key physical and chemical parameters used in formulating the CSTR model are summarized in Table I. These values are based on experimental data and literature reference [26]. These parameters form the foundation of the dynamic model, enabling the development of accurate simulations and robust control algorithms. The detailed understanding of these variables is crucial for engineers and researchers working on advanced control techniques such as model predictive control (MPC), adaptive control, and intelligent optimization methods applied to CSTR systems.

TABLE I. KEY PARAMETERS USED IN FORMULATING THE CSTR MODEL

Parameters	Symbol	Value	Unit
Exponential factor	k_o	7.2×10^{10}	$1/s$
Flow rate	Q	100	m^3/s
Volume of reactor	V	100	m^3
Jacket temperature	T_j	280	K
Overall heat transfer coefficient	UA	5×10^4	Wb/K
Heat of reaction	ΔH	5×10^4	J/mol
Density × heat capacity	δc_p	239	$J/m^3.K$
Feed stream concentration	$C_{A\,in}$	10	mol/m^3
Feed temperature	T_{in}	350	K
Activation energy	E_a	72.752	KJ/mol
Universal gas constant	R	8.31451	$J/mol.K$

III. QUADRATIC INTERPOLATION OPTIMIZATION

Quadratic interpolation optimization (QIO) [27] is a derivative-free numerical optimization technique that is particularly well-suited for unimodal objective functions where the analytical form of the function is unknown, or its derivatives are unavailable. This method is frequently used in control tuning applications, especially where simulation-based objective functions such as integral error metrics for instance IAE [28], ITAE [29] and ISE [30] are employed and evaluating the objective function is computationally expensive.

