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SCIENTIFIC PAPER

UDC

DESIGN OF INDUSTRY-CENTRIC CONTROLLER FOR MIMO CSTH PROCESS WITH ENHANCED DISTURBANCE REJECTION

Highlights

- A first principle and transfer function model for the CSTH process was developed and validated.
- Conventional PID, MPC, and RTD-A controllers have been designed for the developed model.
- Responses were evaluated via performance indices, focusing on disturbance rejection.

Abstract

This paper focuses on designing an advanced control scheme tailored for large-scale industrial processes, where controllers must maintain effective performance despite significant disturbances and setpoint changes. The primary focus of the proposed RTD-A controller is on robust disturbance rejection. RTD-A possesses the benefits of both conventional PID and MPC control schemes. As model-based methods face challenges in addressing increasingly complex processes, data-driven techniques have gained popularity in industrial system monitoring due to their ability to handle unknown physical models. In this work, both the first-principle and transfer function models of the CSTH system are developed using real-time data and represented as a multi-input, multi-output (MIMO) system. PID, MPC, and RTD-A controllers are then applied to regulate the temperatures of the two tanks. The performance of these controllers is carefully examined using integral performance criteria and the time domain analysis to accurately assess their dynamic behavior and control precision. The results demonstrate that the RTD-A controller exhibits superior performance in mitigating disturbances. The RTD-A control strategy exhibits outstanding performance with near-zero overshoot (0% in servo and about 0.05% in regulatory responses) and stable settling times close to 430 - 440 seconds in both tanks. Although MPC and PID controllers offer quicker responses, their greater overshoot and longer settling times establish RTD-A as the preferred method for achieving reliable, precise, and safe control in industrial processes.

Keywords: CSTH, MIMO, PID, MPC, RTD-A, Disturbance Rejection.

INTRODUCTION

Many industrial processes are inherently multi-variable and can be effectively modeled as multi-input, multi-output (MIMO) systems. The design and implementation of controllers for such MIMO systems present substantial challenges, primarily due to the complex interactions and couplings between the system's feedback loops, which result in dynamic behaviors that require sophisticated control strategies. A quintessential example of such a system is the laboratory-scale continuous stirred tank heater (CSTH) process, which consists of two interlinked tanks and a recirculation valve. This configuration creates a highly interactive system, making it an ideal experimental platform for evaluating and testing the performance and robustness of various control strategies specifically designed for MIMO systems.

The CSTH process, characterized by its non-linear dynamics, demonstrates intricate coupling between the temperature and flow rate within the two tanks. The system provides a versatile environment to examine issues like system stability, transient behavior, setpoint tracking, disturbance rejection, and optimal regulation. As such, it serves as an excellent testbed for developing and valida-

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ting advanced control methodologies that can enhance performance, robustness, and efficiency in industrial process control.

A linearized state-space and transfer function model was developed, and a linear multivariable controller was designed. The structure and fundamental governing equations of the modified CSTH model, utilized in this work, were proposed by Thornhill *et al.* [1]. The just-in-time learning-based data-driven (JITL-DD) method was employed in the continuous stirred tank heater (CSTH) pilot system to derive the mathematical model, as outlined by Zheng *et al.* [2]. In Albagul *et al.* [3], both conventional proportional integral (PI) controllers and PI fuzzy logic controllers were proposed for regulating the concentration in the linear continuous stirred tank reactor (CSTR). It was shown that the fuzzy-based PI controller outperformed the conventional one in terms of controller performance criteria such as integral absolute error (IAE), integral square error (ISE), and settling time [4-6]. Cascade control strategies for temperature regulation in the CSTH process were explored by Mahmood and Nawaf [7]. A deadbeat controller was designed to stabilize the system and achieve optimal adaptive realization for the CSTH process, as discussed by Zhang *et al.* [8], with a focus on meeting specific performance specifications. A dual adaptive model predictive controller (DAMPC) for controlling the temperature in a cascaded CSTH process was designed and validated on a real-time setup by Kumar *et al.* [9]. Mathematical modelling, conventional control, and cascade control of the simulated CSTH process were thoroughly explained by Li and Jiang [10].

In addition, the limitations of traditional PID controllers in industrial applications were analyzed, leading to the introduction of the robustness, setpoint tracking, disturbance rejection - aggressiveness (RTD-A) controller by Ogunnaike and Mukati [11]. This controller combines the simplicity of PID with the features of model predictive controller (MPC), simplifying tuning by normalizing parameters. Simulations on a nonlinear process confirmed its effectiveness, with future research directed towards enhancing stability and optimizing parameter selection. Further advancements in the RTD-A controller were made by Mukati *et al.* [12] by developing tuning rules using M-constrained integral gain optimization to balance performance and robustness. Stability was ensured using an FOPDT model, and the controller was validated experimentally on liquid level and temperature control systems, introducing stability contour plots for optimal parameter selection. The RTDA controller was applied to nonlinear stochastic processes by Febina and Angeline [13], specifically in a conical tank system, demonstrating its advantages over traditional PID controllers and MPC in handling nonlinear dynamics. Moreover, the RTDA was shown to be highly effective in managing both minimum and non-minimum zeros in second-order plus dead time (SOPDT) processes, offering a simpler, more effective, and robust solution compared to IMC and MPC by Anbarasan and Srinivasan [14]. Applications of the RTDA include systems like CSTR and distributed control systems (DCS).

In conclusion, while much of the existing research has focused on the modelling and control of single-stage CSTH systems, advanced control strategies like fuzzy-based PI controllers, cascade control, and adaptive MPC have demonstrated considerable performance improvements. Furthermore, the RTDA controller's combination of PID simplicity and MPC features, along with its ability to handle nonlinear dynamics and optimize stability, presents significant potential for research and optimization in multi-stage CSTH systems and other industrial applications.

This paper is organized as follows: Section II describes the CSTH process setup available in the laboratory. Section III discusses the mathematical modeling of the CSTH process using both the first principle model and the transfer function model, followed by validation with the real-time CSTH process. Section IV covers the implementation of both conventional and proposed controllers. Section V presents the results, while Section VI concludes the paper and outlines future research directions.

PROCESS DESCRIPTION

The CSTH is a sophisticated multivariable system widely used in industries like chemicals and pharmaceuticals. This system serves as a module for regulating and analyzing the temperature of liquids. Temperature measurement and control in industrial settings cover a broad range of applications and requirements. To address these diverse needs, the process control industry has developed numerous sensors and cutting-edge control strategies to regulate temperature, both in industrial and domestic settings.

The process flow diagram of the CSTH process available in the Department of Instrumentation Engineering, MIT campus, is shown in Figure 1.

The CSTH process involves two separate water storage tanks. The cold water entering Tank 1 is heated by an electrical heater. The overflow from Tank 1 is transferred to Tank 2, where it is heated by a separate electrical heater. Before the heating process begins, both Tank 1 and Tank 2 are maintained at steady-state levels. A portion of the outflow from Tank 2 is recirculated back into Tank 1, which introduces the additional multivariable interaction and additional complexity to the system, while the remaining water is drained. The outflow rate is adjusted to ensure that the steady-state levels in both tanks are maintained during the recirculation process. The first-principle and transfer function models were developed based on steady-state parameter values from the real-time setup, and their responses were validated by comparing them with actual process data.

