

A Real-Time PID Gain Method for Speed Regulation of Horizontal Centrifuges Via Improved Adaptive Genetic Algorithm

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Keywords : horizontal centrifuge; speed regulation; PID gain coefficient; RT-PID-IAGA; real-time update.

ABSTRACT

In centrifuge speed control, the gain coefficients of the PID controller (Proportional-Integral-Derivative controller) directly affect control performance and efficiency. Traditional parameter tuning relies on experience and trial-and-error, making it difficult to obtain optimal settings. To overcome this, an RT-PID-IAGA (Real-Time PID optimization based on Improved Adaptive Genetic Algorithm) is proposed. The method constructs a multi-objective fitness function considering speed error, overshoot, and settling time, and uses an adaptive genetic algorithm to optimize the PID coefficients in real time. A feedback-based control system is then established, enabling dynamic updating of parameters to maintain near-optimal performance. Comparative experiments with standard GA and conventional PID show that RT-PID-IAGA significantly improves control accuracy and response speed in centrifuge speed regulation.

INTRODUCTION

As a highly efficient solid-liquid separation device, the horizontal centrifuge is widely used in various fields such as industry, construction and medicine. In the construction field, foundation construction often generates a large amount of slurry, which must undergo a slurry separation process before discharge. Therefore, the efficiency of slurry separation is not only related to the effective utilization of resources but also directly affects environmental protection.

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Consequently, optimizing the operational performance of the horizontal centrifuge to ensure its stable and efficient operation is of great practical significance.

During centrifuge operation, the Proportional-Integral-Derivative (PID) controller is widely used because of its simple structure, easy implementation, and reliable control performance. It achieves precise regulation of the separation process by adjusting key parameters such as rotational speed and centrifugal force. The gain parameters of the standard PID controller are typically tuned using manual adjustment, the Ziegler-Nichols method, or the Cohen-Coon method. However, these traditional approaches rely heavily on experience and repeated trial and error, making it difficult to quickly obtain near-optimal parameters, which often results in unsatisfactory control performance.

To overcome these limitations, researchers have explored intelligent optimization algorithms for PID tuning. Luis Mora et al. employed metaheuristic methods, including genetic algorithm, particle swarm optimization, and cross-entropy algorithm, confirming their superiority in PID parameter optimization. Xinming Fan et al. proposed IPSO (Improved Particle Swarm Optimization), which introduced nonlinear inertia weight adjustment and a boundary buffering mechanism; simulations verified its effectiveness. Xiangzhong Meng and Baoye Song developed a fast genetic algorithm to accelerate convergence. Jiasheng Li and Wenguo Li applied an online GA-based optimization with an anti-saturation strategy to wind power systems, significantly improving the power factor. Jiuqi Han et al. introduced a fruit fly optimization algorithm (FOA)-based PID tuning method, which yielded excellent closed-loop performance. Dwi Ana Ratna Wati and Rakhmat Hidayat optimized an air heater PID controller using a genetic algorithm with settling time and overshoot as objectives, achieving markedly better step response than the Ziegler-Nichols method.

In recent years, GA (Genetic Algorithm) has been widely applied to optimize PID controller gain parameters. AGA (Adaptive Genetic Algorithm) offers

notable advantages by dynamically adjusting parameters such as crossover and mutation rates, thereby improving convergence speed and optimization accuracy, and making it more suitable for nonlinear and dynamic systems. The fitness function, a core component of GA, evaluates the quality of individuals by calculating their fitness in a specific environment. A higher fitness value indicates better performance and directly influences selection, crossover, and mutation, thus shaping the final solution. Various fitness function designs have been explored in different fields. For example, in astronomy, a novel fitness function based on GZM (Galaxy Zoo: Mergers) has been validated in simulations; in data management, a new design accelerated GA optimization, reducing execution time by up to 66% compared with standard GA; and in path planning, a multi-objective function combining path length, safety, and energy consumption improved both convergence and path quality.

This study addresses the speed regulation of centrifuges, where speed error, overshoot, and settling time are selected to construct a multi-objective fitness function. We propose RT-PID-IAGA (Real-Time PID optimization based on an Improved Adaptive Genetic Algorithm), which embeds IAGA into a real-time control system for dynamic optimization of PID gains. During feedback adjustment, the method continuously updates PID coefficients, ensuring that the controller uses the optimal values from the current population. Compared with traditional methods, RT-PID-IAGA significantly accelerates response speed while maintaining high accuracy in centrifuge speed regulation. The remainder of this paper is organized as follows: Section 2 introduces the structure and mathematical model of the horizontal centrifuge. Section 3 details the design of RT-PID-IAGA. Section 4 presents comparative simulation results against standard GA and standard PID. Section 5 draws conclusions.

