A Data-Driven Approach for PIDs Tuning in Energy-intensive Industry: Application to Evaporator in Kraft Pulp Mill

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Abstract

Proportional-integral-derivative (PID) controllers are widely used in industrial processes, and finding the most appropriate PID parameters plays an important role in optimizing plant operation. However, tuning a large number of PIDs is a labor-intensive task that often leaves many control engineers uncertain about how to proceed. To tackle this problem, this article provides an automated approach to select and recommend the appropriate set of numerical values for P, I, and D. Our approach is an open-loop PID autotuner which is based on a data-driven model that represents the physical process and an ensemble of optimization algorithms. To evaluate the effectiveness of our approach, we tuned four PIDs that are responsible for controlling multiple-effect evaporators, a critical piece of equipment in kraft pulp manufacturing used to evaporate and concentrate black liquor. The results show clear success in tuning several PIDs automatically with basic process knowledge and minimum effort.

Keywords
PID Tuning, Data-driven, Model Identification, Optimization and Complex Industrial Processes.

1. Introduction
Due to simplicity and ease of implementation, proportional-integral-derivative (PID) controllers have been extensively used in industrial processes over the past few decades, which consist of almost 90% of controllers in industrial control loops s (Al-Bargothi et al. 2019). They capture the system historical behaviors through the integration part and forecast the future behavior of the system via the differentiation part (Lakhani et al. 2021).
At the same time, the advancement of modern science and technology improves the complexity of industrial processes, leading to potential problems such as unstable control loops (Shamsuzzoha 2018), which may contribute to the low effectiveness of PID tuning.

Initially, PID controllers were manually tuned by the control engineers and operators with their empirical knowledge. This method does not need too much advanced technical support, but it depends on the personal professional ability, which cannot ensure the accuracy and adaptability of tuning. Apart from manual tuning, PID tuning approaches are categorized into heuristic tuning, rule-based tuning, and model-based tuning (Lakhani et al. 2021). Heuristic tuning is based on trial and error according to the prior knowledge on the control processes and its corresponding PID parameters, which is easy to implement but time-consuming. It also fails to guarantee that the selected PID parameters are optimal (Bucz and Kozáková 2018). Thus, heuristic tuning is usually used to provide an initial guess of the PID parameters. Rule-based tuning applies simple models for the approximation of the process on the basis of the step test. Ziegler-Nichols, Chien, Hrones and Reswick, Cohen-Coon, Kappa-Tau, and Lambda tuning are some commonly used rule-based tuning methods (Seborg et al. 2016). However, these methods are quite sensitive to discrepancies between the approximation model and the true control process, and they are only suitable for simple systems.

Model-based tuning, which is also known as optimization-based tuning, is able to provide the optimal PID parameters when the model is sufficiently precise. However, it is difficult to obtain a precise model and to determine whether it is accurate enough in the real-world industrial processes due to the requirement of system identification (Abushawish et al. 2020). To mitigate the aforementioned issues in the existing methods and improve the tuning performance, several advanced tuning methods have been developed by combining traditional PID tuning with advanced techniques, including self-tuning (Khodadadi and Ghadiri 2018), auto-tuning (Borase et al. 2021), genetic tuning (Porter and Jones 1992), and robust and optimal tuning (Kristiansson and Lennartson 2002).

Industrial processes are complex and involve a large number of PIDs, as well as being dynamic and non-linear. Also, there are different regimes of operations, this results in several setpoints that PIDs must target. Consequently, for control engineers, tuning is a tedious task that requires a lot of time and effort. In addition, there are many different approaches to PID tuning, each with its own advantages and disadvantages.
In order to address the challenge of tuning, we propose a hybrid approach to automate the tuning of PID. The approach combines simulator for industrial process, data from bump tests to model the first order plus dead-time (FOPDT), and several optimization algorithms.

The following is an outline of our contributions to the tuning of PIDs:

- A simulation process based on the industrial application is used for PID tuning, and the simulator is used to gather sufficient bump test data to understand the dynamic of the process.
- Several optimization algorithms are used to obtain the parameters of FOPDT.
- Combined with the result of optimization, the internal model control (IMC) method is adopted to recommend the PID parameters.