This system is a 5-input and 3-output system. The inputs include the flow rates for Tank 1 (F_1), Tank 2 (F_2), and the recirculating flow rate from Tank 2 to Tank 1 (F_R), each controlled by separate valves. Q_1 and Q_2 represent the heat inputs to the heaters in Tank 1 and Tank 2, respectively. The outputs are the temperatures (T_1 and T_2) of Tank 1 and Tank 2, and the water level (h_2) in Tank 2. The steady-state values for the real-time CSTH process are provided in Table 1.

MODELLING AND VALIDATION OF CSTH PROCESS

The first principle model is modified to suit the CSTH process in the laboratory and is validated using the process parameters of the real-time system [1].

Using Stephanopoulos [15] as the benchmark, the first principle model for the CSTH process has been further refined and modified as follows [1]:

$$V_1\frac{dT_1}{dt}=\frac{Q_1}{\rho C_p}+F_1(T_i-T_1)+F_R(T_2-T_1) \quad (1)$$

$$V_2\frac{dT_2}{dt}=\frac{Q_2}{\rho C_p}+F_2(T_1-T_2)-F_R(T_2-T_1)-U[2\pi r_2 h_2](T_2-T_a) \quad (2)$$

$$A_2\frac{dh_2}{dt}=F_2-[F_{out}+F_R] \quad (3)$$

The steady-state values are computed by performing an open-loop response analysis of the real-time CSTH process by Balakotaiah and Luss [16]. Initially, the flow rates of the tanks are regulated to maintain stable levels in both tanks. Once the steady-state level is established in Tank 2, the heater is activated to achieve the initial steady-state temperatures of Tank 1 (T_{1s}) and Tank 2 (T_{2s}). Upon reaching the initial steady state, a step change is introduced to Heater-1 to establish the first steady-state temperatures for Tank 1 (T_{1f}) and Tank 2 (T_{2f}).

Subsequently, a second step change is applied to Heater-2 to attain the second steady-state temperatures for Tank 1 (T_{1ss}) and Tank 2 (T_{2ss}). The specific heat capacity and heat transfer coefficient are derived by analyzing the steady-state thermal response curve of either Tank 1 or Tank 2, and then approximated using the following relations:

$$C_p=\frac{qQ}{m\Delta T} \quad (4)$$

$$U=\frac{Q+wC_p(T_i-T_{ss})}{A(T_{ss}-T_a)} \quad (5)$$

$$A=2\pi rh \quad (6)$$

where are C_p is the specific heat capacity, U is the heat transfer coefficient, w is the inlet flow rate, Q is the electrical heat energy given to the tank, m is mass of liquid in the tank, ΔT is the temperature change, T_i is the initial temperature of liquid, T_{ss} is the steady state temperature of liquid, T_a is the atmospheric temperature of liquid, A is the area of the liquid in the tank, r is the radius of the tank, and h is the steady state height of the tank.

For the sake of simplicity, the proposed work considers Q_1 and Q_2 as the manipulated variables for controlling the temperatures of Tank 1 and Tank 2, respectively. Figure 2(a) illustrates the real-time steady-state response of the system.

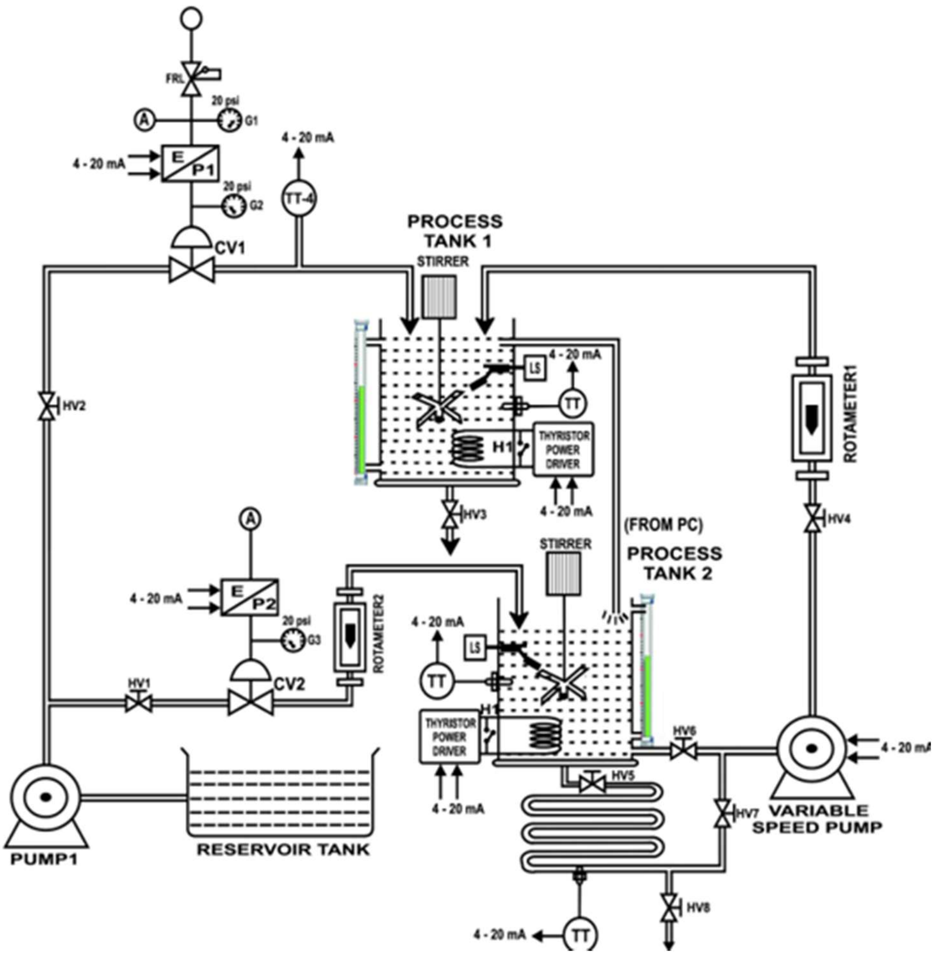


Figure 1. Schematic Diagram of CSTH Process.

Table 1. Nominal model parameters.

Parameter	Description	Value
V_1	Volume of Tank 1	0.23565 m^3
V_2	Volume of Tank 2	0.20737 m^3
A_2	Area of Tank 2	0.9426 m^2
r_2	Radius of Tank 2	0.15 m
T_1	Steady state temperature of Tank 1	40 °C
T_2	Steady state temperature of Tank 2	41.6 °C
h_2	Steady state level of Tank 2	0.22 m
T_i	Inlet water temperature of Tank 1	36 °C
T_a	Atmospheric temperature	40 °C
F_1	Input flow rate of Tank 1	2.8 10^{-5} m^3/s
F_2	Input flow rate of Tank 2	5.85 10^{-5} m^3/s
F_{out}	Output flow rate of Tank 2	2.3 10^{-5} m^3/s
F_R	Recirculating flow rate from Tank 2 to Tank 1	3.55 10^{-5} m^3/s
Q_1	Heat input to Tank 1	375 J/s
Q_2	Heat input to Tank 2	375 J/s
C_p	Specific heat capacity	4546 $JKg^{-1}K^{-1}$
U	Heat transfer coefficient	274.2 W/m^2K

The first-principle model is implemented using the nominal values obtained from the real-time data, and the corresponding responses are generated using MATLAB Simulink, as depicted in Figure 2(b). The real-time data is used to derive the transfer function model for the proposed CSTH process. As outlined by Bequette [17], the system can be modeled using three different methods: the 63.5% method, the two-point method, and the slope method. Additionally, another general approach, the system identification method with MATLAB, is also applied. All four methods are employed to determine the transfer function model, with the most suitable one selected for validation. For the proposed CSTH process, the transfer function model derived using the 63.5% method provides the most accurate steady-state responses compared to the other methods. The transfer function elements for the CSTH process, modeled as a MIMO system, are as follows:

$$G_{11} = \frac{0.2\, e^{-7.25s}}{s+0.02} \tag{7}$$

$$G_{12} = \frac{0.32\, e^{-2.5s}}{s+0.0159} \tag{8}$$

$$G_{21} = \frac{0.18\, e^{-10s}}{s+0.0088} \tag{9}$$

$$G_{22} = \frac{0.24\, e^{-8.25}}{s+0.0053} \tag{10}$$

The steady-state response of the transfer function model for the proposed CSTH process is obtained using MATLAB Simulink and is presented in Figure 2(c).

