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Optimized PID Tuning in Pyrolysis Temperature Control Using Genetic Algorithm and Particle Swarm Optimization

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ABSTRACT

Temperature control is crucial for maintaining stable and effective thermal treatment in pyrolysis system. For this application, Proportional-Integral-Derivative (PID) controller is frequently utilized due to its ease of use and efficiency. This study aims to evaluate and compare the performance of classical and metaheuristic tuning methods for PID controllers in pyrolysis temperature control. This work compares conventional Ziegler-Nichols (ZN) and Cohen-Coon (CC) methods with metaheuristic optimization techniques, specifically Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), for tuning PID controller parameters. The main contribution of this research is the demonstration of improved control performance and computational efficiency using PSO-based PID tuning for pyrolysis applications. Simulation results show that PID controllers that the parameters tuned by GA and PSO achieve faster and smoother responses, with small overshoot, compared to classical methods. From both methods, PSO provides balanced performance with the shortest rise time (30.66 s), fastest settling time (50.80 s), and lowest overshoot (1.15%). Although both GA and PSO can maintain the set point of 500 °C with satisfactory transient response, PSO also shows better convergence efficiency, with smaller iteration numbers and lower computational effort. The results indicate that PSO-tuned PID is suitable for pyrolysis temperature control applications.

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1. INTRODUCTION

Pyrolysis process is a thermochemical method that converts plastic waste into useful biofuels by decomposing polymers in an oxygen-limited environment [1]. Due to its potential to reduce environmental pollution and provide renewable energy, pyrolysis has become popular solution for managing plastic waste and supporting green energy initiatives [2−3]. The efficiency and quality of the products produced by pyrolysis process are highly influenced by precise temperature control in the process [4]. Therefore, an appropriate temperature controller is required to ensure stable thermal conditions, improve process efficiency, and optimize energy usage.

There are numerous studies related to temperature control in pyrolysis systems. Due to its simplicity, intuitive design, and good performance in linear systems, Proportional-Integral-Derivative (PID) controller become the most popular control strategy in temperature control system [5−7]. PID

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parameters can be tuned using classical methods, such as manual tuning, Ziegler–Nichols (ZN), and Cohen–Coon (CC), which rely on reaction curves [8−10]. However, when applied to systems with slow dynamics and large time constants, these methods frequently lead to high overshoot, oscillatory responses, and sub-optimal results [11−13]. Optimization-based algorithm, such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), aim to minimize control error for improved performance based on certain objective function [14]. Furthermore, frequency-domain approaches ensure robustness, while modern techniques including metaheuristic optimization and fuzzy logic adapt to nonlinear or complex systems [15].

In this paper, PID parameters will be selected by comparing conventional ZN and CC methods with metaheuristic optimization techniques, namely GA and PSO. The contribution of this paper is to provide insight into how these advanced tuning methods can improve temperature control performance in pyrolysis heater systems by analyzing their transient and steady state responses while considering optimization effort. Finally, the best approach among them will be selected as optimized tuning method for PID temperature control of pyrolysis process.

2. RESEARCH METHOD

This paper presents simulation-based investigation to compare the performance of PID tuning methods, specifically classical approaches with metaheuristic optimization. This research focus on tuning techniques from the conventional ZN and CC methods to the more modern GA and PSO. The behavior of each controller is analyzed by evaluating its step response, with analysis centered on their ability to reach and maintain desired set point in pyrolysis heater temperature control.

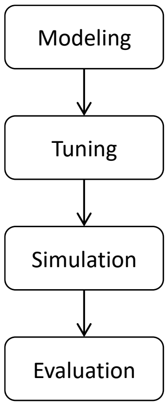

Figure 1. Research flow diagram

Figure 1 shows general flow of the research, which has four main steps: modeling, tuning, simulation, and evaluation. This study starts with the redefinition of mathematical model for thermal system of pyrolysis reactor, refering previous literature. After that, classical and metaheuristic methods are used to adjust the PID parameters. Subsequently, these parameters are used in the simulation to see how the system reacts to the inputs. Then, the performance is evaluated by comparing the response characteristics of each tuning method to see how well they kept the temperature stable and accurate.