The remaining parts of this paper are organized as follows. Section 2 describes the details of the proposed PID-tuning framework for open-loop process. The effectiveness of the proposed framework is manifested by the case study in Section 3. Finally, conclusions are drawn in the last section. The limitations of this work and the future perspective are also presented.

2. FOPDT-Based Model and IMC for PID Tuning Framework

A PID controller can be represented as (Johnson and Moradi 2005)

$$u(t) = K_c\left(e(t) + \frac{1}{\tau_i}\int e(t)dt + \tau_d\frac{de(t)}{dt}\right) \tag{1}$$

where K_c, τ_i and τ_d are controller gain, integral time and derivative time, respectively (see Figure 1). The P, I and D parameters are the respective K_c, K_c/τ_i and $K_c\tau_d$. The control variable and the error value are represented by $u(t)$ and $e(t)$, accordingly.

This work aims to autotune the PID parameters in an open-loop configuration, meaning that the feedback loop is temporarily disconnected. For this purpose, it is necessary to select and build a model that represents the process dynamics. Then the model parameters can be used in conjunction with a rule-based approach to calculate the PID parameters (see Eq. (3)). In the present study, the FOPDT model is chosen due to its interpretability and ease of implementation, making it one of the most commonly used identification methods (Muresan and Ionescu 2020). The FOPDT model is an empirical approximation of stable dynamic processes s (Murrill 1967), and its formulation is

$$\tau_p\frac{dy(t)}{dt} = -y(t) + Ku(t-\theta_p) \tag{2}$$

where $y(t)$ denotes the process variable obtained by FOPDT at time t, K is the gain of the process, τ_p is the process time constant, and θ_p is the process dead time.

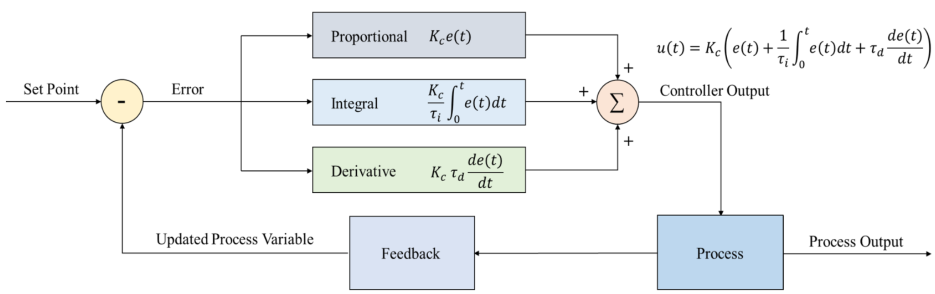

Figure 1. Block diagram of PID control in a closed-loop process

In this research, IMC tuning rule (Rivera et al. 1986) is adopted to study the connections between FOPDT and PID parameters. IMC is a common tuning correlation for PID control. While many PID controller tuning rules target quick responsivity but compromise loop stability to achieve that quick response, IMC tuning rule provide a workable option where control loop stability is an issue. With IMC, the PID parameters are calculated by the following equation (Tajjudin et al. 2018):

$$\begin{aligned} K_c &= \frac{1}{K}\frac{\tau_p}{\tau_c+\theta_p} \\ \tau_i &= \tau_p + 0.5\theta_p \\ \tau_d &= \frac{\tau_p\theta_p}{2\tau_p+\theta_p} \end{aligned} \tag{3}$$

where τ_c is the IMC filter constant, and it shall be settled within one to three fold the value of τ_p. For aggressive tuning, τ_c is equal to one τ_p, and for conservative tuning, τ_c should be three times the τ_p.