Table 2 illustrates the steady-state values of the proposed CSTH process in real time, including those for both the first-principle and transfer function models.

By comparing the responses and steady-state values of the first principle model and the transfer function model, it is determined that the transfer function model better matches the real-time steady-state values. Therefore, the transfer function model is utilized for the controller design of the proposed CSTH process.

IMPLEMENTATION OF CONTROLLERS

PID Controller

The PID controller, a traditional feedback control method, adjusts the manipulated variable (such as heater input) by responding to the difference between the desired setpoint and the actual temperature. Its simplicity and reliability make it a widely used approach.

The parameters of the PID controller are calculated using the Z-N method for the control action [18]. The PID control parameters are configured as follows: Tank 1's controller is set to P = 1.540, I = 0.019, and D = 3.68, while Tank 2's controller is set to P = 0.337, I = 0.004, and D = 0.592.

Model Predictive Controller

Model predictive control (MPC) is an advanced control technique that utilizes a model to forecast the future behavior of a dynamic system and optimize control inputs based on these predictions.

The prediction horizon (P) determines how many future time steps the MPC considers when predicting system behavior. This enables the controller to anticipate disturbances or reference changes. The optimal choice of P depends on the system's dynamics; for slower systems, a longer prediction horizon is typically more useful, as it provides a broader view of future behavior. However, extending the horizon too much can increase computational demands and potentially delay the system's response.

The control horizon (*M*) refers to the number of future control actions the MPC optimizes. A smaller *M* reduces computational complexity but limits the controller's ability to adjust future actions. On the other hand, a larger *M* offers greater flexibility but requires more computational power. For example, with a prediction horizon of 10, the controller predicts the system's behavior for the next 10 intervals, while a control horizon of 2 optimizes the control actions for the next two intervals, with subsequent inputs remaining constant. Thus, the optimized values for the controller are the prediction horizon of 10 and the control horizon of 2.

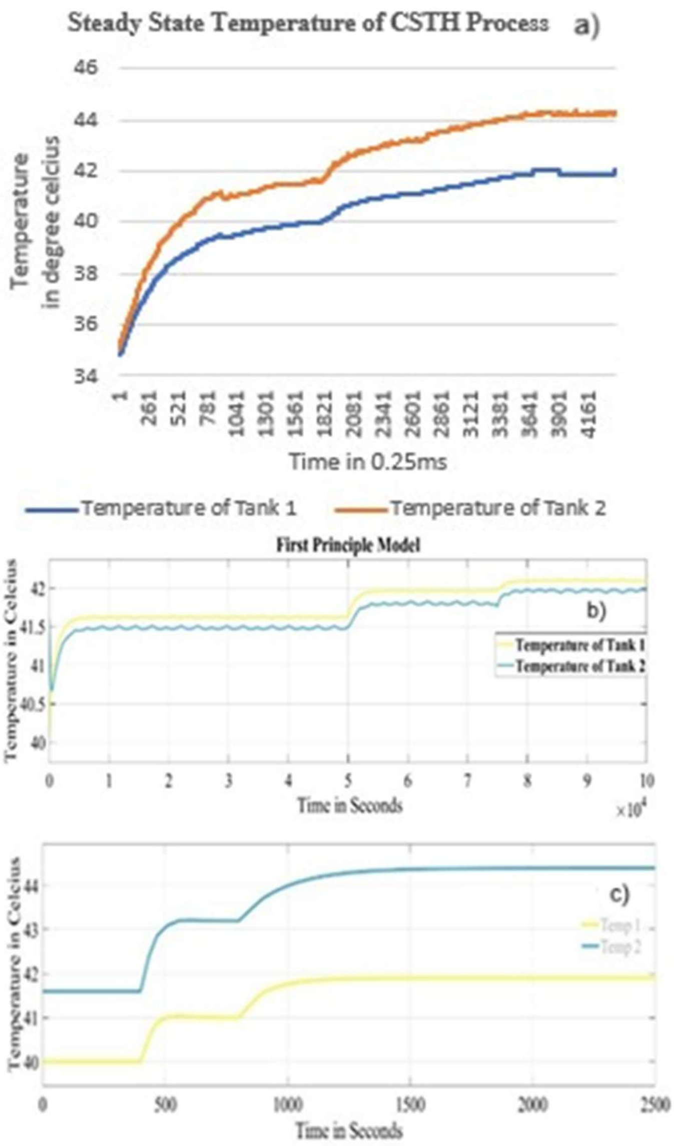


Figure 2. Steady state responses of different models: (a) response of real-time CSTH process, (b) response of first principle model, and (c) response of transfer function model.

RTD-A Controller

The RTD-A controller is an innovative solution designed to tackle the challenges of controlling nonlinear systems. A standout feature is its ability to independently adjust parameters for setpoint tracking, disturbance rejection, robustness, and aggressiveness. This flexibility simplifies control design and ensures optimal performance for each objective, without the need for the complex interdependent adjustments required by traditional controllers. By combining the simplicity of a PID controller with the advanced predictive capabilities of MPC, the RTD-A controller offers a powerful and user-friendly approach for controlling nonlinear systems. This hybrid method capitalizes on the strengths of both PID and MPC, overcoming common tuning issues and providing superior system performance.

One of the major advantages of the RTD-A controller is its robustness in handling uncertainties. It remains reliable even when there are discrepancies between the system model and the actual plant, making it particularly suitable for dynamic environments where precise models are hard to obtain. Additionally, studies have demonstrated that the RTD-A controller outperforms alternatives like PI-IMC and MPC in areas such as disturbance rejection and setpoint tracking, confirming its effectiveness in managing nonlinear system behavior.

The block diagram of the RTD-A controller is shown below in Figure 3, which illustrates the structure of a robust predictive control system designed to track a desired setpoint, handle disturbances, and ensure overall system robustness. The process begins with the reference trajectory, which generates a target path ($y_t(k)$) based on the setpoint (s_p). The control input calculation block determines the control signal $u(k)$ by minimizing the error between the reference trajectory and the predicted output ($\hat{y}(k)$), taking into account parameters like setpoint tracking (σ_T) and control aggressiveness (σ_A).

The plant represents the actual physical system, which generates the output $y(k)$ in response to the control signal. A model of the plant predicts the system's output, and this prediction is compared to the actual output to calculate the error $e(k)$. The current disturbance estimation block processes this error to identify any disturbances affecting the system, while the future disturbance prediction block forecasts their impact.

