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Research Paper

Overcoming Dead Time in Thermal Processes: A Comparative Evaluation of PID-SP and PID-IMC Control Strategies

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Abstract

Dead time is a critical factor that often causes instability in process systems, so appropriate control strategies are needed to address it. This study focuses on the outlet temperature control of a stirred-tank heater that exhibits dead time. A 10 L laboratory-scale tank equipped with an electric heater was constructed, and the long outlet pipeline introduces a measurable delay in the temperature response. The outlet temperature is maintained by adjusting the electrical heating input, while PID parameters are tuned using the Process Reaction Curve (PRC) method. Two control strategies are examined: PID with Smith Predictor (PID-SP) and PID with Internal Model Control (PID-IMC). System models were implemented and tested using XCOS/Scilab. Closed-loop simulation results indicate that PID-IMC performs better than PID-SP, as indicated by a lower integral absolute error (IAE). These results provide evidence of the practical advantages of PID-IMC in compensating for dead time in thermal process systems and offer useful guidance for improving process control design in industrial applications.

Keywords: *Dead Time, IMC, PID, Smith-Predictor, Thermal System.*

INTRODUCTION

From a process control perspective, pure delay, or dead time, is a major source of instability. As Stephanopoulos (1984) noted, larger dead times make processes increasingly difficult to control and often lead to unstable responses. Dead time is the delay between an input change and its effect, often occurring in multi-capacity chemical processes. The presence of long connecting pipes introduces significant dead time, causing a delayed response of the output to input changes (Marlin, 1995). Therefore, investigating the dynamics and control of the process system with dead time is essential for improving process stability and performance.

Luyben (2002) emphasized that proper tuning of proportional–integral–derivative (PID) parameters is essential for process stability. Although PID tuning methods such as the process reaction curve (PRC) and open-loop on–off test have been successfully applied in laboratory-scale systems (Hermawan and Haryono, 2010; Alvaro et al., 2018; Hermawan and Puspitasari, 2018), their potential for addressing dead-time challenges in thermal processes remains underexplored. Prior studies confirmed that properly tuned PID controllers outperform P and PI controllers by producing stable, rapid, and robust responses (Hermawan and Haryono, 2010; Hermawan and Puspitasari, 2018). This study extends those findings by evaluating integrated PID-Smith predictor (PID-SP) and PID-Internal Model Control (PID-IMC) strategies, offering new insights into practical dead-time compensation for process industries.

Conventional methods such as the Smith Predictor and its variants have been applied to mitigate dead time in process systems (Kravaris & Wright, 1989; Stojic et al., 2001; Panda et al.,

2006; Juneja et al., 2010). While effective, they often struggle with robustness and practical implementation. This study addresses that gap by evaluating integrated PID-IMC and PID-SP strategies as practical and reliable alternatives for dead-time compensation in thermal processes.
This study focuses on controlling a 10 L stirred tank heater with dead time through a combination of laboratory experiments and dynamic simulations. PID parameters were tuned using the simple yet effective Process Reaction Curve (PRC) method, while advanced strategies such as PID-SP and PID-IMC were implemented to compensate for dead time. The process model was rigorously analyzed in XCOS to assess closed-loop performance. By integrating experimental validation with model-based simulation, this work highlights practical approaches to dead-time compensation in thermal processes and demonstrates the superior effectiveness of PID-IMC over conventional methods.

LITERATURE REVIEW

Dead time (also referred to as time delay) is a fundamental challenge in process control because it causes the system output to lag behind the input by a fixed duration. This delay arises naturally in many thermal and chemical processes due to transport lags, sensor delays, and actuator dynamics (Stephanopoulos, 1984; Smith & Corripio, 1997; Seborg et al., 2017). In the frequency domain, dead time introces an exponential factor $e^{-t_D s}$ that contributes significant phase lag, reducing stability margins and complicating the design of conventional feedback controllers such as PID. Without appropriate compensation, systems with dead time often exhibit sluggish responses, oscillations, or even instability when controlled using standard methods (Kravaris & Wright, 1989; Stojic et al., 2001; Panda et al., 2006; Karan & Dey, 2023; Hermawan et al., 2024).

The Smith Predictor (SP), first proposed by Smith (1957), remains one of the most established methods for dead-time compensation. By using a process model, the SP predicts the process output as if no delay were present, thereby restoring effective feedback action. Although highly effective when the model is accurate, the SP is sensitive to mismatches in process dynamics or delay estimation. To overcome this limitation, extensions like the Analytical Predictor, Inferential Control, and Internal Model Control (IMC) were developed, sharing a common mathematical basis but offering alternative design perspectives (Kravaris & Wright, 1989).

In recent years, several modern methods to handle dead time have been developed, especially combining modified SP (MSP) structures with IMC-based tuning. For example, an MSP with IMC tuning was proposed for second-order, delay-dominated processes and processes with right-half plane (RHP) dynamics, showing improved setpoint tracking and disturbance rejection with smooth responses and minimal overshoot (Karan & Dey, 2023). In another work, a simple modified Smith predictor was used for integrating time-delayed processes (IPTD), using a sole closed-loop time constant from IMC design to reduce tuning complexity, achieving zero overshoot on setpoint change and fast disturbance recovery (Divakar et al, 2024). Also, work on fractional-order IMC and Smith Predictor combinations has shown good robustness and performance under parameter variations, especially for integrating and unstable processes with long dead time (Korupu & Muthukumarasamy, 2021).

Modern dead-time compensation methods use a structured design. The process model is divided into a delay-free part, such as FOPDT (Juneja et al., 2010), IPTD (Divakar et al, 2024), or a second-order system with dominant delay (Karan & Dey, 2023; Hermawan et al, 2024). An inner loop, or predictor, typically a Smith predictor or its modified form, compensates for the delay. An outer IMC-based controller or filter then balances performance and robustness through a single tuning parameter, usually the closed-loop time constant. Recent studies enhance these frameworks using fractional-order filters, lead-lag or PD/PI elements, and additional features to improve robustness against model mismatch and disturbances. Collectively, MSP–IMC designs achieve faster stabilization, minimal overshoot, smoother control effort, strong disturbance rejection, and improved robustness against uncertainty.