3. The Proposed Approach for Tuning PID Parameters

To tune the PID parameters K_c, τ_i and τ_d through the data, FOPDT and IMC, we need first to find the K, τ_p, and θ_p that minimize the objective function in Eq. (4), which represents the sum-of-squares error (SSE) between the y (see Eq. (2)) and the plant output y_p. The values of y_p are collected from bump tests.

$$\begin{aligned} &\min_{K,\tau_p,\theta_p} \sum \left[y(t) - y_p(t)\right]^2 \\ &s.t. \quad \tau_p > 0 \quad \theta_p > 0 \end{aligned} \tag{4}$$

Once the values of K, τ_p, and θ_p are obtained, the IMC rule can be used to recommend the values of K_c, τ_i and τ_d. However, the selection of an optimizer is a challenge. Moreover, PIDs in industrial processes usually control variables with different dynamics and behaviors. Therefore, there is no single optimizer that can help adjust the parameters of all PIDs in an industrial process. Consequently, several optimizers are studied. It is worth mentioning that computing power (CPU and GPU) has increased considerably over the past 15 years, which is a major driver for successfully integrating and deploying various operations research algorithms. In addition, these varieties are available using open-source Python libraries. Using the "Scipy. optimize" library in Python, various optimization methods were tested and applied to find the optimal PID parameters. In terms of unconstrained minimization, conjugate gradient (CG) algorithm, Newton-CG algorithm, Newton conjugate gradient trust-region (trust-ncg) algorithm, Newton GLTR trust-region Krylov subspace (trust-krylov) algorithm (Jorge and Stephen 2006) are applied for the comparison. With respect to constrained minimization, and constrained optimization by linear approximation (COBYLA) (Powell, 2007) are adopted to optimize PID parameters. For bound-constrained minimization, approaches are considered involving limited-memory BFGS algorithm for bound-constrained optimization (L-BFGS-B) (Byrd et al. 1995), Powell's conjugate direction (Powell) method (Press et al. 2007), truncated Newton (TNC) algorithm (Jorge and Stephen 2006), bound optimization by quadratic approximation (BOBYQA) (Powell 2009). Apart from the above methods, particle swarm optimization (PSO) and genetic algorithm (GA) are also used for PID tuning.

To recap our approach which is demonstrated in Figure 2, we first conduct bump tests on the variables that require control}, which are done in an open-loop mode. Second, several selected optimizers need to be performed to adjust the FOPDT parameters (see Eqs. (2) and (4)). Considering both the coefficient of determination (R^2) (Draper and Smith 1998) and process time, the optimizer with the best performance is selected, and the corresponding set of parameters (K, τ_p, and θ_p) obtained by the optimizer is used to determine further PID parameters K_c, τ_i and τ_d). Afterwards, by using the IMC tuning method, the PID parameters are calculated in the following three modes: aggressive, moderate, and conservative. Finally, the simulator is used to obtain the appropriates values of the PIDs.

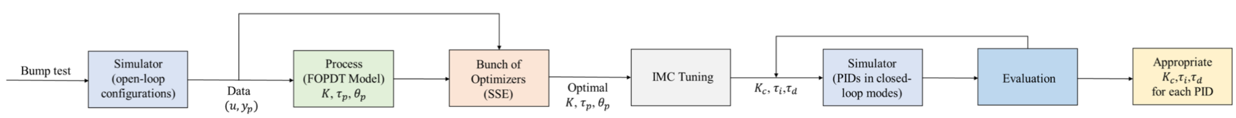

Figure 2. Proposed method for simplifying PID tuning in chemical industrial processes: a schematic representation

4. Case Study

4.1 Process Description

The proposed approach has been tested and validated using data generated with a dynamic simulation of a multiple-effect evaporators (MEV) system. This system represents a major part of the chemical recovery cycle in Kraft pulp mills. Its role is to increase the dissolved solids content of black liquor generated in the wood chips pulping line from around 13%-17% to around 50%. The system uses steam for black liquor water evaporation. More details about the MEV design and operation are provided as follows.