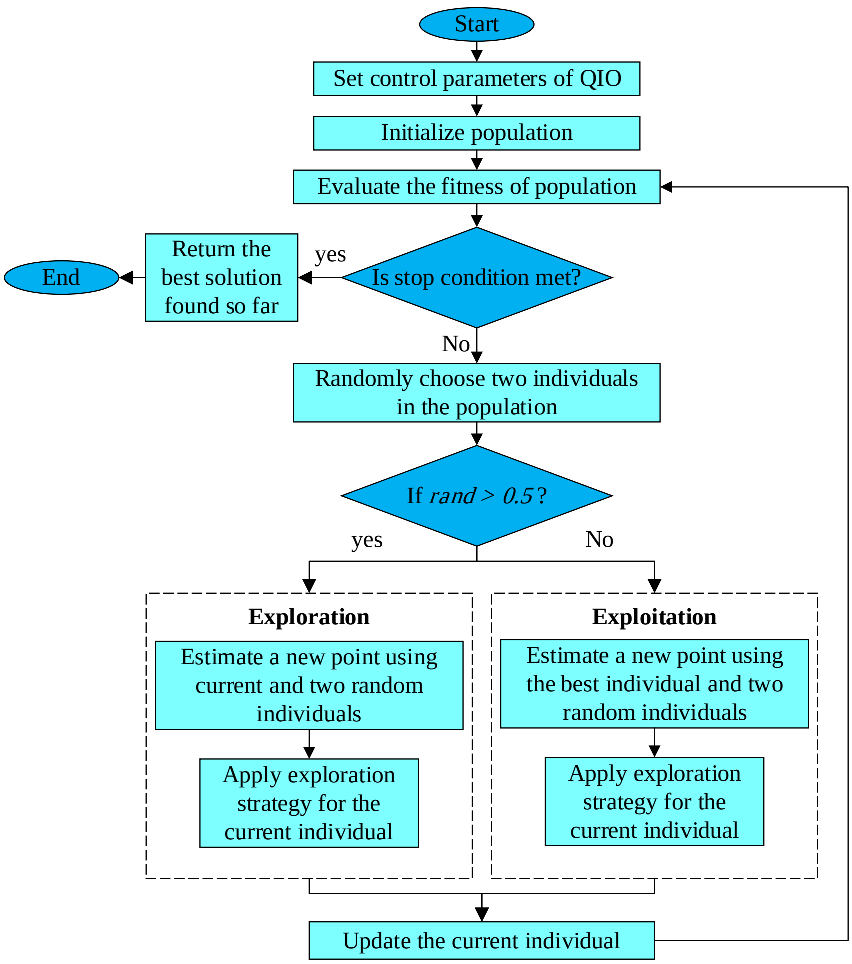

Fig. 2. Flowchart of QIO

QIO works by approximating the objective function using a quadratic polynomial fitted to three data points. The idea is to replace the actual cost function $f(x)$ with a second-order polynomial that interpolates three known points $(x_1, f_1), (x_2, f_2), (x_3, f_3)$, where x_i are scaler input parameters and $f_i = f(X_i)$ are the corresponding cost values. The general form of the interpolating quadratic polynomial is:

$$f(x) = ax^2 + bx + c \tag{6}$$

To locate the minimum of this quadratic approximation, we use the standard result that the minimum of a parabola $f(x) = ax^2 + bx + c$ $(for\ a > 0)$ occurs at $x_{min} = -b/2a$. To compute this directly from three points without explicitly solving for a and b, a more compact and numerically stable formula can be derived based on divided differences (as in (7)). This expression yields a new estimate x_{min}, which is then used to evaluate a new function value. The point with the highest cost is discarded, and the three-point set is updated for the next iteration. This process is repeated until convergence is achieved, typically when the change in x_{min} or $f(x_{min})$ falls below a specified threshold.

$$x_{min} = \frac{(x_1^2 - x_2^2)(f_3 - f_2) + (x_2^2 - x_3^2)(f_1 - f_2) + (x_3^2 - x_1^2)(f_2 - f_1)}{2[(x_1 - x_2)(f_3 - f_2) + (x_2 - x_3)(f_1 - f_2) + (x_3 - x_1)(f_2 - f_1)]} \tag{7}$$

$$U(s) = K_P[\alpha R(s) - Y(s)] + \frac{K_I}{s}[R(s) - Y(s)] + K_D \frac{Ns}{s+N}[\beta R(s) - Y(s)] \tag{8}$$

IV. Proposed Control Method

A. QIO for 2-DOF PID Tuning

In this study, we adopt the quadratic interpolation optimization (QIO) algorithm to tune the parameters of the proposed two-degree-of-freedom (2-DOF) PID controller for the nonlinear CSTR process. QIO is a recently developed metaheuristic optimization technique inspired by generalized quadratic interpolation (GQI), introduced to enhance both exploration and exploitation in the search space. Unlike traditional interpolation methods, QIO is a population-based approach that constructs and leverages interpolating quadratic curves among candidate solutions to estimate optimal search directions [13]. The proposed 2-DOF PID controller is expressed as given in (8) where $R(s)$, $Y(s)$, and $U(s)$ denote the reference input, output response, and control action, respectively. The gains K_P, K_I, K_D and parameters α, β and N govern the behavior of the 2-DOF controller. Fig. 3 illustrates the 2-DOF PID control structure.

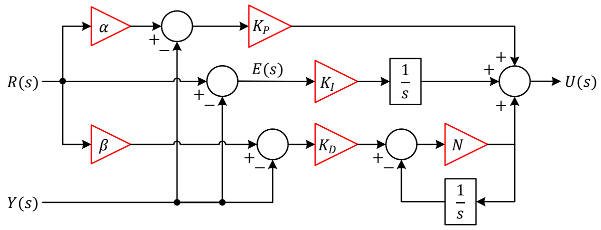

Fig. 3. Block diagram of 2-DOF PID controller

1) Objective Function

The controller parameters are optimized to minimize a multi-objective cost function that balances tracking accuracy and transient performance, defined as:

$$IAE = \int_0^{t_f} |e(t)|dt \tag{9}$$

where, minimize CF cost function is defined as:

$$CF = \rho \times IAE + (1 - \rho) \times OS \tag{10}$$

where, OS, $e(t) = r(t) - y(t)$ are normalized percent overshoot and the instantaneous error signal respectivly. In addition, $\rho = 0.85$, and $t_f = 2$ s. Fig. 4 depicts the QIO-based controller tuning workflow for the CSTR process.