By integrating all these components, the controller adapts dynamically to disturbances, ensuring robust and accurate tracking of the desired trajectory. The control action $u(k)$ is designed to minimize the difference between the predicted output of the model and the reference trajectory over the prediction horizon *P*.

$$u(k) = \left(\frac{1}{b}\right)\left(\frac{\sum_{i=1}^{P} \eta_i \psi_i(k)}{\sum_{i=1}^{P} \eta_i^2}\right) \quad (11)$$

$$\psi_i = y_t(k+i) - a^i \hat{y}(k) - \hat{e}_d(k+i) \quad (12)$$

where *P* is the prediction horizon determined by control aggressiveness σ_A, η_i is the process parameter, $\Psi_i(k)$ is the stipulated error, $y_t(k+i)$ is the desired output trajectory and $\hat{y}(k)$ is the predicted output.

The aggressiveness parameter σ_A depends on the prediction horizon *P* and is given by:

$$P = 1 - \left(\frac{\tau}{t_s}\right) ln(1 - \sigma_A) \quad (13)$$

In this robust predictive control system, several key components are crucial in determining the control action:

Table 2. Steady state values of the proposed CSTH process.

	Inputs		Outputs					
	Heater-1 (J/s)	Heater-2 (J/s)	Tank 1 temperature (°C)			Tank 2 temperature (°C)		
			RT	FPM	TFM	RT	FPM	TFM
Initial Steady State	375	375	40	41.5	40	41.6	41.6	41.6
First Steady State	450	375	41.1	41.8	41.1	43.2	41.9	43.2
Second Steady State	450	450	42	41.9	41.9	44.3	42.1	44.4

RT - Real time; FPM - First principle model; TFM - Transfer function model

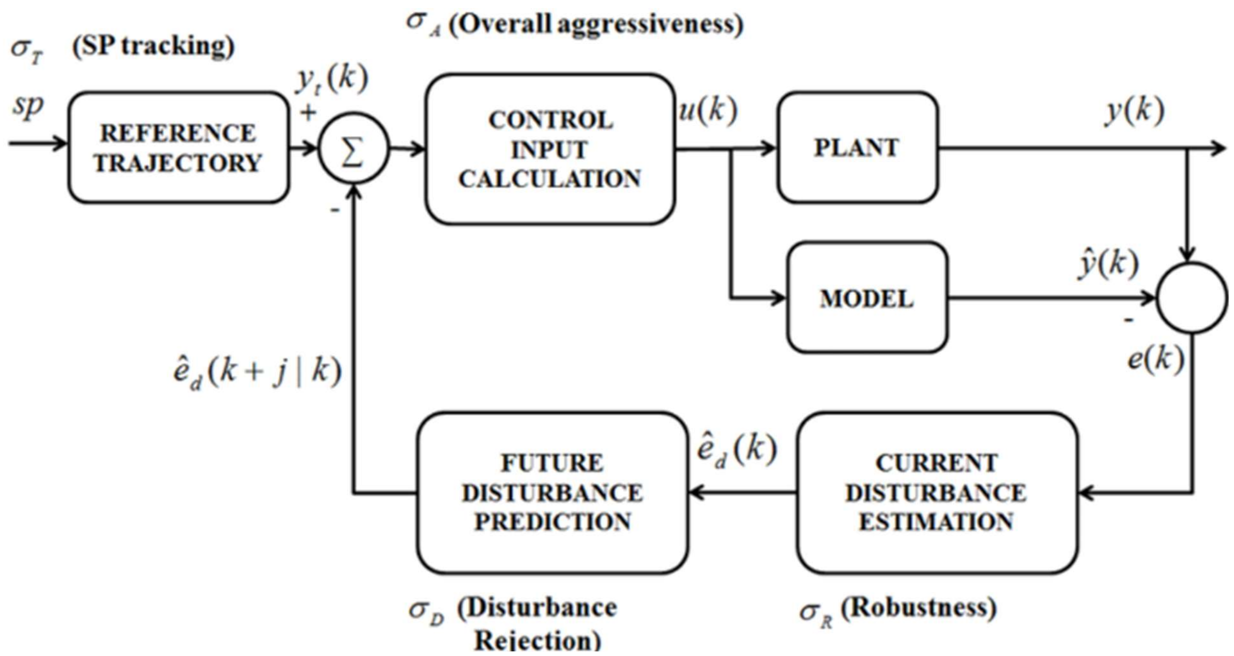


Figure 3. Block diagram of RTD-A controller.

In this robust predictive control system, several key components are crucial in determining the control action:

Projected effect of past control actions: This component evaluates the influence of previously applied control signals on the system's current and future behavior. It ensures that the control action accounts for the system's dynamics and the delayed effects of earlier inputs.

Reference trajectory *(σ_T):* The reference trajectory defines the desired output path the system should follow over time. By comparing the predicted output to this trajectory, the controller calculates the error and adjusts the control action to maintain setpoint tracking.

Projected effect of unmeasured disturbances: This component estimates disturbances that cannot be directly measured by using the error signal *e(k)* and predictive techniques. By forecasting their future impact, the controller can proactively address these disturbances and minimize their effect on system performance.

Together, these components ensure precise setpoint tracking, effective disturbance rejection, and robust control.

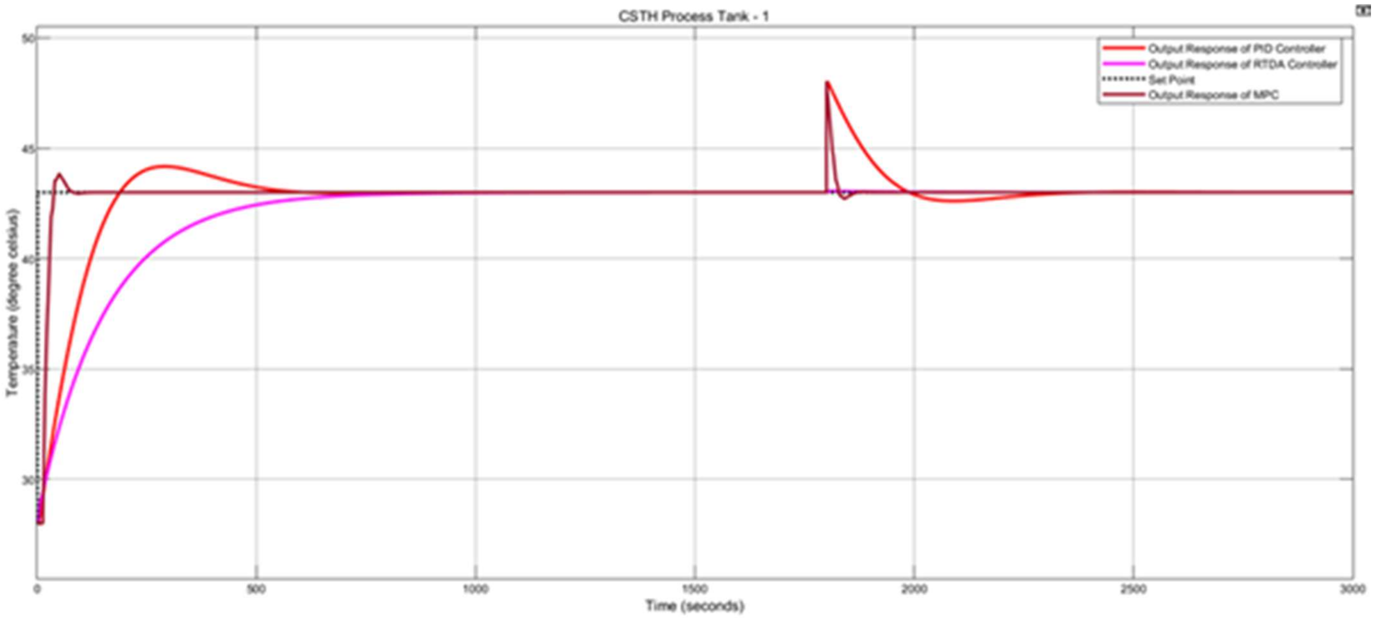
The tuning parameters for each performance aspect of the controller are as follows:

- *Robustness:* $0 < \sigma_R < 1$, depends on the current disturbance effect $\hat{e}_d(k)$
- *Setpoint tracking:* $0 < \sigma_T < 1$, depends on the desired output trajectory $y_t(k+i)$
- *Disturbance rejection:* $0 < \sigma_D < 1$, depends on the predicted future disturbance effect $\hat{e}_d(k+i)$
- *Overall aggressiveness:* $0 < \sigma_A < 1$, depends on the prediction horizon *P*. The tuned values are presented in Table 3.

RESULTS AND DISCUSSION

Simulation Results

The servo and regulatory performance of the proposed controller is validated on the CSTH process. The Tank 1 and Tank 2 temperature set points are perturbed by ±20 % for validating the servo performance. For validating the regulatory response, a perturbation of about +5 °C change in temperature is given (by changing the recirculation water flow rate) at the 1800th time instant.



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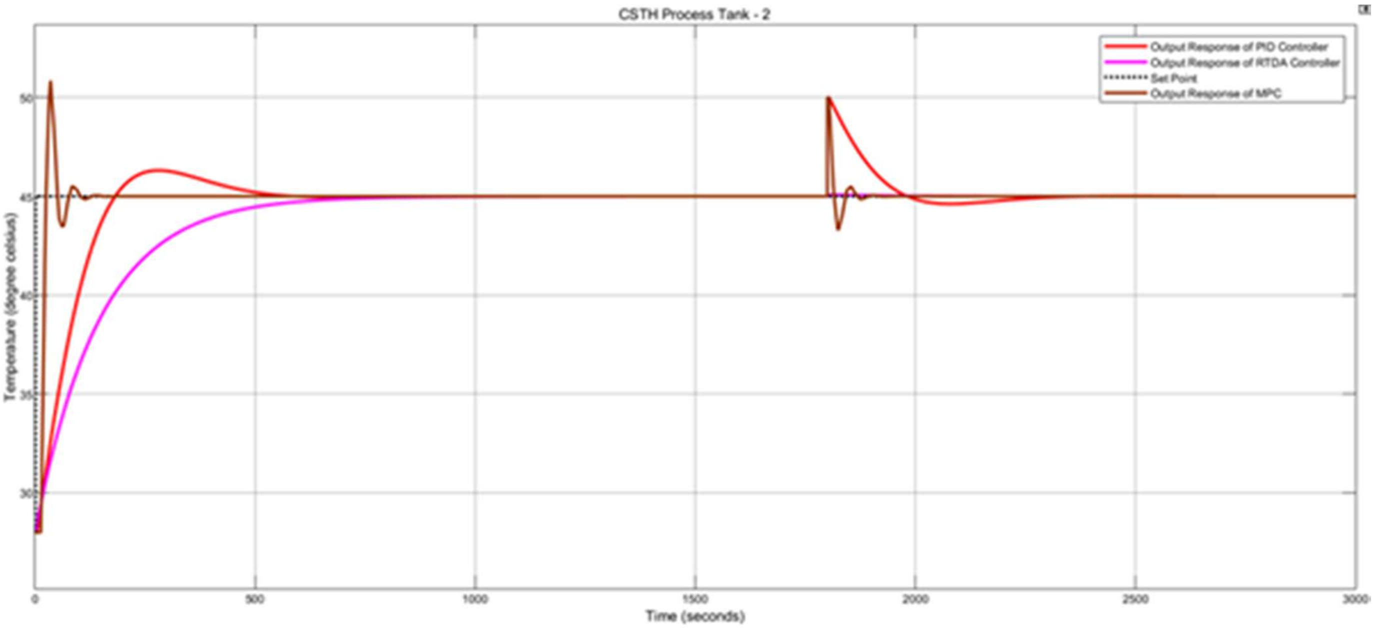


b)

Figure 4. Analysis of the temperature responses of Tank 1 and Tank 2 with different controllers (temperature in °C vs time in seconds): (a) Comparative response of the Tank 1 temperature for different controllers and (b) comparative response of the Tank 2 temperature for different controllers.

Table 3. Parameter values for RTD-A controller.

Controller parameter	Gain value for Tank 1	Gain value for Tank 2
Robustness (σ_R)	0.3	0.3
Setpoint Tracking (σ_T)	0.2	0.2
Disturbance Rejection (σ_D)	0.1	0.1
Overall Aggressiveness (σ_A)	0.3	0.3

The servo and regulatory responses of PI, MPC, and RTD-A controllers for the temperature of Tank 1 and Tank 2 are depicted in Figure 4(a) and Figure 4(b), respectively.

The performance criteria for the obtained responses of the PI, MPC, and RTD-A controllers for both Tank 1 and Tank 2 temperatures are listed in Table 4.

Inference

1. PID controller: The PID controller consistently performs poorly for both Tank 1 and Tank 2, exhibiting high error values, slow response times, and long-term instability.
2. MPC controller: The MPC controller shows a significant improvement over the PID, with better error reduction, faster stabilization, and enhanced overall system stability.
3. RTD-A controller: The RTD-A controller outperforms both the MPC and PID controllers in terms of peak process

variable values. However, compared to the RTD-A, the MPC reaches the setpoint more quickly.

In conclusion, the PID controller consistently underperforms for both Tank 1 and Tank 2, showing high error values, slow response times, and long-term instability, making it unsuitable for this application. The MPC controller provides a significant improvement over the PID, with better error reduction, faster stabilization, and enhanced system stability. However, it still slightly falls short of the RTD-A controller in terms of long-term error minimization. The RTD-A controller outperforms both the MPC and PID controllers in peak process variable values, offering the best balance of error reduction, stability, and response time for regulating the temperatures of Tank 1 and Tank 2. While the MPC reaches the setpoint more quickly, the RTD-A excels in long-term performance, making it the most effective choice for this application.

Additionally, the RTD-A controller excels in disturbance rejection, outperforming both the PID and MPC controllers. Figure 5(a) and Figure 5(b) offer a detailed comparison of disturbance rejection for Tank 1 and Tank 2 temperatures across the different controllers. The RTD-A controller can reject disturbances more quickly and with less overshoot than the PID and MPC controllers.

The disturbance rejection characteristics of these controllers are summarized below:

RTD-A Controller

- Response characteristics: The RTDA controller quickly rejects disturbances, rapidly bringing the system to the desired setpoint with minimal overshoot and no noticeable oscillations.
- Settling time: The settling time is longer than that of the MPC controller, due to the predictive action for disturbance handling.
- Disturbance rejection performance: This controller excels in rejecting disturbances, providing a fast, stable, and precise response.