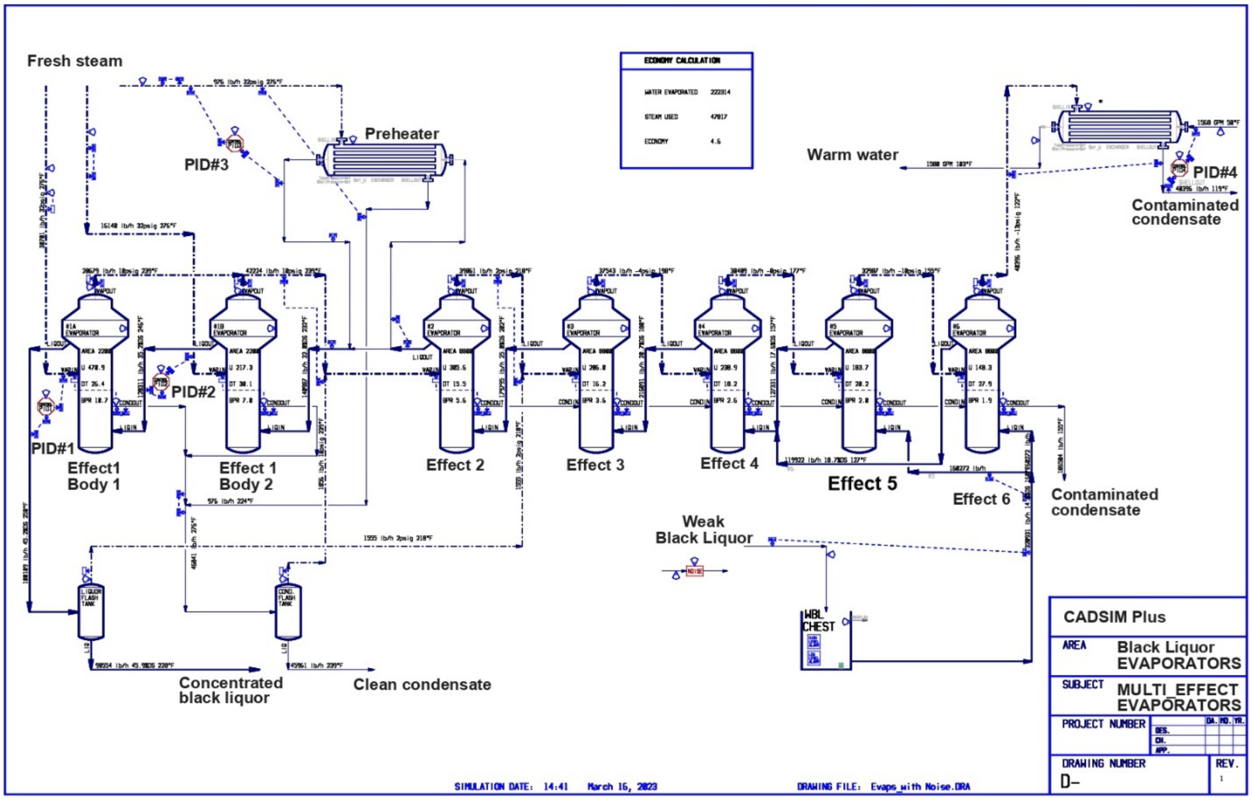

Figure 3. Flowsheet of black liquor multi-effect evaporators-CADSIM

This energy-intensive system is characterized by non-linear behaviors and a constant change of its dynamics. Indeed, many parameters can affect the dynamics of the systems including the incremental increase in the fouling of the heat transfer areas, changes in system operating conditions and a high variability of the black liquor physical properties due to changes in wood species and pulping conditions. The parameters of the local PID controllers of this system should be tuned regularly to adjust to system dynamics changes and therefore maintain efficient control of the system. The MEV that has been selected in this work contains six effects as shown in Figure 3. The first effect includes two parallel evaporators. The vacuum is created and maintained by a surface condenser. A preheater is installed between the first and the second effect and aims to preheat part of the liquor leaving the third effect. This system contains four PID controllers. PID 1 controls solid concentration of black liquor (SCBL1) leaving the first evaporator. PID 2 controls the solid concentration of black liquor leaving the second evaporator (SCBL2). PID 3 aims to control the temperature of black liquor out of the preheater (TBLP). PID 4 is used to control the temperature of the condensed vapor in the surface condenser (TCV).