Despite extensive studies on dead-time compensation, most prior works remain limited to theoretical models or simulations, with few validated experimentally on real thermal systems. Most SP and IMC designs are evaluated under idealized conditions, neglecting the nonlinearities and disturbances present in real processes. Comparative studies of PID-SP and PID-IMC in small-scale thermal systems remain limited, creating a gap between theoretical development and practical performance.

To address this, the present study investigates the control of a 10 L stirred tank heater with dead time through combined laboratory experiments and dynamic simulations. PID parameters were tuned using the Process Reaction Curve (PRC) method, while PID-SP and PID-IMC strategies were implemented for dead-time compensation. The system model was analyzed in XCOS to assess closed-loop performance and robustness. The integral absolute error (IAE) criterion was applied to evaluate controller performance. Lower IAE values indicated superior stability, faster settling, and smoother control effort, confirming the method's practicality and robustness for thermal processes with significant dead time.

RESEARCH METHOD

Figure 1 depicts the experimental setup of the single-tank heating system. Water enters Tank 1 (No. 1) at a flow rate $f(t)$ [L/min] and temperature $T_1(t)$ [^oC], where it is heated by an electric heater (No. 4) with power regulated by a watt controller (No. 5) and homogenized by a mechanical stirrer (No. 6a) to ensure uniform temperature distribution. The tank is designed with an overflow system to maintain a constant liquid volume. Water temperatures in Tank 1 and Tank 2 are measured by thermocouples (Nos. 6a and 6b), respectively, where the response in Tank 2 indicates a transportation delay. Temperature readings are displayed on an LCD (No. 7) and recorded on a laptop (No. 8). A flowmeter (No. 9), solenoid valve (No. 10), and LCD (No. 11) measure and display the inlet water flow rate.

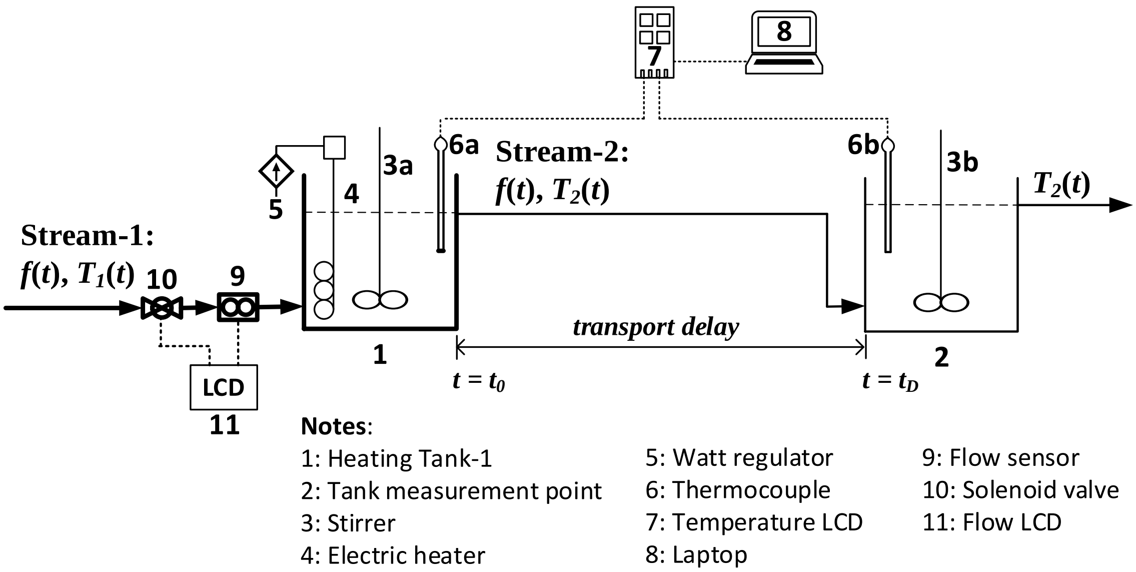


Figure 1. Experimental apparatus setup.

The Open Loop Model

The state equation with dead time in deviation form is expressed as follows:

$$\tau_1 \frac{d\Gamma_2(t-t_D)}{dt} + \Gamma_2(t-t_D) = K_1 \mathrm{F}(t-t_D) + K_2 \Gamma_1(t-t_D) + K_3 \mathrm{Q}_{e1}(t-t_D) \tag{1}$$

where: process gains: $K_1 \left[\frac{(\,^{\mathrm{o}}\mathrm{C})(\mathrm{minute})}{\mathrm{L}}\right]$, $K_2\ (dimensionless)$, $K_3 \left[\frac{(\mathrm{minute})(\,^{\mathrm{o}}\mathrm{C})}{(\mathrm{kJ})}\right]$ and process time constant: τ_1 [minute] are defined as follows:

$$K_1 = \frac{\bar{T}_1 - \bar{T}_2}{\bar{f}} \tag{2}$$

$$K_2 = \frac{\bar{f}}{\bar{f}} = 1 \tag{3}$$

$$K_3 = \frac{1}{\bar{f}\rho c_p} \tag{4}$$

$$\tau_1 = \frac{V_1}{\bar{f}} \tag{5}$$

The flow rate $\mathrm{F}(t)$, temperatures $\Gamma_1(t)$ and $\Gamma_2(t)$, and electric heating energy $\mathrm{Q}_{e1}(t)$ in deviation term are expressed as follows:

$$\mathrm{F}(t) = f(t) - \bar{f} \tag{6}$$

$$\Gamma_1(t) = T_1(t) - \bar{T}_1 \tag{7}$$

$$\Gamma_2(t) = T_2(t) - \bar{T}_2 \tag{8}$$

$$\mathrm{Q}_{e1}(t) = q_{e1}(t) - \bar{q}_{e1} \tag{9}$$

where $\bar{f}$ is the initial water flow rate, $\bar{T}_1$ and $\bar{T}_2$ are the initial temperatures of stream-1 and stream-2, and $\bar{q}_{e1}$ is the initial electric heating energy of Tank-1. The Laplace transform of Equation (1) is

$$\Gamma_2(s) = \frac{K_1 e^{-t_D s}}{\tau_1 s+1} \mathrm{F}(s) + \frac{K_2 e^{-t_D s}}{\tau_1 s+1} \Gamma_1(s) + \frac{K_3 e^{-t_D s}}{\tau_1 s+1} \mathrm{Q}_{e1}(s) \tag{10}$$