STRUCTURE AND MATHEMATICAL MODEL OF HORIZONTAL CENTRIFUGE

Structural principle of horizontal centrifuge

The core components of the horizontal centrifuge include the drum, screw conveyor, differential, and main and auxiliary motors. During operation, solid particles in sludge water, being denser than the liquid phase, quickly settle on the inner wall of the drum under strong centrifugal force. The relative motion between the screw conveyor and the drum continuously drives the deposited solids toward the drying zone at the small end, where they are further dewatered and discharged through the solids outlet. Meanwhile, the clarified liquid overflows from the large end through the liquid outlet, completing the solid-liquid separation. A schematic diagram of the centrifuge is shown in Fig. 1

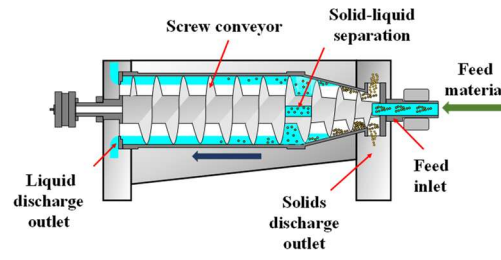


Fig. 1 Schematic diagram of the centrifuge

The centrifugal force acting on the solid particles is calculated as shown in Equation (1).

$$F_c = m\omega^2 r \quad (1)$$

where F_c is the centrifugal force acting on the solid particles, m is the mass of the particles, ω is the angular velocity of the rotor, and r is the radial distance of the particles from the rotation axis.

In specific experiments, for ease of setting and comparison, RCF (Relative Centrifugal Force) is commonly used to describe the centrifugal intensity. The equation for relative centrifugal force is shown in Equation (2).

$$RCF = \frac{F_c/m}{g} = \frac{\omega^2 r}{g} \quad (2)$$

where g is the gravitational acceleration at the Earth's surface.

Mathematical model of horizontal centrifuge

The motor used in this study is an asynchronous motor. The voltage equations of the standard asynchronous motor stator in the d-q (direct-quadrature) axis coordinate system are shown in Equation (3).

$$\begin{cases} u_d = R_s i_d + \frac{d\psi_d}{dt} - \omega_e \psi_q \\ u_q = R_s i_q + \frac{d\psi_q}{dt} + \omega_e \psi_d \end{cases} \quad (3)$$

where u_d is the stator d-axis voltage, u_q is the stator q-axis voltage, R_s is the stator winding resistance, i_d is the stator d-axis current, i_q is the stator q-axis current, ψ_d is the stator d-axis flux linkage, ψ_q is the stator q-axis flux linkage, and ω_e is the electrical angular velocity.

The voltage equations of the standard asynchronous motor rotor in the d-q axis coordinate system are shown in Equation (4).

$$\begin{cases} u_{dr} = R_r i_{dr} + \frac{d\psi_{dr}}{dt} - (\omega_e - \omega_r) \psi_{qr} \\ u_{qr} = R_r i_{qr} + \frac{d\psi_{qr}}{dt} + (\omega_e - \omega_r) \psi_{dr} \end{cases} \quad (4)$$

where u_{dr} is the rotor d-axis voltage, u_{qr} is the rotor q-axis voltage, R_r is the rotor winding resistance, i_{dr} is the rotor d-axis current, i_{qr} is the rotor q-axis current, ψ_{dr} is the rotor d-axis flux linkage, ψ_{qr} is the rotor q-axis flux linkage, and ω_r is the mechanical angular velocity.

The stator and rotor flux linkage coupling equations are shown in Equation (5).

$$\begin{cases} \psi_d = L_s i_d + L_m i_{dr} \\ \psi_q = L_s i_q + L_m i_{qr} \\ \psi_{dr} = L_m i_d + L_r i_{dr} \\ \psi_{qr} = L_m i_q + L_r i_{qr} \end{cases} \quad (5)$$

where L_s is the stator self-inductance, L_r is the rotor self-inductance, and L_m is the main magnetizing

inductance.

The electromagnetic torque equation is shown in Equation (6).

$$T_e = \frac{3}{2}p(\psi_d i_q - \psi_q i_d) = \frac{3}{2}pL_m(i_q i_{dr} - i_d i_{qr}) \quad (6)$$

where p is the number of pole pairs, and T_e represents the electromagnetic torque.