4.2 Data Generation and Optimizer Selections

The dynamic simulation of the MEV system was developed using CADSIM Plus © process simulation software. The model closely mimics the real system behavior and can simulate different operational scenarios, add noise, conduct open-loop bump tests, incorporate PIDs to control specific variables, and generate datasets. During the open-loop bump test, a noise with $N(\mu, \sigma = 1)$ was added to each manipulated variable. In the closed-loop configuration test for PIDs, a variability was added to the weak black liquor with $N(\mu, \sigma = 5)$ and a noise with $N(\mu, \sigma = 1)$. It should be mentioned that variability and noise propagate through all MEV and introduce dynamics and noisy signals to all variables in the MEV. For this study, the simulation was linked to MS Excel for feeding the simulation with input data, performing bump tests, datasets generation and testing the obtained PID parameters. The simulation could also be linked to Python for online tests performing.

To conduct a bump test and collect data on the process variables that require control, we adjusted the manipulated variables in CADSIM at various steps. The process variables under consideration in this case study are SCBL1, SCBL2, TBLP, and TCV. We obtained four different sets of data (see Table 1) to estimate the parameters of the four FOPDT models. The sampling time used was 0.1 simulation time.

Table 1. Length of data sets to build the four FOPDT model

FOPDT Models	Samples
1	3401
2	2901
3	2901
4	2907

Based on the proposed framework, we evaluated eleven optimizers listed in Tables 2-5 to tune the PIDs using the available data. These optimizers were applied to obtain the parameter values of four FOPDT models, which were then used to calculate the parameters of four PIDs using Eq. (3). The assessment of optimizers is based on two criteria: (1) the convergence time of each optimizer, and (2) the coefficient of determination (R^2) between the predicted and actual values of the FOPDT models. According to the definition of R^2, the closer its value is to 1.0, the more precise is the FOPDT model.

4.3 Results and Discussion

The datasets generated (see Table 1) from the bump tests contain the manipulated variables and the process variables (u, y_p). These 4 datasets are fed to the 11 selected optimizers to obtain the values of (K, τ_p, and θ_p). There are 4 process variables to be controlled. Additionally, 4 parameters (K_c, τ_i, τ_d and τ_c) need to be determined by values of (K, τ_p, and θ_p) based on the IMC tuning rule. In Tables 2 and 3, trust-ncg, trust-krylov, Powell, BOBYQA gave the most accurate results (see bold values). In Table 4, the highest values of R^2 are given to the following optimizers: Powell, TNC, BOBYQA, and GA. In Table 5, the two optimizers (trust-ncg and trust-krylov) are the most accurate according to their R^2. In addition, CG, Newton-CG, L-BFGS-B, Powell, TNC, BOBYQA, PSO, COBYLA, and GA perform well since their R^2 values are reasonable ($0.9 < R^2 < 1.0$). For each optimizer, the IMC rule is used to calculate the parameters of the PIDs (see Eq. (3)). Finally, the simulator is used to evaluate and select the optimizers that must be used to calculate the parameters of the 4 PIDs. Several setpoints that represent different operational regimes are used during the evaluation. The selected optimizers are Powell, BOBYQA, COBYLA. By using these optimizers and the IMC, the recommended parameters of the 4 PID controllers are obtained and demonstrated in Table 6. The tuning results of the four PIDs are depicted in Figure 4. It is evident from the figure that all four PIDs are capable of regulating the process variables effectively, without causing overshoot and with reasonable rise time. Consequently, the proposed approach can tune several PID controllers in a complex chemical process based on data and with minimum knowledge about the process.

Table 2. Accuracy of the optimizers for capturing the dynamics of the process variable: SCBL1

Optimization Methods	R^2	Process Time/s
CG	0.8870	117.27
Newton-CG	0.8870	609.38
trust-ncg	**0.9062**	3697.97
trust- krylov	**0.9062**	3437.59
COBYLA	0.8093	236.11
L-BFGS-B	0.9601	94.61
Powell	**0.9602**	**147.80**
TNC	0.8877	6636.41
BOBYQA	**0.9602**	297.39
PSO	0.9601	8189.12
GA	0.8782	23985.33

Table 3. Accuracy of the optimizers for capturing the dynamics of the process variable: SCBL2

Optimization Methods	R^2	Process Time/s
CG	0.9534	115.48
Newton-CG	0.9442	549.41
trust-ncg	**0.9535**	4708.28
trust- krylov	**0.9535**	3842.41
COBYLA	0.9504	32.91
L-BFGS-B	0.9529	16.47
Powell	**0.9535**	**114.80**
TNC	0.9532	6109.89
BOBYQA	**0.9535**	**279.34**
PSO	0.9531	369.58
GA	0.9534	25027.81