B. Controller Parameter

The controller parameters obtained from each optimization algorithm are presented in Table II. QIO-tuned parameters lie well within the defined feasible ranges and offer a balanced configuration, contributing to the superior closed-loop performance discussed in subsequent sections.

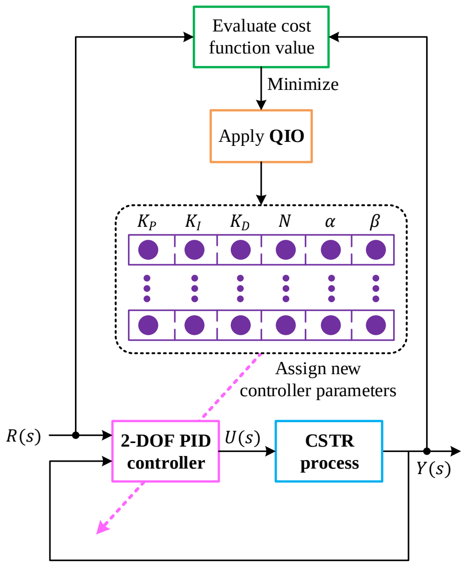

Fig. 4. Proposed QIO-based 2-DOF PID control approach for CSTR process

TABLE II. Obtained Controller Parameters via QIO, GCRA, SMA, DE and PSO

Parameter	Range	QIO	GCRA	SMA	DE	PSO
K_P	[1, 100]	20.6040	23.4136	18.0695	16.1738	19.8695
K_I	[1, 100]	57.9826	67.2805	67.1113	44.0146	96.6640
K_D	[0.001, 2]	0.1137	0.1442	0.1006	0.1347	0.1266
N	[10, 500]	402.5572	322.4220	283.1537	333.0291	465.3266
α	[0.1, 2]	0.9989	0.9825	0.9800	1.0087	0.9573
β	[0.1, 2]	1.8332	1.0817	1.9807	1.9234	1.7108

V. Comparative Simulation Results

This section presents a comprehensive comparison of the proposed QIO-based 2-DOF PID controller with several well-established optimization algorithms, namely GCRA, SMA, DE, and PSO. Additionally, a benchmark comparison is conducted against recent PID tuning results reported in the literature, including coot bird optimization algorithm (CBOA), water cycle algorithm (WCA), dragonfly algorithm (DA), and teaching–learning-based optimization (TLBO)-based controllers. The goal is to validate the efficacy and superiority of QIO in tuning the 2-DOF PID parameters for temperature control in a CSTR process. All algorithms were executed under identical experimental conditions: a population size of 20, 100 total iterations, and 30 independent runs to ensure statistical consistency and mitigate stochastic variability.

A. Statistical Performance Comparison

Table III summarizes the statistical results of the cost function values (CF) obtained by QIO, GCRA, SMA, DE, and PSO across 30 runs. The proposed QIO algorithm outperforms all competitors with the lowest average CF value of 0.1867, accompanied by a low standard deviation of 0.0099, indicating both high accuracy and robustness.

TABLE III. Statistical Results of QIO, GCRA, SMA, DE and PSO

Measure	QIO	GCRA	SMA	DE	PSO
Average	0.1867	0.2320	0.2447	0.2521	0.2741
Standard deviation	0.0099	0.0098	0.0106	0.0099	0.0119
Minimum	0.1758	0.2169	0.2296	0.2375	0.2563
Maximum	0.2179	0.2470	0.2712	0.2764	0.3001

The nonparametric Wilcoxon rank-sum test, summarized in Table IV, further confirms that the performance differences are statistically significant, with p-values well below 0.05 for all pairwise comparisons. In each case, QIO is statistically superior.

TABLE IV. Nonparametric Wilcoxon Test for QIO with Respect to GCRA, SMA, DE and PSO

Measure	QIO versus GCRA	QIO versus SMA	QIO versus DE	QIO versus PSO
p-value	1.7344E−06	1.7344E−06	1.7344E−06	1.7344E−06
Superior	QIO	QIO	QIO	QIO

B. Time Domain Performance Analysis

Fig. 5 and Fig. 6 show the step response of the reactor temperature under different controllers. As shown in Fig. 5 and Fig. 6, the QIO-based controller has the best performance among other optimization methods.