2.1. Pyrolysis System

Pyrolysis is a thermochemical process in which organic materials are decomposed at high temperatures in the absence of oxygen environment. This process can be used to produce char, liquid biofuel, and gases. Product quality is highly dependent on reactor temperature treatment so that proper temperature control becomes essential. It can be seen from pyrolysis process diagram in Figure 2 that an extruder moves the feedstock into pyrolysis reactor. Inside, it is heated by a heater in nitrogen atmosphere to ensure an oxygen-free environment. The substance decomposes thermally under these conditions, producing solid residue and vapors. A cyclone is used to remove the solid char, and catalytic reactor is used to further enhance the vapor phase. The resulting vapors are then condensed to obtain liquid biofuel as the main product, while the produced gas is sent back to the heater as fuel [16].

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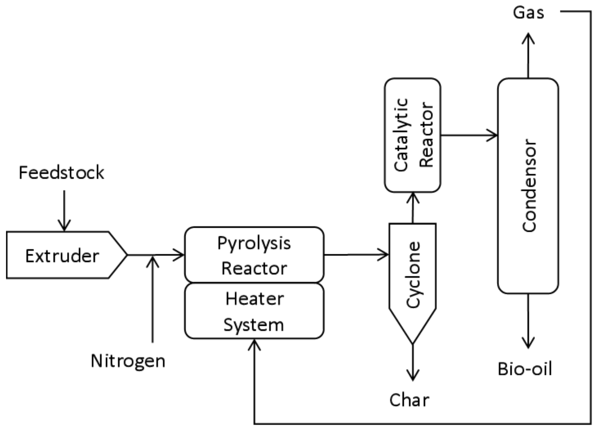

Figure 2. Pyrolysis process diagram

From temperature control perspective, the heater system consists of the pre-heater process, main heater, and second heater stage. This study will be focused on the main heater stage, which governs the temperature dynamics. This stage is modeled as second-order transfer function and is used for step-response simulations to evaluate PID tuning performance in terms of rise time, overshoot, settling time, and steady-state accuracy. The plant model used in this study is adopted from Muharto *et al.* [17] based on real heater model to allow consistent performance comparison. The system dynamics are represented by the following transfer function:

$$G(s) = \frac{1.737 \times 10^{-5}}{s^2 + 0.004285s + 6.179 \times 10^{-7}} \tag{1}$$

2.2. Temperature Control

For effective and consistent thermal treatment in the pyrolysis process, the temperature of reactor must be controlled as temperature directly influences reaction process and product quality. In this system, the error signal for PID controller is produced by comparing the measured reactor temperature with reference set point.

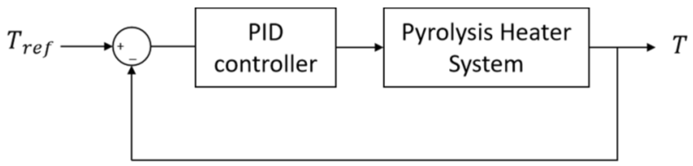

Figure 3. Pyrolysis temperature control block diagram

Figure 3 shows the closed loop temperature control structure applied in this work. The output of the controller adjusts the pyrolysis heater system and the heat input is changed to respond to dynamics of the system in order to hold the system at the desired operating temperature. The main controller used in this system is PID due to its proven effectiveness and simplicity in industrial thermal systems, and a step-response analysis is used to define system behavior for different settings of the PID controller.

2.3. PID Tuning and Optimization

The control performance of PID controller is affected by its parameters, namely proportional gain (Kp), integral time (Ti), and derivative time (Td). Therefore, this paper analyzes the classical tuning methods, Ziegler-Nichols (ZN) and Cohen-Coon (CC), and compares them with the metaheuristic methods, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). While the classical methods tune the PID parameters using system reaction curves, or ultimate gain and offer a simple rules of thumb approach, GA and PSO aim to tune the PID parameters by minimizing a predetermined cost function, typically relating to control errors, to achieve an improved system response speed and smoothness.