Table 4. Accuracy of the optimizers for capturing the dynamics of the process variable: TBLP

Optimization Methods	R^2	Process Time/s
CG	0.8990	75.72
Newton-CG	0.8990	578.28
trust-ncg	0.9007	2051.16
trust- krylov	0.9007	2084.56
COBYLA	0.8900	882.64
L-BFGS-B	0.8972	206.38
Powell	**0.9011**	**176.17**
TNC	**0.9011**	8482.73
BOBYQA	**0.9011**	**138.94**
PSO	0.8985	6372.62
GA	**0.9011**	7404.08

Table 5. Accuracy of the optimizers for capturing the dynamics of the process variable: TCV

Optimization Methods	R^2	Process Time/s
CG	0.9587	62.52
Newton-CG	0.9587	539.27
trust-ncg	**0.9614**	5242.67
trust- krylov	**0.9614**	4372.88
COBYLA	0.7753	882.64
L-BFGS-B	0.9519	27.83
Powell	0.9593	**107.64**
TNC	0.9587	624.77
BOBYQA	0.9570	**45.08**
PSO	0.9511	6784.86
GA	0.9324	31759.06

Table 6. Accuracy of the optimizers for capturing the dynamics of the process variable: TCV

PID Controller	K_c	τ_i	τ_d	τ_c
PID 1	187.9	4.8	2.5	1.0
PID 2	153.0	3.6	0.9	3.0
PID 3	19.0	2.3	0	3.0
PID 4	-3000.0	0.1	0	3.0