MPC Controller

- Response characteristics: The MPC controller initially shows considerable oscillations and overshoot before stabilizing near the setpoint.
- Settling time: It demonstrates the fastest settling time compared to other controllers.
- Disturbance rejection performance: While the MPC controller eventually rejects the disturbance, its performance is moderate, owing to the overshoot and oscillations observed during the transient phase.

PID Controller

- Response characteristics: The PID controller exhibits a slow and steady approach to the setpoint without oscillations. However, it takes considerably longer to stabilize.
- Settling time: It has the longest settling time, reflecting its sluggish response to disturbances.
- Disturbance rejection performance: The PID controller has the least effective disturbance rejection, due to its delayed response and extended settling time.

In terms of performance metrics such as ISE, IAE, ITSE, and ITAE, the MPC controller outperforms both the RTD-A and PID controllers. While the RTD-A controller excels in disturbance rejection, it falls short in these performance metrics because it doesn't exactly track the setpoint before the disturbance is introduced, due to the predictive action for disturbance handling. However, it converges closely to the setpoint, with deviations typically below 0.08, as illustrated in Figure 6. The RTD-A's response includes the entire time response when calculating integral errors, which contributes to its lower performance compared to the MPC. However, this drawback can be disregarded due to the RTD-A controller's exceptional overall performance, particularly in disturbance rejection.

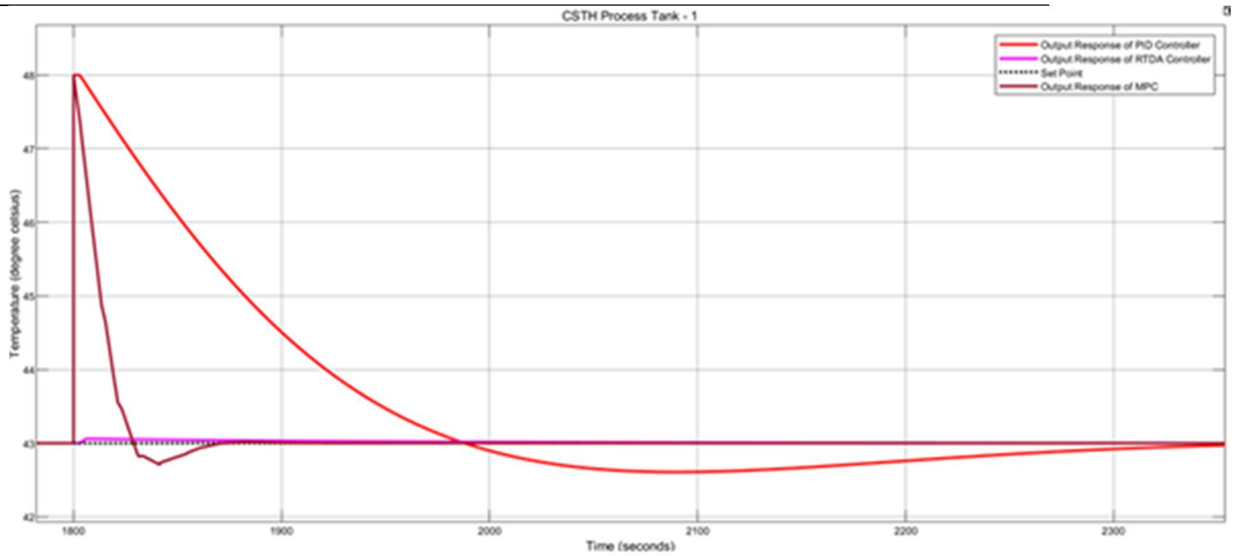
The RTD-A controller offers the best disturbance rejection, providing a fast and stable response with minimal overshoot. The step response characteristics for both servo and regulatory responses in Tank 1 and Tank 2 reveal that the RTD-A method delivers the most stable and controlled performance among the three control strategies. In the servo response, RTDA achieves zero overshoot (0% in both tanks), with peak values of 43 and 45, and settling times of 437 s (Tank 1) and 428 s (Tank 2), ensuring smooth and steady control despite having slower rise times (191 s and 195 s). In contrast, although MPC offers faster rise times (17.75 s and 21.30 s) and shorter settling times (33.18 s and 68.58 s), it shows higher overshoot (2.10% and 13.09%), which is not recommended for industrial applications. For regulatory response, RTDA again outperforms by maintaining minimal overshoot (0.05% and 0.06%) and significantly faster settling times (437 s and 428 s) compared to PID (1928 s and 1921 s) and MPC (1809 s and 1833 s), which exhibit large overshoot values (~11-13%) and long stabilization periods. Even though MPC and PID provide quicker initial actions, RTD-A is the most reliable and robust control strategy, particularly suited for applications demanding long-term stability, safety, and precision.

CONCLUSION

This paper presents the development of the first principle model for the CSTH process, derived from steady-state real-time data, and the transfer function model, which is obtained from real-time measurements. Both models are validated using data obtained from the real-time experimental setup. Conventional PID, MPC, and RTD-A controllers are designed for the 2x2 transfer function model, and their performance is systematically evaluated. For regulatory response, RTD-A outperforms by maintaining minimal overshoot (0.05% and 0.06%) and significantly faster settling times (437 s and 428 s) compared to PID (1928 s and 1921 s) and MPC (1809 s and 1832 s), which exhibit large overshoot values (~11-13%) and long stabilization periods. Even though MPC and PID provide quicker initial actions, RTD-A is the most reliable and robust control strategy, particularly suited for applications demanding long-term stability, safety, and precision. Based on the result analysis, the RTD-A controller is identified as the optimal choice for disturbance rejection in regulating the temperatures of Tank 1 and Tank 2 in the CSTH process, making it highly suitable for industrial process control applications.

Table 4. Performance metrics of Tank 1 and Tank 2.

Controller	Tank 1				Tank 2			
	ISE	IAE	ITSE	ITAE	ISE	IAE	ITSE	ITAE
PID	11880	1834	-536300	1028000	14470	1939	-520900	997900
MPC	4031	399.1	93050	123600	5384	516.4	-47410	159300
RTD-A	16700	2272	330800	367400	20960	2480	337500	384100



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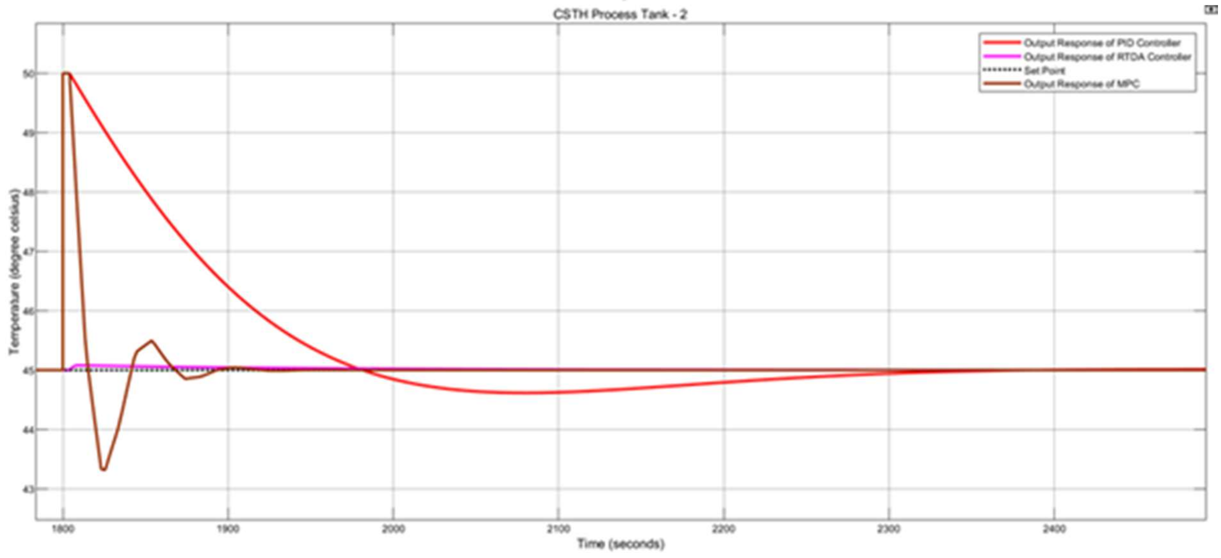

b)