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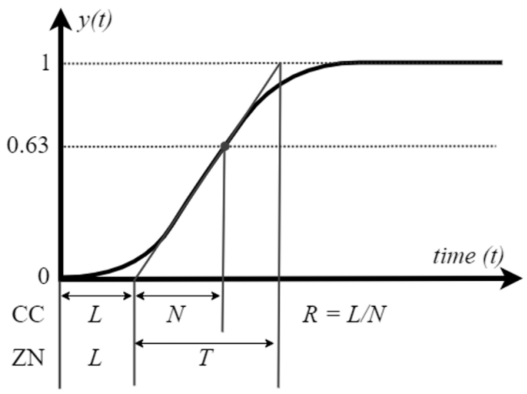

Figure 4. S-curve of ZN and CC tuning methods

The application of the ZN and CC tuning methods in this study are illustrated in Figure 4 and Table 1, respectively. Both methods are used in setting the PID controller parameters based on the process reaction curve from an open-loop step response. From the S-curve response, parameters of process delay and time constant are used to calculate the proportional, integral, and derivative parameters according to specific tuning rules. The parameter L is used to quantify the apparent process delay (dead time) and is defined as the time span between the step input is applied and the point where the tangent at the inflection point intersects the time axis. The parameter N reflects the speed of the process response to the input change and describes the slope of the tangent line at the inflection point, while the ratio R=L/N is used in CC method to characterize the process further for controller parameter calculation.

Table 1. ZN and CC PID tuning rule

Tuning Method	K_p	T_i	T_d
ZN	$1.2\frac{T}{\mathrm{L}}$	$2L$	$0.5L$
CC	$\frac{P}{\mathrm{NL}}\left(1.33+\frac{R}{4}\right)$	$L\left(\frac{30+3R}{9+20\mathrm{R}}\right)$	$\frac{4L}{11+2\mathrm{R}}$

The performance of the PID controller in the optimization process is evaluated using the objective function. In the present study, the controller parameters are introduced as a vector $\theta = [K_p, T_i, T_d]$. The optimizer seeks to reduce the ITAE (Integral of Time-weighted Absolute Error), which is used to measure tracking error within the limits of a defined acceptable transient performance. In the case of a unit step input, the tracking error is defined as $\mathrm{e(t)} = [1 - \mathrm{y(t)}]$. The objective function is formulated under an overshoot constraint as follows

$$J(\theta) = \begin{cases} \int_0^{t_s} t|e(t)|dt, & OS \leq 0.02 \\ \int_0^{t_s} t|e(t)|dt + 10^6(OS - 0.02), & OS > 0.02 \end{cases} \tag{2}$$

where t_s refers to simulation time and OS refers to maximum overshoot. A penalty term is added to the overshoot > 2% to force the optimized controller to meet the transient response specification.

Table 2 shows the optimization settings for GA and PSO techniques applied to tune the PID parameters. For each controller optimization, three control parameters are considered as decision variables. To define a feasible and stable search space, parameter limits. are constrained to a lower and upper range of [0, 100, 50] and [20, 1000, 200] respectively. These limits are designed to prevent the search from unreasonable control parameters but are still effective to provide the desired convergence towards the optimal solution.

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Table 2. GA and PSO Optimization Parameters

Algorithm	Parameter	Value
GA	Population size (*N*)	20
	Maximum generation (*Gen*)	50
	Number of variables (*nvars*)	3
	Crossover probability (*Pc*)	0.8
	Mutation probability (*Pm*)	0.1
PSO	Number of particles (*m*)	20
	Maximum iteration (*Iter*)	50
	Number of variables (*k*)	3
	Inertia weight (*w*)	0.7
	Cognitive coefficient (c_1)	1.5
	Social coefficient (c_2)	1.5
	Maximum velocity (*vmax*)	0.1 x (ub-lb)

Procedure of GA applied in this study is provided in Table 3. The algorithm processes population candidates of potential solutions through selection, crossover, and mutation using fitness evaluation. The evolutionary process is repeated until the stopping criterion is met and results in optimal controller parameters. Furthermore, the fitness function is created to reduce error in the system and enhance the control performance. Therefore, the GA provides a structured way of investigating the search space and obtaining strong and near optimal controller parameters.