Confidence Level

The confidence level (CL) indicates the degree of correlation between the open-loop model and the laboratory observation data, ranging from 0 to 100%. A higher CL value reflects greater confidence in the model. A high CL demonstrates the reliability of the open-loop model and its suitability for control system design applications (Hermawan et al., 2024). The CL for the open-loop model is given as follows:

$$\mathrm{CL} = 1 - \mathrm{abs}\left(T_2^{\mathrm{lab}} - T_2^{\mathrm{model}}\right) \tag{11}$$

Process Reaction Curve

PID parameters can be tuned in the laboratory using an open-loop test by manually applying a step change to the manipulated variable (MV). This method is simple and can be implemented with basic equipment (Hermawan et al., 2024). The open-loop response typically exhibits a sigmoidal characteristic, known as the process reaction curve (PRC). PRC can be approximated by a first-order-plus-dead-time (FOPDT) model (Smith & Corripio, 1997; Camacho & Smith, 2000; Hermawan & Haryono, 2010; Espin et al., 2024; Hermawan et al., 2024) as follows:

$$G_{PRC}(s) = \frac{\Gamma_2(s)}{Q_{e1}(s)} = \frac{K_{\mathrm{PRC}} e^{-t_D s}}{t_p s+1} \tag{12}$$

Gain K_{PRC}, time constant t_p, and *time delay* t_D can be determined as follows:

$$K_{\mathrm{PRC}} = \frac{\Delta \mathrm{CV}}{\Delta \mathrm{MV}} = \frac{\Delta T_2}{\Delta q_{e1}} \tag{13}$$

$$t_p = \frac{3}{2}(t_2 - t_1) \tag{14}$$

In this work, times t_1 and t_2 are determined based on the CV response result. The PRC parameters (K_{PRC}, t_p, t_D) are used to calculate the PID values (K_c, τ_I, τ_D) through tuning methods such as Ziegler–Nichols, as shown in Table 1 (Smith dan Corripio,1997).

Feedback Controller

The transfer function of the conventional PID feedback controller is given as follows:

$$G_c(s) = \frac{Q_{e1}(s)}{E(s)} = K_c + \frac{K_c}{\tau_I s} + K_c \tau_D s \tag{15}$$

Error (E) can calculated as follows:

$$E(s) = \Gamma_2^{\mathrm{SP}}(s) - \Gamma_2(s) \tag{16}$$

Smith Predictor (SP)

To eliminate the effect of dead time, the open-loo, edback signal is adjusted to carry current information rather than delayed information (Hermawan et al., 2024). The current output/information is denoted as $\Gamma_2^*(s)$ and expressed as follows:

$$\Gamma_2^*(s) = G_C(s) G_p(s) \Gamma_2^{SP}(s) \tag{17}$$

Table 1. Ziegler-Nichols model.

Controller	K_c	τ_I	τ_D
P	$\frac{1}{K_{\mathrm{PRC}}}\frac{t_p}{t_D}$		
PI	$\frac{0.9}{K_{\mathrm{PRC}}}\frac{t_p}{t_D}$	$3.3t_D$	
PID	$\frac{1.2}{K_{\mathrm{PRC}}}\frac{t_p}{t_D}$	$2.0t_D$	$0.5t_D$

Equation (17) is obtained by adding the following term:

$$\Gamma_2'(s) = (1 - e^{-t_d s})G_c(s)G_p(s)\Gamma_2^{SP}(s) \tag{18}$$

Therefore:

$$\Gamma_2'(s) + \Gamma_s(s) = \Gamma_2^*(s) \tag{19}$$

A dead-time compensator (Smith predictor) estimates the delay effect of the manipulated variable on the process output using a prediction model. This method is effective only if the process transfer function and dead time are accurately known (Stephanopoulos, 1984).

Internal Model Control (IMC)

IMC has become a widely adopted method for improving control performance in process systems with dead time, particularly in the chemical industry. IMC employs model inversion with low-pass filtering to deliver systematic control design that ensures rapid and robust response in first-order plus dead time systems (Morari & Zafiriou, 1989). IMC modeling follows Seborg et al. (2017). For simplicity, the transfer functions of the measurement device and control valve are assumed as $G_M(s) = G_V(s) = 1$. The process model is represented as $G(s) = G_p(s)e^{-t_D s}$. The approximated model $\tilde{G}(s)$ is a FOPDT transfer function as follows:

$$\tilde{G}(s) = \frac{Ke^{-t_D s}}{\tau s+1} \tag{20}$$

In general, $\tilde{\Gamma}_2 \neq \Gamma_2$ because$\tilde{G}(s) \neq G(s)$. The IMC block diagram will be equivalent to the conventional FBC block diagram if the controllers $G_c(s)$ abd $G_c^*(s)$ satisfy the following equation:

$$G_c = \frac{G_c^*}{1-G_c^*\tilde{G}} \tag{21}$$

The IMC transfer function $G_c^*(s)$ is written as follows:

$$G_c^*(s) = \frac{\left(1+\frac{t_D}{2}s\right)(\tau_1 s+1)}{K(\tau_c s+1)} \tag{22}$$

where τ_c is the desired closed-loop time constant. In this study, for robust control, τ_c is taken as three times t_D, i.e., $\tau_c = 3t_D$ (Seborg et al., 2017).