The QIO-based controller achieves faster convergence and zero overshoot, as further detailed in Table V. Among all algorithms, QIO exhibits the lowest rise time (0.0120 s), shortest settling time (0.0669 s), and zero percent overshoot, all within the 2% tolerance band.

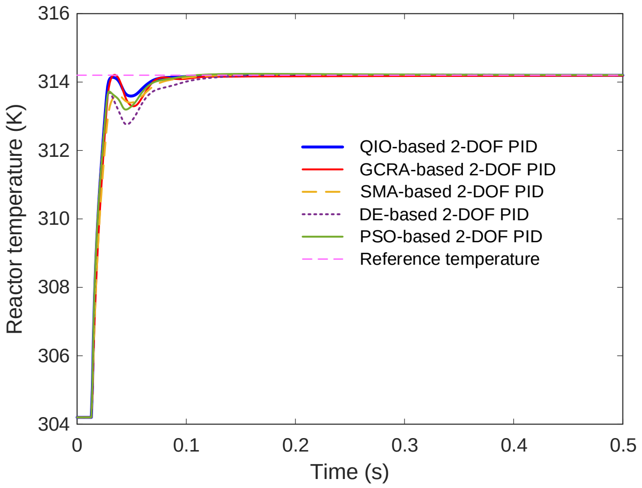

Fig. 5. Step response showing the reactor temperature for QIO, GCRA, SMA, DE and PSO based 2-DOF PID controllers

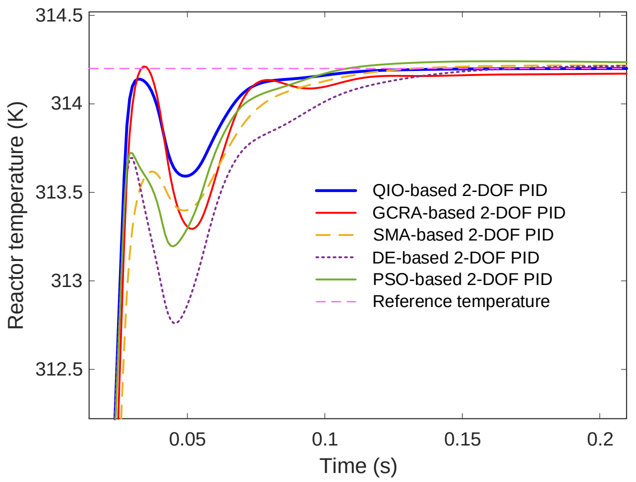

Fig. 6. An enlarged view of Fig. 5

TABLE V. Rise Time, Settling Time and Percent Overshoot for QIO, GCRA, SMA, DE and PSO based 2-DOF PID Controllers

Normalized metrics	QIO	GCRA	SMA	DE	PSO
t_r (s)	0.0120	0.0127	0.0151	0.0124	0.0124
t_s (s)	0.0669	0.0694	0.0776	0.0984	0.0708
OS (%)	0	0.1097	0.1702	0.1661	0.4075

C. Steady-State Error and IAE Evaluation

Table VI provides steady-state error e_{ss} and IAE values for each method. QIO once again achieves the lowest IAE (0.2068) and a practically negligible steady-state error (1.16E−04 %). These metrics affirm QIO's superior tracking accuracy and disturbance rejection capability.

TABLE VI. Steady State Error and IAE Values for QIO, GCRA, SMA, DE and PSO based 2-DOF PID Controllers

Error metrics	QIO	GCRA	SMA	DE	PSO
e_{ss} (%)	1.1634E−04	0.0143	0.0014	0.0128	2.0103E−04
IAE	0.2068	0.2358	0.2401	0.2501	0.2296

D. Comparison with Recent Literature

To further validate the competitiveness of QIO, its performance is benchmarked against recent PID tuning results from CBOA, WCA, DA, and TLBO approaches (Table VII) [26]. Fig. 7 and Fig. 8 present the corresponding step responses. As shown in Table VIII, the QIO-based controller substantially outperforms all reported methods, delivering the fastest rise time, shortest settling time, and zero overshoot, surpassing even the best existing results. Moreover, Table IX shows that QIO achieves the lowest IAE (0.2068) and the smallest steady-state error, marking a significant advancement over existing techniques in both precision and transient quality.