Table 3. Genetic Algorithm (GA) Pseudocode

Step	Algorithm
1	Define GA parameters: population size (*N*), maximum generation (*Gen*), crossover probability (*Pc*), mutation probability (*Pm*), and objective function f.
2	Randomly initialize population of candidate solutions within predefined search bounds.
3	Evaluate fitness value *f(xi)* for each individual.
4	Initialize iteration counter n=0.
5	While $g < Gen$ do
6	Perform selection process based on fitness value.
7	Apply crossover operation with probability *Pc*.
8	Apply mutation operation with probability *Pm*.
9	Evaluate fitness value of the new offspring population.
10	Replace population with newly generated individuals.
11	Determine the best individual solution.
12	Increase generation counter $g = g + 1$.
13	End While
14	Output optimal solution representing controller parameters.

The following Table 4 provides the PSO algorithm utilized in this study as pseudocode. This table describes the sequential order to be followed during the optimization process, which consists of particle initialization, fitness evaluation, and the iterative updates of velocity and position of the particles based on the personal best and the global best solutions. This pseudocode describes the optimization process to determine the controller parameters and the iterative search process the swarm performs until a stopping criterion is met.

Table 4. Particle Swarm Optimization (PSO) Pseudocode

Step	Algorithm
1	Define PSO parameters: number of particles (*m*), maximum iteration (*Iter*), dimension (*k*), inertia weight (*w*), cognitive coefficient (c_1), social coefficient (c_2), and objective function *f*.
2	Randomly initialize particle positions pi and velocities vi within predefined search bounds.
3	Evaluate the fitness value $f(p_i)$ of each particle.

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Step	Algorithm
1	Define PSO parameters: number of particles (m), maximum iteration (*Iter*), dimension (k), inertia weight (w), cognitive coefficient (c_1), social coefficient (c_2), and objective function f.
4	Set individual best position pbesti=pi and determine global best position gbest.
5	Initialize iteration counter n=0.
6	While n < *Iter* do
7	For each particle $i = 1,2,\ldots.,m$:
8	Update particle velocity: $v_{ij} = wv_{ij} + c_1\gamma_1(pbest_{ij} - p_{ij}) + c_2\gamma_2(gbest_{ij} - p_{ij})$
9	Update particle position: $f(p_i) = p_{ij} + v_{ij}$
10	Evaluate updated fitness value $f(p_i)$.
11	Update *pbesti* if a better solution is obtained.
12	Update global best position *gbest*.
13	Increase iteration counter n=n+1.
14	End While
15	Output optimal solution represented by *gbest*.

3. RESULTS AND DISCUSSION

To evaluate the performance of the PID controller under different tuning methods, step response simulations were conducted using MATLAB. In these simulations, classical tuning methods (ZN and CC) and metaheuristic optimization techniques (GA and PSO) were applied to determine the PID parameters. The performance of each method is compared using performance metrics such as rise time, settling time, overshoot, and steady-state error, which describe how quickly and accurately the system reaches the desired temperature.