Figure 5. Emphasizing the disturbance rejection efficacy in the temperature profiles of Tank 1 and Tank 2 across different controller configurations (temperature in °C vs time in seconds): (a) highlighting the disturbance rejection of Tank 1 temperature for different controllers, and (b) highlighting the disturbance rejection of Tank 2 temperature for different controllers.

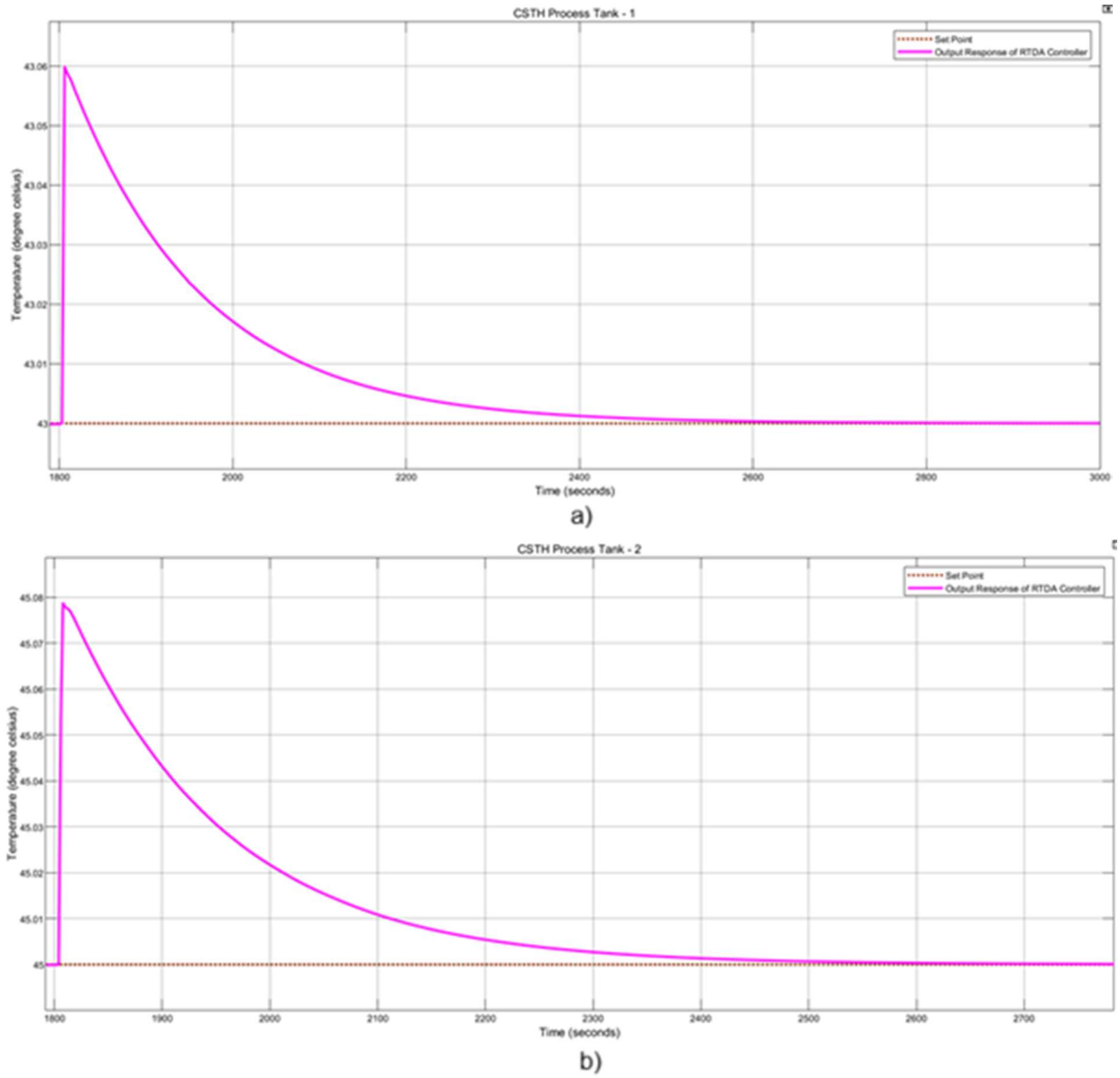

Figure 6. Emphasizing the disturbance rejection efficacy in the temperature profiles of Tank 1 and Tank 2 for RTD-A controller (Temperature *in °C* Vs Time *in seconds): (a) highlighting the disturbance rejection of the Tank 1 temperature for RTD-A controller, and (b) highlighting the disturbance rejection of the Tank 2 temperature for RTD-A controller.*

ABBREVIATIONS

CSTH - continuous stirred tank heater
CSTR - continuous stirred tank reactor
DAMPC - dual adaptive model predictive controller
DCS - distributed control systems
IAE - integral absolute error
ISE - integral square error
ITAE - integral time absolute error
ITSE - integral time square error
JITL-DD- just-in-time learning based data-driven
MIMO - multiple input multiple output
MPC - model predictive controller
PI - proportional integral
PID - proportional integral derivative
PI-IMC - proportional integral-internal model controller
RTD-A - robustness, setpoint tracking, disturbance rejection – aggressiveness
SOPDT - second-order plus dead time

NOMENCLATURE

V_1 - volume of tank 1 (m^3)
V_2 - volume of tank 2 (m^3)
A_1 - area of tank 1 (m^2)
A_2 - area of tank 2 (m^2)
r_1 - radius of tank 1 (m)
r_2 - radius of tank 2 (m)
T_1 - steady state temperature of tank 1 (°C)
T_2 - steady state temperature of tank 2 (°C)
h_1 - steady state level of tank 1 (m)
h_2 - steady state level of tank 2 (m)
T_i - inlet water temperature of tank 1 (°C)
T_a - atmospheric temperature (°C)
F_1 - input flow rate of tank 1 (m^3/s)
F_2 - input flow rate of tank 2 (m^3/s)
F_{out} - output flow rate of tank 2 (m^3/s)
F_R - recirculating flow rate from Tank 2 to Tank 1 (m^3/s)
Q_1 - heat input to tank 1 (J/s)