Controller Performance

An identical disturbance system was constructed to evaluate the effectiveness of all control strategies. Closed-loop error integrals after input disturbance adjustments were computed to assess performance. The integral absolute error (IAE) criterion was employed to compare controller performance quantitatively, defined as follows:

$$\mathrm{IAE} = \int_0^t |\varepsilon(t)|dt \tag{23}$$

where the error ε is defined in the time domain and expressed as follows:

$$\varepsilon(t) = T_2^{SP} - T_2(t) \tag{24}$$

FINDINGS AND DISCUSSION

The Open Loop Experiment Results

The open-loop experiment was conducted to obtain the steady-state operating conditions of the stirred tank heater, which serve as the baseline for subsequent control design and evaluation. As summarized in Table 2, the inlet flow rate was maintained at 6 L/min with an inlet water temperature of 26.5 °C, while the outlet temperature stabilized at 28.7 °C under an electric heating input of 54 kJ/min. These results confirm that the system responds with a measurable temperature rise of 2.2 °C across the tank under steady heating, indicating a balance between the heat supplied and the thermal load carried by the continuous inflow. With a tank volume of 7.9 L, water density of 0.997 kg/L, and specific heat capacity of 4.186 kJ/kg·°C, the thermal capacity of the system can be quantified, allowing for accurate modeling of energy accumulation and dissipation. Importantly, the open-loop response highlights the inherent delay between energy input and outlet temperature change, reflecting the system's dead time characteristics. This behavior justifies the need for advanced control strategies, such as PID-SP and PID-IMC, to overcome the limitations of conventional PID tuning in processes where dead time significantly impacts control performance.

As shown in Table 3, the steady-state parameters obtained from the laboratory data confirm the suitability of the FOPDT model for the stirred tank heater. The negative flow rate gain (K_1= –0.36 °C·min/L) highlights the dilution effect of increased inflow, while the heater gain (K_3 = 0.040 °C·min/kJ) quantifies the system's heating efficiency. The process time constant (τ_1 = 1.32 min) and dead time (t_D = 0.35 min) indicate a relatively rapid but delayed response, which is critical for control tuning. These findings highlight the necessity of accounting for dead time to ensure stable and effective control performance.

Table 2. Steady state variables

No	Steady state variable	Value
1	Tank-1 inlet flowrate, $f\left[\frac{\mathrm{L}}{\mathrm{minute}}\right]$	6
2	Tank-1 inlet temperature, T_1 [°C]	26.5
3	Tank-1 outlet temperature, T_2 [°C]	28.7
4	Tank-1 electric heating energy, $\left[\frac{\mathrm{kJ}}{\mathrm{minute}}\right]$	54
5	Tank-1 volume, V_1 [L]	7.9
6	Water density, $\rho\left[\frac{\mathrm{kg}}{\mathrm{L}}\right]$	0.997
7	Water heat capacity, $C_p\left[\frac{\mathrm{kJ}}{\mathrm{kg.\ ^oC}}\right]$	4.186

Table 3. Steady state parameter

No	Steady state parameter	Value
1	Tank-1 inlet flowrate gain, $K_1\left[\frac{(\ ^oC)(\mathrm{minute})}{\mathrm{L}}\right]$	-0.36
2	Tank-1 inlet temperature gain, K_2 [dimensionless]	1
3	Tank-1 electric heater gain, $K_3\left[\frac{(\mathrm{minute})(\ ^oC)}{(\mathrm{kJ})}\right]$	0.040
4	Tank-1 process time constant, τ_1 [minutes]	1.32
5	Dead time in the measurement point, t_D [minute]	0.35

Figure 2 shows the open-loop XCOS diagram of the stirred tank heater with dead time. At steady state, the simulated outlet temperature and gains matched the laboratory results in Tables 2–3, confirming the FOPDT model and the proper implementation of transport delay. The saved time series were then used to validate the model and to initialize closed-loop simulation for PID-SP and PID-IMC.

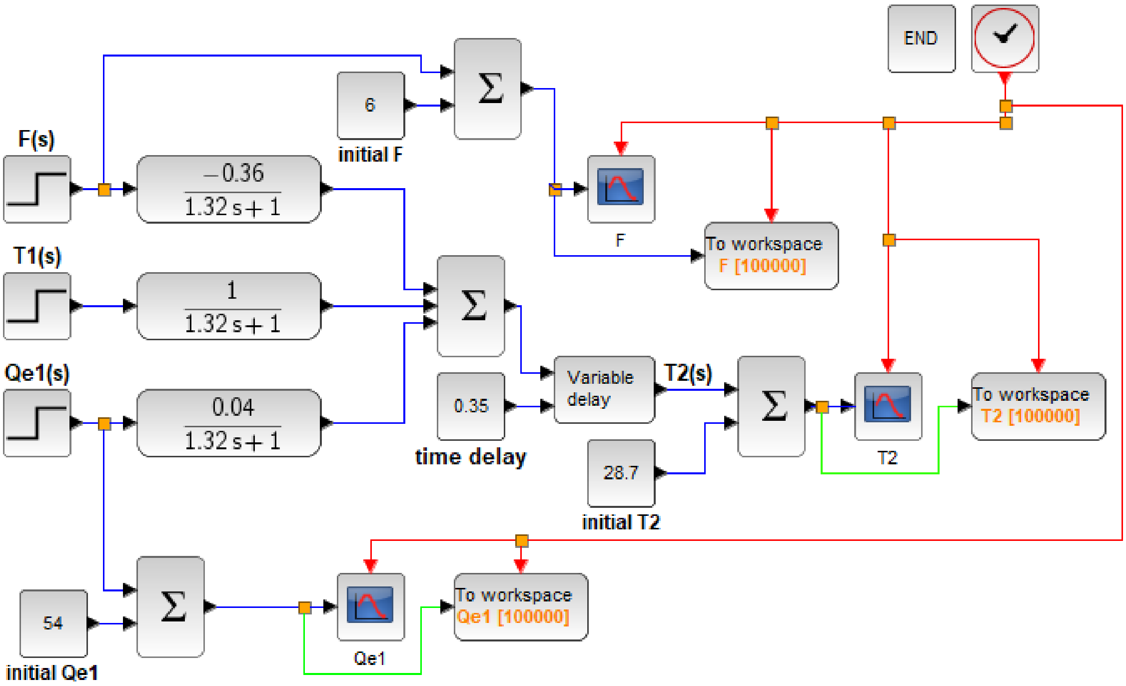


Figure 2. The open-loop XCOS diagram.