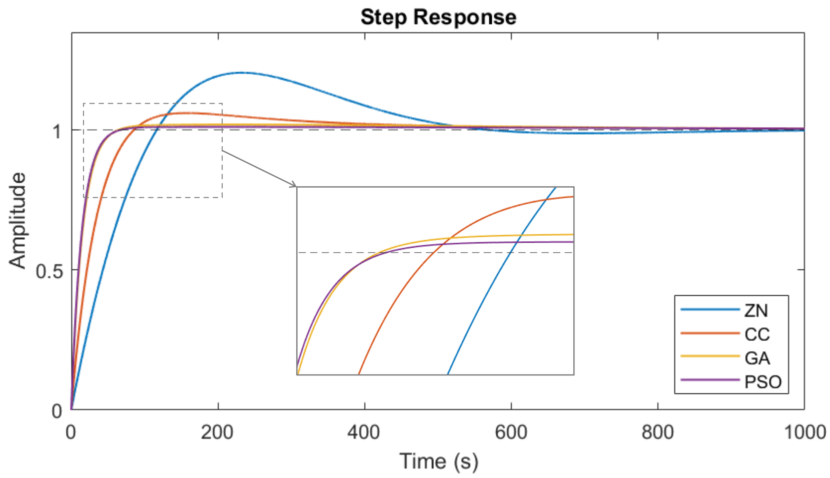

Figure 5. Cost function of GA and PSO

Figure 5 represents step responses of the PID controlled system using ZN, CC, GA, and PSO tuning methods. The ZN-tuned response shows the largest overshoot and the slowest convergence, indicating oscillatory and less stable behavior. The CC method has better transient response but still requires long time to fully achieve steady state. On other hand, GA and PSO significantly produce faster and smoother responses with minimal overshoot. It can be seen that GA and PSO have very close responses but GA shows slightly higher overshoot. Among them, PSO achieves the fastest and most stable convergence to the reference value, showing the best control performance for the system.

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Table 5. Comparison of step responses for different tuning methods

Tuning Method	PID Parameters			Step Response Performance			
	K_p	T_i	T_d	Rise Time (s)	Settling Time (s)	Overshoot (%)	Steady-State Error
ZN	8.54	366.00	92.00	88.57	508.60	20.50	0.0013
CC	13.89	974.00	129.00	56.29	428.48	6.10	0.0059
GA	20.00	556.91	189.08	31.93	51.35	1.99	0.0045
PSO	20.00	950.92	200.00	30.66	50.80	1.15	0.0055

Table 5 provides the performance comparison of four PID tuning methods, namely ZN, CC, GA, and PSO. The comparison is based on rise time, settling time, overshoot, and steady-state error, which describe how well the temperature control system responds to a step change. The ZN method shows relatively the worst performance. Although its steady-state error is small, it produces very long settling time (508.60 s) and high overshoot (20.50%), indicating excessive oscillations and slow stabilization. This behavior is not suitable for pyrolysis temperature control system, which require stable and smooth operation. While, the CC method improves the response compared to ZN, reducing the overshoot to 6.10% and shortening the rise time. However, the settling time is still high (428.48 s), describing the system needs long time to reach steady conditions.

In contrast, the GA-based tuning provides much faster and more stable response. The rise time decreases to 31.93 s and the settling time to 51.35 s, while the overshoot is limited to 1.99%, indicates that GA can effectively balance speed and damping. The PSO method produces the best performance, achieves the shortest rise time and settling time of 30.66 s and 50.80 s respectively, with the lowest overshoot of 1.15%. Although the steady-state error produced by PSO is slightly higher than GA, the difference is very small and still acceptable for real practical performance.

Overall, the results show that metaheuristic optimization methods, in this case GA and PSO, outperform classical ZN and CC tuning. Among them, PSO provides the most balanced response, suitable for pyrolysis temperature control. These two optimization methods can therefore be applied to PID controllers for pyrolysis temperature control, as provided by simulation result in Figure 6.