Q_2 - heat input to tank 2 (J/s)
C_p - specific heat capacity (JKg^{-1}K^{-1})
U - heat transfer coefficient (W/m^{2}K)
Q - electrical heat energy given to the tank (J/s)
m - mass of liquid in the tank (kg)
ΔT - change in temperature (°C)
T_{ss} - steady state temperature of liquid (°C)
A - area of the liquid in the tank (m^2)
r - radius of the tank (m)
h - steady state height of the tank (m)
P - proportional parameter of PID controller
I - integral parameter of PID controller
D - derivative parameter of PID controller
$y_t(k)$ - target path of RTD-A controller
s_p - setpoint of process where the RTD-A controller is implemented
u(k) - control signal of RTD-A controller
$\hat{y}(k)$ - predicted output of RTD-A controller
σ_T - setpoint tracking parameter of RTD-A controller
σ_A - control aggressiveness parameter of RTD-A controller
σ_T - disturbance rejection parameter of RTD-A controller
σ_R - robustness parameter of RTD-A controller
y(k) - generated output in response to the control signal of RTD-A controller
e(k) - error signal of predicted system's output and actual output of RTD-A controller
P - prediction horizon for both MPC and RTD-A controller
M - control horizon for MPC controller
η_i - process parameter
$\Psi_i(k)$ - stipulated error of RTD-A controller
$y_t(k+i)$ - desired output trajectory of RTD-A controller

REFERENCES

[1] N.F. Thornhill, S.C. Patwardhan, S.L. Shah, J. Process Control 18 (2008) 347-360. https://doi.org/10.1016/j.jprocont.2007.07.006

[2] J. Zheng, H. Wang, H. Zhou, T. Gao, IEEE Seventh Int. Conf. Intell. Control Inf. Process Siem Reap, Cambodia (2016) p. 98-104. https://ieeexplore.ieee.org/document/7885883.

[3] A. Albagul, M. Saad, Y. Abujeela, Int. J. Comput. Sci. Electron. Eng. 2 (2014) 130-134. https://www.researchgate.net/publication/324165363.

[4] A. Simorgh, A. Razminia, V. Shiryaev, Math. Comput. Simul. 173 (2020) 16-31. https://doi.org/10.1016/j.matcom.2020.01.010.

[5] V. Kabila, G. Devadhas, Indian J. Sci. Technol. 8 (2015) 1-7. https://indjst.org/articles/comparative-analysis-of-pid-and-fuzzy-pid-controller-performance-for-continuous-stirred-tank-heater https://doi.org/10.17485/ijst/2015/v8i23/85351.

[6] A.D. Priya, G. Tamilselvan, T. Rajesh, Int. J. Adv. Sci. Eng. Res. 10 (2018) 78-81. https://www.ciitresearch.org/dl/index.php/fs/article/view/FS032018006.

[7] Q.A. Mahmood, A.T. Nawaf, Mater. Today: Proc. 42 (2022) 2545-2552. https://doi.org/10.1016/j.matpr.2020.12.577.

[8] Y. Zhang, Y. Yang, S.X. Ding, L. Li, IEEE Trans. Ind. Electron. Control Instrum. 61-11 (2014) 6409-6417. https://ieeexplore.ieee.org/document/6718131.

[9] K. Kumar, T.A.N. Heirung, S.C. Patwardhan, B. Foss, IFAC-Papers Online 48 (2015) 545-550. https://www.sciencedirect.com/science/article/pii/S2405896315011052.

[10] X. Li, X. Jiang, Int. Conf. Adv. Control, Autom. Artif. Intell., Shenzhen, China (2018), p. 163-167. https://www.atlantis-press.com/proceedingsacaai-18/25892485.

[11] B.A. Ogunnaike, K. Mukati, J. Process Control 16 (2006) 499-509. https://doi.org/10.1016/j.jprocont.2005.08.001.

[12] K. Mukati, M. Rasch, B.A. Ogunnaike, J. Process Control 19 (2009) 272-287. https://doi.org/10.1016/j.jprocont.2008.03.004.

[13] C. Febina, V.D. Angeline, Int. Conf. Adv. Electr., Comput., Commun. Sustainable Technol. Bhilai, India (2021) p. 1-8. https://ieeexplore.ieee.org/document/9392600.

[14] K. Anbarasan, K. Srinivasan, ISA Trans. 57 (2015) 231-244. https://doi.org/10.1016/j.isatra.2015.02.016.

[15] G. Stephanopoulos, Chemical Process Control, Prentice Hall, New Jersey (1984), p. 43. https://www.google.co.in/books/edition/Chemical_Process_Control/rhUTrgEACAAJ?hl=en ISBN: 9788177584035

[16] V. Balakotaiah, D. Luss, Chem. Eng. Sci. 38 (1983) 1709-1721. https://doi.org/10.1016/0009-2509(83)85028-3.

[17] B.W. Bequette, Process Control: Modeling, Design, and Simulation, Prentice Hall, New Jersey (2003), p. 196. https://books.google.co.in/books/about/Process_Control.html?id=PdjHYm5e9d4C ISBN: 0-13-206889-3

[18] A. O'Dwyer, in Handbook of PI and PID Controller Tuning Rules. Imperial College Press, London (2009), p. 350. https://www.google.co.in/books/edition/Handbook_Of_Pi_And_Pid_Controller_Tuning/hF-7CgAAQBAJ?hl=en&gbpv=1&dq=pid+controller+tuning&pg=PR7&printsec=frontcover

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NAUČNI RAD

PROJEKTOVANJE INDUSTRIJSKOG CENTRIČNOG KONTROLERA ZA PROCES SA KONTINUALNIM REAKTOROM SA MEŠANJEM SA VIŠE ULAZA I VIŠE IZLAZA SA POBOLJŠANIM ODBACIVANJEM POMREMEĆAJA

Ovaj rad se bavi projektovanjem napredne šeme upravljanja prilagođene velikim industrijskim procesima, gde kontroleri moraju da održavaju efikasne performanse uprkos značajnim poremećajima i promenama zadatih vrednosti. Primarni fokus predloženog RTD-A kontrolera je na robusnom odbacivanju poremećaja. RTD-A poseduje prednosti i konvencionalnih PID i MPC šema upravljanja. Kako se metode zasnovane na modelima suočavaju sa izazovima u rešavanju sve složenijih procesa, tehnike vođene podacima su stekle popularnost u praćenju industrijskih sistema zbog svoje sposobnosti da obrađuju nepoznate fizičke modele. U ovom radu, i modeli prvog principa i modeli prenosne funkcije sistema sa kontinualnim reaktorom sa mešanjem su razvijeni korišćenjem podataka u realnom vremenu i predstavljeni kao sistem sa više ulaza i više izlaza. PID, MPC i RTD-A kontroleri se zatim primenjuju za regulisanje temperatura dva rezervoara. Performanse ovih kontrolera su pažljivo ispitane korišćenjem integralnih kriterijuma performansi i analize vremenskog domena kako bi se precizno procenilo njihovo dinamičko ponašanje i preciznost upravljanja. Rezultati pokazuju da RTD-A kontroler pokazuje superiorne performanse u ublažavanju poremećaja. RTD-A strategija upravljanja pokazuje izvanredne performanse sa skoro nultim prekoračenjem (0% u servo i oko 0,05% u regulatornim odzivima) i stabilnim vremenima smirivanja blizu 430-440 sekundi u oba rezervoara. Iako MPC i PID kontroleri nude brže odzive, njihovo veće prekoračenje i duže vreme smirivanja čine RTD-A preferiranom metodom za postizanje pouzdane, precizne i bezbedne kontrole u industrijskim procesima.

Ključne reči: Kontinualni reaktor sa mešanjem, više ulaza i više izlaza, PID, MPC, RTD-A, odbacivanje poremećaja.