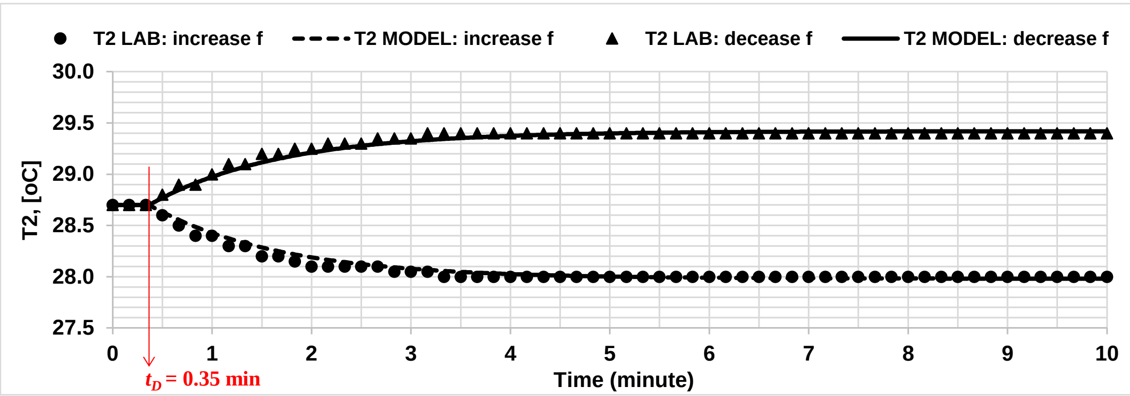


Figure 3. The open loop response to the flow disturbance changes.

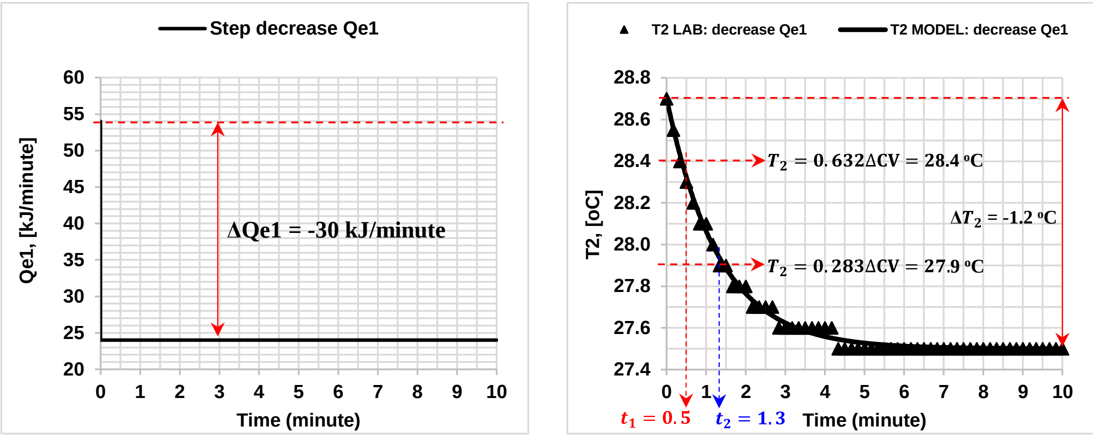
Table 4. Confidence Level (CL)

Disturbance	CL
F increase	97.52%
F decrease	97.56%

Figure 3 shows that the model response is in close agreement with the laboratory data for both increasing and decreasing flow disturbances. The outlet temperature decreases when the flow rate increases and rises when the flow rate decreases, with both responses reflecting the measured dead time of 0.35 min. Minor deviations observed during the transient phase are likely due to experimental disturbances, yet the model successfully captures the essential dynamic characteristics, including transient behavior, steady-state values, and overall trends. The confidence levels (CL) in Table 4 further reinforce this visual agreement, reaching 97.52% for flow increase and 97.56% for flow decrease. Such high CL values confirm that the developed FOPDT model provides a reliable representation of the real process under open-loop conditions and is sufficiently accurate to serve as a foundation for control system design and analysis.

Tuning Experiment Results

Figure 4 shows the process reaction curve obtained from a step decrease of 30 kJ/min in heater input. The outlet temperature dropped by approximately 1.2°C, with a measured dead time of 0.5 minutes and a time constant of 1.3 minutes. The close match between laboratory and model responses confirms the suitability of the FOPDT model for PID tuning. The PRC tuning results for PID-SP are listed in Table 5. Since the PRC tuning was unsuitable for PID-IMC, the controller was retuned using *trial and error* to achieve a faster and more stable response. Table 6 presents the returned results, which demonstrate the improved performance.



(a) MV: $q_{e1}(t)$ **(b) CV: $T_2(t)$**

Figure 4. Process Reaction Curve for tuning of PID parameters.

Table 5. PRC tuning results for PID-SP

Controller	$K_c\left[\frac{kJ}{^oC.minute}\right]$	τ_I [minute]	τ_D [minute]
P-SP	300		
PI-SP	270	0.33	
PID-SP	360	0.20	0.05

Table 6. Tuning parameters for PID-IMC

Controller	$K_c\left[\frac{kJ}{^oC.minute}\right]$	τ_I [minute]	τ_D [minute]
P-IMC	100		
PI-IMC	100	1.2	
PID-IMC	100	1.2	0.01

Closed Loop Simulation Results

The closed-loop XCOS diagrams for PID-SP and PID-IMC are shown in Figures 5 to 10. Figure 11 illustrates the applied flow disturbance used to evaluate the robustness of the control configurations. Initially, the inlet flow rate is maintained at 8 L/min until minute 6, after which it is suddenly decreased to 4 L/min and held constant for the remainder of the simulation. This step disturbance serves as a critical test condition for the stirred tank heater with dead time, as it represents a significant variation in the process input. This disturbance tests how well the proposed controllers (PID-SP and PID-IMC) reject input variations and maintain stability. The responses show how effectively each configuration handles sudden process changes while keeping the system stable.