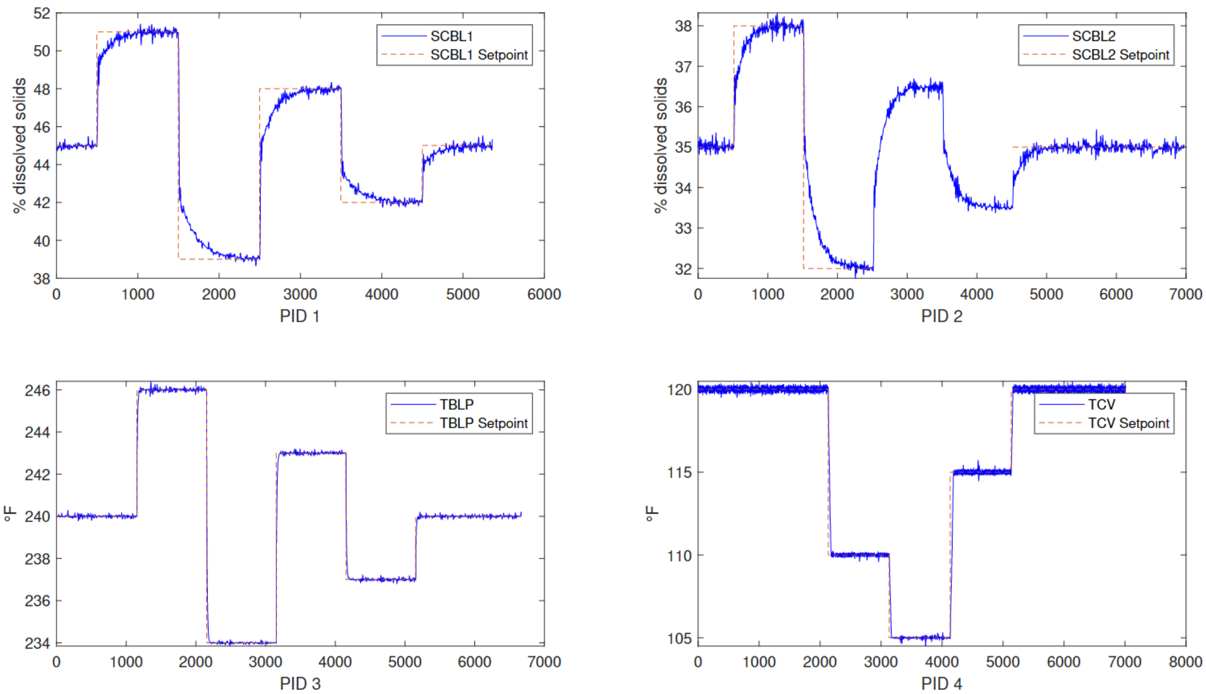

Figure 4. Performance evaluation of PIDs with setpoints and controlled variables

5. Conclusions

This paper proposes a systematic PID tuning framework based on a FOPDT model for an industrial open-loop process, and its effectiveness of controlling the concentration of black liquor is shown by a case study of an evaporator system in Kraft pulp manufacturing. For this energy-intensive industrial application, optimization algorithms including CG, Newton-CG, trust-ncg, trust-krylov, COBYLA, L-BFGS-B, Powell, TNC, BOBYQA, PSO, and GA can achieve the function of PID tuning. After taking into account the metrics of R^2, convergence time, and closed-loop simulation, it has been established that the Powell and BOBYQA optimization methods are the most appropriate choices for optimizing the four PIDs.

For future research, it would be valuable to conduct a thorough examination of FOPDT as a model identification technique in order to assess its benefits and drawbacks in relation to other methods. Furthermore, our proposed approach will be validated by testing it on real-world applications. Moreover, there is potential for exploring alternative directions, such as utilizing advanced machine-learning and reinforcement-learning techniques to tune PID directly in a closed-loop configuration.

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Haitian Zhang is a Ph.D. Candidate in Chemical Engineering (University of Waterloo, CA). Her research focuses on process monitoring and fault diagnosis based on machine learning algorithms in the field of process systems engineering. Prior to her doctoral study, she secured her Bachelor's and Master's degrees in Chemical Engineering from Xi'an Jiaotong University. She had two PRES conference papers and three journal papers in her masteral program. During the period of her doctoral study, she also published two papers related to multivariate statistical analysis.

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Hakim Ghezzaz received a master's in Chemical Engineering from Polytechnique Montréal in 2011. He is currently a process engineer at the CanmetENERGY Research Centre of Natural Resources Canada (NRCan), located in Varennes, Québec, Canada. His research interests include applied thermos dynamics, process systems engineering, multivariate statistical techniques, data-driven fault detection and diagnosis. Before joining CanmetENERGY, he worked for many years in different industries including oil & gas, petrochemical and pulp & paper. During his industrial experience, he was in charge of many projects in process and product design, detailed engineering and process troubleshooting. He has also conducted several studies for energy integration and optimization of the industrial facilities.

Mouloud Amazouz holds a PhD degree in Mechanical Engineering from Polytechnique Montréal, the University of Montréal, Canada. Mouloud has more than 25-year experience in leading, performing, and managing research & development and technology demonstration and deployment at CanmetENERGY, an energy innovation center of Natural Resources Canada (NRCan). He is specialized in the areas of advanced data analytics and artificial intelligence for efficient energy and resource use in the process industry.

Ali Elkamel is a Full Professor of Chemical Engineering (University of Waterloo, CA). He is also cross appointed in Systems Design Engineering. He holds a BSc in Chemical Engineering and BSc in Mathematics from Colorado School of Mines, MSc in Chemical Engineering from the University of Colorado, and PhD in Chemical Engineering from Purdue University. His specific research interests are in computer-aided modeling, optimization, and simulation with applications to energy planning, sustainable operations, and product design. His activities include teaching graduate and undergraduate courses, supervising post doctorate and research associates, and participation in both university and professional societal activities. He is also engaged in initiating and leading academic and industrial teams, establishing international and regional research collaboration programs with industrial partners, national laboratories, and international research institutes. He supervised over 120 graduate students (of which 47 are PhDs) and more than 45 post-doctoral fellows/research associates. He has been funded for several research projects from government and industry. Among his accomplishments are the Research Excellence Award, the Excellence in Graduate Supervision Award, the Outstanding Faculty Award, and IEOM Awards. He has more than 425 journal articles, 175 proceedings, 50 book chapters, and has been an invited speaker on numerous occasions at academic institutions throughout the world. He is also a co-author of six books.

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