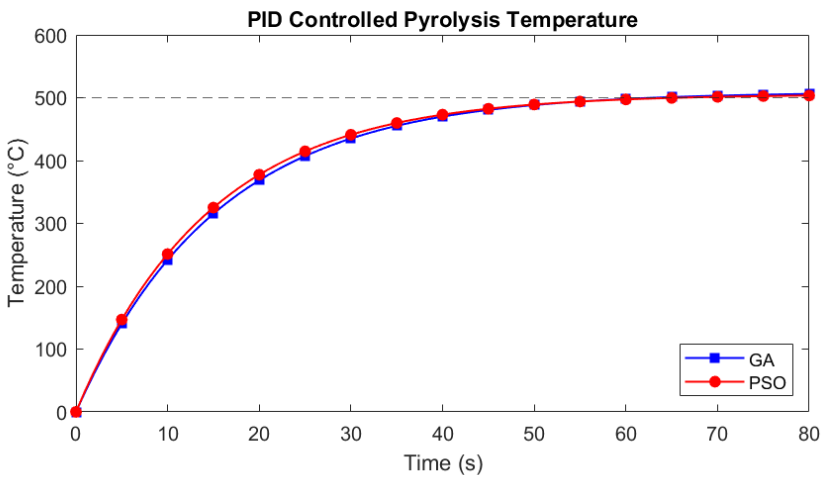

Figure 6. PID Controlled Pyrolysis Temperature

The comparison of PID controllers tuned by GA and PSO for pyrolysis temperature control shows some differences between the two methods. As shown in the temperature graph, both techniques are capable to control the system to targeted set point of 500 °C with acceptable transient response. The responses of PID controllers tuned by GA and PSO have similar rise times and settling time patterns, indicating that both algorithms can find controller parameters that deliver satisfactory closed-loop performance without overshoot for the heater temperature of pyrolysis process, which contributes to reduced thermal energy loss. While, small differences in time response and steady-state accuracy show that the methods can maintain the required thermal conditions for the pyrolysis system effectively.

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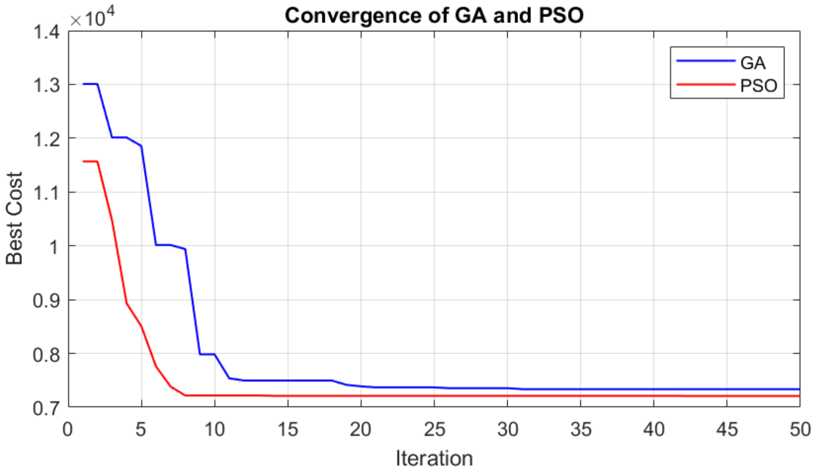

Figure 7. Cost function of GA and PSO

Although the control performances are similar, it can be observed that PSO has better advantage in terms of optimization efficiency as shown in the convergence characteristics of both methods. The convergence graph in Figure 7 shows that PSO reduces the cost function faster and with smaller iteration numbers than GA, meaning lower computational effort during parameter searching. This behavior indicates shorter processing times and reduced computational resources when finding optimal PID parameters. Since the control performance is similar, PSO is preferable primarily for its computational efficiency. In practical applications, where PID tuning may need to be repeated under varying operating conditions, the lower computational load of PSO provides more advantage without compromising control performance.

4. CONCLUSION

This study demonstrates the effectiveness of PID parameters selection using metaheuristic optimization methods, particularly GA and PSO, that provide better performance for pyrolysis temperature control compared to classical tuning methods. The simulation results represent that both GA and PSO achieve faster and smoother responses with minimal overshoot compared to ZN and CC, however PSO offers the most balanced performance, resulting the shortest rise time, fastest settling time, and lowest overshoot. The main contribution of this study is the quantitative demonstration that PSO-based PID tuning significantly improves both dynamic response and optimization efficiency compared to classical methods for pyrolysis temperature control. In addition, PSO shows higher convergence efficiency, requiring only fewer iterations and lower computational effort. These findings indicate that PSO-tuned PID controller is well suited for maintaining stable and effective thermal conditions in pyrolysis systems. Practically, the proposed approach can be implemented in real pyrolysis systems to achieve more stable temperature regulation, reduced energy loss, and improved process reliability under varying operating conditions.

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