Figure 12 presents the comparative closed-loop responses of PID-SP and PID-IMC. In the CV responses, both controllers are able to track setpoint changes and compensate for flow disturbances. PID-SP produces smoother dynamics with less oscillation, while PID-IMC responds faster but with higher oscillatory behavior. For the MV responses, PID-IMC shows more stable and moderate energy adjustments, whereas PID-SP exhibits sharper fluctuations after the disturbance. However, when considering the Integral Absolute Error (IAE) results in Table 7, PID-IMC achieves the lowest IAE value (208.24), indicating superior overall performance compared to PID-SP (271.41). This result confirms that, despite its slightly more oscillatory CV behavior, PID-IMC provides a faster response with better accuracy and disturbance rejection efficiency.

IMC is a model-based control strategy that uses an internal process model to predict plant dynamics and proactively correct control loop errors. By combining model inversion with a low-pass filter, IMC achieves a balance between rapid response and robustness, even under model mismatch. This systematic and straightforward design approach is particularly effective for first-order plus dead time (FOPDT) systems (Morari & Zafiriou, 1989). IMC provides an effective solution to mitigate stability loss and transient response degradation that often occur when dead time is significant, a condition frequently observed in real plants (Seborg et al., 2017). IMC enhances stability and output performance in dead-time processes, even under nonlinear and slow dynamics (Juneja et al., 2010; Seborg et al., 2017). It provides effective dead-time compensation and disturbance rejection beyond the capability of conventional PID control, making it practical for modern chemical process industries (Kravaris & Wright, 1989; Espin et al., 2024).

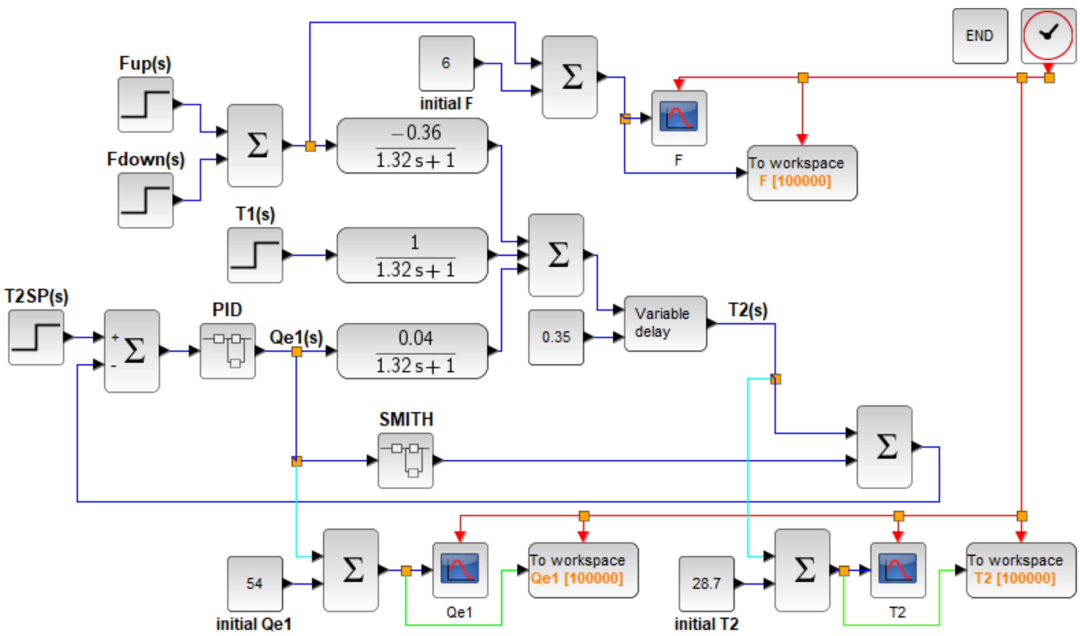


Figure 5. PID-SP XCOS diagram.

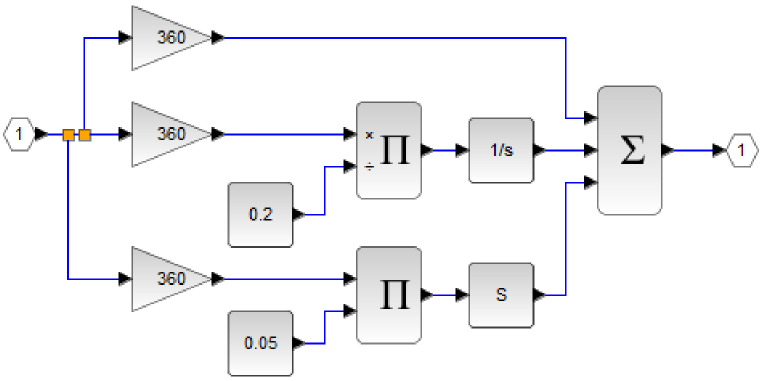


Figure 6. PID Sub-XCOS diagram in PID-SP.

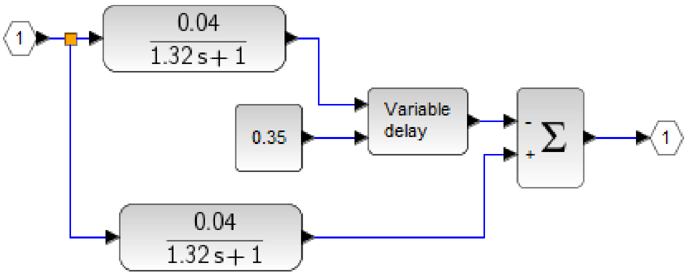


Figure 7. SP Sub-XCOS diagram in PID-SP.