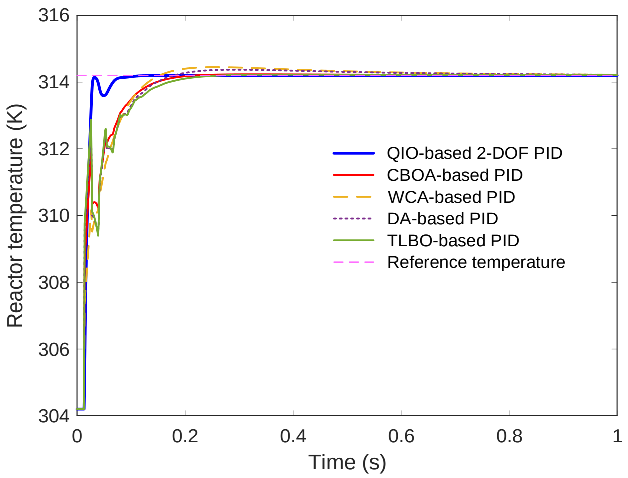

Fig. 7. Comparative step response with respect to reported works

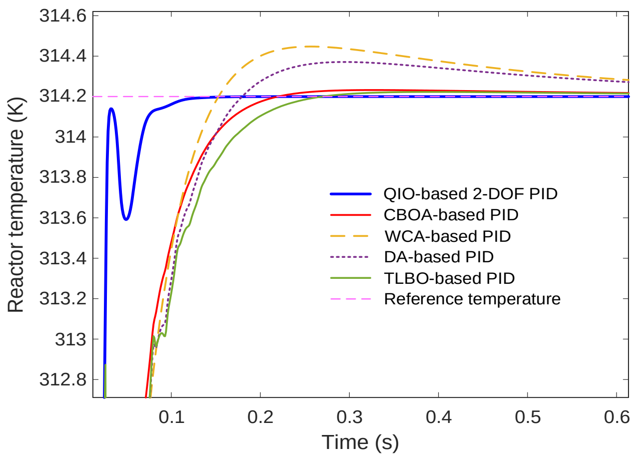

Fig. 8. Enlarged view of Fig. 7

TABLE VII. THE PID PARAMETERS REPORTED IN RECENT WORKS

Parameter	CBOA	WCA	DA	TLBO
K_P	14.480	12.146	13.299	13.936
K_I	34.519	39.840	40.130	32.297
K_D	0.220	0.157	0.268	0.278

TABLE VIII. COMPARATIVE RISE TIME, SETTLING TIME AND PERCENT OVERSHOOT VALUES OF PROPOSED APPROACH WITH RESPECT TO REPORTED PID WORKS

Normalized metrics	QIO	CBOA	WCA	DA	TLBO
t_r (s)	0.0120	0.0723	0.0775	0.0833	0.0857
t_s (s)	0.0669	0.1474	0.3601	0.1483	0.1704
OS (%)	0	0.3237	2.4750	1.7114	0.2284

TABLE IX. COMPARATIVE STEADY STATE ERROR AND IAE VALUES OF PROPOSED APPROACH WITH RESPECT TO REPORTED PID APPROACHES

Error metrics	QIO	CBOA		WCA	DA	TLBO
e_{ss} (%)	1.1634E−04	0.0557		0.0519	0.0658	0.0505
IAE	0.2068	0.3745		0.4928	0.4422	0.3891

VI. CONCLUSION

This paper proposed an enhanced temperature control strategy for CSTRs by combining a 2-DOF PID controller with the QIO algorithm. The controller was tuned using a composite cost function, and simulation results confirmed its superior performance over GCRA, SMA, DE, and PSO in terms of response speed, accuracy, and robustness. Despite promising results, the method was only validated in simulation. Real-time implementation and robustness under uncertainty remain open challenges. The approach is applicable to industrial process control, offering better stability and energy efficiency. Future research can explore real-time deployment, hybrid adaptive-QIO methods, and extension to more complex nonlinear systems.

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