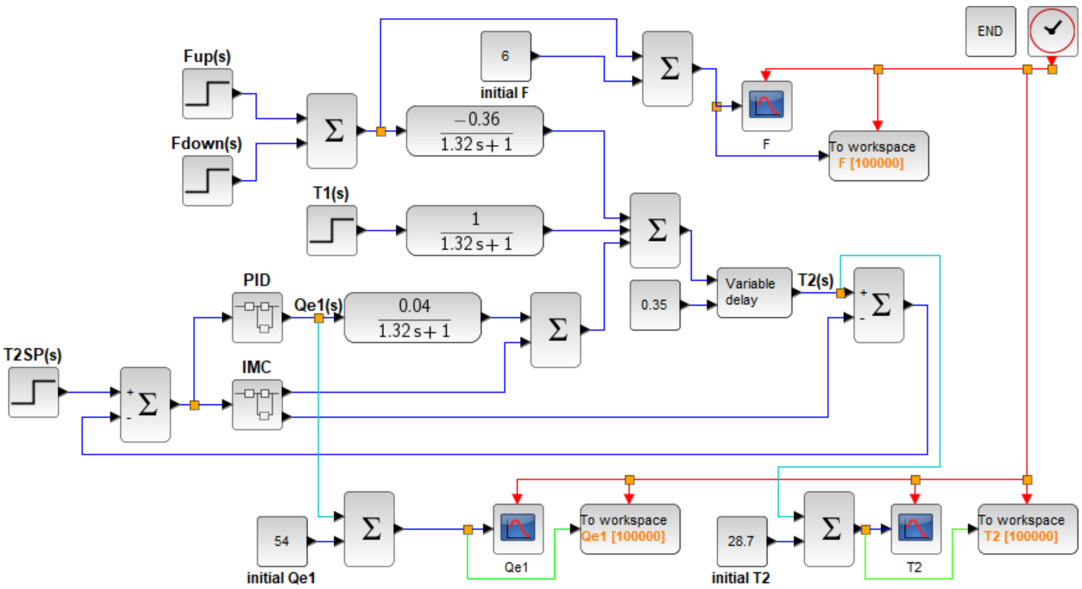


Figure 8. PID-IMC XCOS diagram.

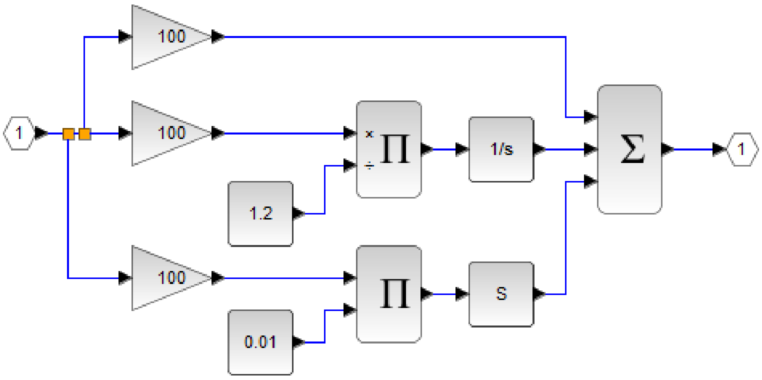
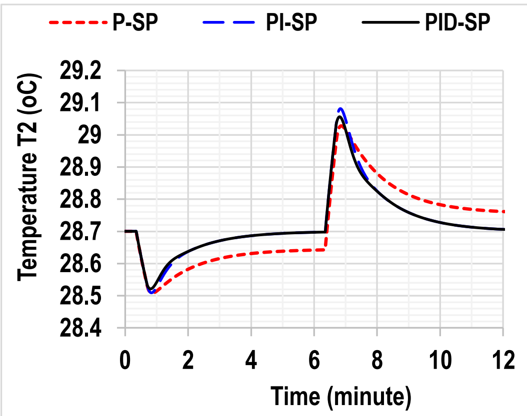


Figure 9. PID Sub-XCOS diagram in PID-IMC

CONCLUSIONS AND FURTHER RESEARCH

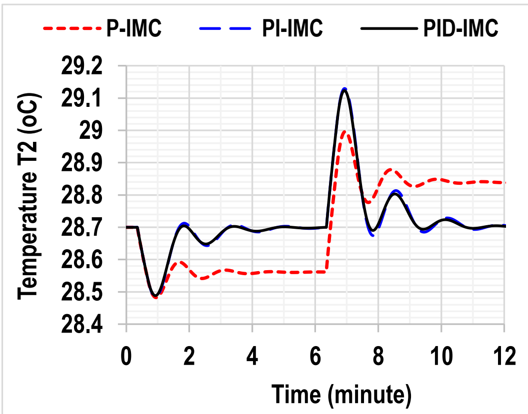
This study successfully investigated the process dynamics, temperature controller tuning, dynamic simulation, and control of a stirred tank heater with dead time using both laboratory-scale open-loop experiments and closed-loop dynamic simulations in XCOS. To address the dead time challenge, two integrated control strategies, PID-SP and PID-IMC, were implemented and evaluated. Both controllers effectively compensated for dead time and ensured stable closed-loop responses. The PID-IMC demonstrated superior performance, delivering faster stabilization with negligible chattering, as reflected by only minor high-frequency fluctuations in electrical energy. These findings highlight the robustness and practicality of PID-IMC for thermal processes with dead time and provide a valuable reference for the design of advanced process control configurations in industrial applications.

Integrated PID-SP

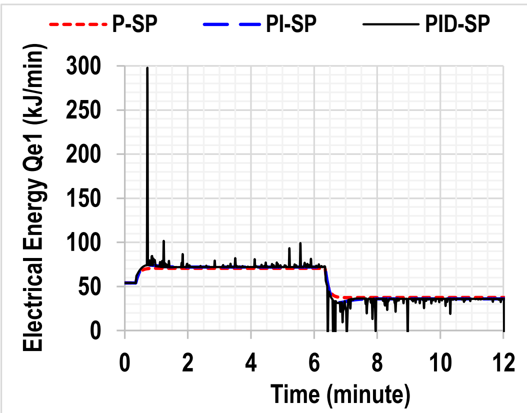


(a) CV response for PID-SP

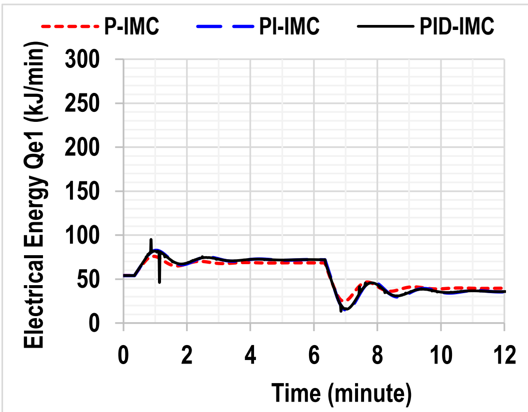
Integrated PID-IMC



(b) CV response for PID-IMC



(c) MV response for PID-SP



(d) MV response for PID-IMC

Figure 12. Comparative responses between PID-SP and PID-IMC

Table 7. IAE results

Controller	IAE	Controller	IAE
P-SP	1295.92	P-IMC	2654.92
PI-SP	282.64	PI-IMC	221.76
PID-SP	271.41	**PID-IMC**	**208.24**

LIMITATIONS AND FURTHER RESEARCH

Despite these promising results, the experiments were limited to a simplified single-input-single-output (SISO) thermal process under controlled laboratory conditions. Factors such as strong nonlinearities, model uncertainty, and measurement noise were not extensively investigated. Moreover, the controller evaluation focused mainly on setpoint tracking and disturbance rejection under nominal conditions, without considering actuator constraints or multivariable interactions. Further studies are needed to assess the robustness of the proposed PID-IMC configuration under multivariable and industrial conditions. Such validation would confirm its scalability and suitability for real process applications.

Building on these results, future research could focus on extending PID-IMC to nonlinear or multivariable thermal systems, where process interactions and varying operating conditions may pose greater challenges. Investigating adaptive or auto-tuning approaches would also enhance controller robustness against model mismatch and process disturbances. Furthermore, experimental validation in pilot- or industrial-scale facilities, along with energy efficiency assessments, could provide more detailed information about the scalability and sustainability of the proposed strategies.

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REFERENCES

Alvaro, R. J., Maria, & David, F. B. (2018). Level control in a system of tanks in interacting mode using Xcos software. *Contemporary Engineering Sciences, 11*, 63–70. https://doi.org/10.12988/ces.2018.712206

Camacho, O., & Smith, C. A. (2000). Sliding mode control: An approach to regulate nonlinear chemical processes. *ISA Transactions, 39*, 205–218. https://doi.org/10.1016/S0019-0578(99)00043-9

Divakar, K., Kumar, M. P., Dhanamjayulu, C., & Gokulakrishnan, G. (2024). A technical review on IMC-PID design for integrating process with dead time. *IEEE Access, 12*, 124845–124870. https://doi.org/10.1109/ACCESS.2024.3453828

Espin, J., Camacho, C., & Camacho, O. (2024). Control of non-self-regulating processes with long time delays using hybrid sliding mode control approaches. *Results in Engineering, 22*, 102113. https://doi.org/10.1016/j.rineng.2024.102113

Hermawan, Y. D., & Haryono, G. (2010). Dynamic simulation and composition control in a 10 L mixing tank. *Reaktor, 14*(2), 95–100. https://doi.org/10.14710/reaktor.14.2.95-100

Hermawan, Y. D., & Puspitasari, M. (2018). Tuning of PID controller using open loop on-off method and closed loop dynamic simulation in a 10 L mixing tank. *Contemporary Engineering Sciences, 11*(101), 5027–5038. https://doi.org/10.12988/ces.2018.810550

Hermawan, Y. D., Yusuf, Y., Andari, E. R., Rahma, A. A., Kurniarto, M. N. T., Simanulang, V., Rahman, A. A., Majid, N., & Sulistyarso, H. B. (2024). Design of adaptive-PID-Smith control in the two-mixing tank series. *Smart Science, 12*(3), 445–461. https://doi.org/10.1080/23080477.2024.2350818

Juneja, P. K., Ray, A. K., & Mitra, R. (2010). Various controller design and tuning methods for a first order plus dead time process. *International Journal of Computer Science & Communication, 1*(2), 161–165. http://www.csjournals.com/IJCSC/PDF1-2/34..pdf

Karan, S., & Dey, C. (2023). IMC-based modified Smith predictor for second order delay dominated processes with RHP. *ISA Transactions, 142*, 254–269. https://doi.org/10.1016/j.isatra.2023.08.009

Korupu, V. L., & Muthukumarasamy, M. (2021). A comparative study of various Smith predictor configurations for industrial delay processes. *Chemical Product and Process Modeling, Advance Online Publication*, 1–32. https://doi.org/10.1515/cppm-2021-0026

Kravaris, C., & Wright, R. A. (1989). Deadtime compensation for nonlinear processes. *AIChE Journal, 35*(9), 1535–1542. https://doi.org/10.1002/aic.690350914

Luyben, W. L. (2002). *Plantwide dynamic simulators in chemical processing and control* (pp. 25–33). Marcel Dekker.

Marlin, T. E. (1995). *Designing processes and control systems for dynamic performance* (2nd ed., pp. 97–337). McGraw-Hill.

Morari, M., & Zafiriou, E. (1989). *Robust process control*. Prentice Hall.

Panda, R. C., Hung, S. B., & Yu, C. C. (2006). An integrated modified Smith predictor with PID controller for integrator plus deadtime processes. *Industrial & Engineering Chemistry Research, 45*, 1397–1407. https://doi.org/10.1021/ie0580194

Seborg, D. E., Edgar, T. F., Mellichamp, D. A., & Doyle III, F. J. (2017). *Process dynamics and control* (4th ed., pp. 368–394). John Wiley & Sons.

Smith, C. A., & Corripio, A. B. (1997). *Principles and practice of automatic process control* (2nd ed., pp. 1–367). John Wiley & Sons.

Stephanopoulos, G. (1984). *Chemical process control: An introduction to theory and practice* (pp. 1–393). Prentice Hall.

Stojic, M. R., Matijevic, M. S., & Draganovic, L. S. (2001). A robust Smith predictor modified by internal models for integrating process with dead time. *IEEE Transactions on Automatic Control, 46*(8), 1293–1298. https://doi.org/10.1109/9.940937