The mechanical motion equation is shown in Equation (7).

$$J \frac{d\omega_r}{dt} = T_e - B\omega_r - C_d \omega_r^2 \quad (7)$$

where B is the viscous damping coefficient, $B\omega_r$ represents the viscous damping term, C_d is the fluid resistance coefficient, $C_d \omega_r^2$ represents the slurry fluid resistance term, and J represents the equivalent moment of inertia.

IMPLEMENTATION OF RT-PID-IAGA

Establishment of fitness function

AGA is an optimization algorithm that can dynamically adjust genetic operations to improve optimization efficiency. In AGA, the fitness function is a key step that directly determines the adjustment strategies of crossover rate and mutation rate. In this study, we constructed the fitness function using the error between the target speed and the actual speed of the centrifuge, the system overshoot, and the settling time as the evaluation index. This study defines that the smaller the fitness value, the better the performance of the corresponding individual. Equations (8), (9), and (10) present the formulations of the three-performance metrics: speed error, overshoot, and settling time.

$$E_{speed} = |\omega_{set} - \omega(x)| \quad (8)$$

where ω_{set} is the target speed, $\omega(x)$ is the actual speed, x is an individual in the population, and E_{speed} is the speed error.

$$E_{ovs} = \frac{\omega(x)_{max} - \omega_{set}}{\omega_{set}} \times 100\% \quad (9)$$

where E_{ovs} represents the magnitude of the overshoot, $\omega(x)_{max}$ is the maximum output.

$$E_{ts} = \min\{t \mid \forall \tau \geq t: |\omega(\tau) - \omega_{set}| \leq 0.02\omega_{set}\} \quad (10)$$

where $0.02\omega_{set}$ is the bandwidth threshold, τ is all later time instants starting from time t , $\omega(\tau)$ represents the speeds at all later time instants, and E_{ts} represents the settling time.

The multi-objective fitness function is shown in Equation (11).

$$fitness(x) = w_0 E_{speed} + w_1 E_{ovs} + w_2 E_{ts} \quad (11)$$

where w_0 , w_1 , and w_2 are the weights corresponding to the three indicators: speed error, overshoot magnitude, and settling time, respectively. In this study, the values are set as $w_0=0.5$, $w_1=0.3$, and $w_2=0.2$.

Establishment of crossover rate and mutation rate

This study dynamically adjusts the crossover and mutation rates according to fitness variation to meet the real-time optimization requirements of PID parameters. For crossover adjustment, individuals with fitness much higher than the average are given higher crossover probabilities to enhance global search and avoid inferior convergence. Similarly,

individuals with fitness much lower than the average, which represent superior genes with smaller speed error, are also assigned higher crossover probabilities to promote recombination. When fitness is close to the average, a lower crossover probability is applied to preserve medium-quality genes. For mutation adjustment, superior individuals with small fitness are assigned lower mutation rates to prevent gene damage, while inferior individuals with large fitness are assigned higher mutation rates to broaden the search range and avoid local optima. The specific formulas for the adaptive crossover rate $P_c(x)$ and mutation rate $P_m(x)$ are given in Equations (12) and (13).

$$P_c(x) = \begin{cases} PC_{max} \cdot \frac{fitness(x) - fitness_{min}}{fitness_{avg} - fitness_{min}} (PC_{max} - PC_{min}), & fitness(x) < fitness_{avg} \\ PC_{max}, & fitness(x) \geq fitness_{avg} \end{cases} \quad (12)$$

$$P_m(x) = PM_{min} + \frac{fitness(x) - fitness_{min}}{fitness_{max} - fitness_{min}} (PM_{max} - PM_{min}) \quad (13)$$

where $fitness(x)$ is the fitness function, $fitness_{min}$ is the minimum fitness, $fitness_{max}$ is the maximum fitness, $fitness_{avg}$ is the average fitness, PC_{max} is the upper limit of the crossover rate, PC_{min} is the lower limit of the crossover rate, PM_{max} is the upper limit of the mutation rate, and PM_{min} is the lower limit of the mutation rate.

Tournament selection

Tournament selection is a commonly used parent selection method in GA. Its core idea is to randomly select several individuals from the population, then perform comparative analysis based on their fitness values, and finally choose the individual with the best fitness as the parent for the next operation. This method only needs to compare a small portion of individuals without global sorting, which ensures high computational efficiency and facilitates implementation in the system. The specific workflow is shown in Fig. 2.

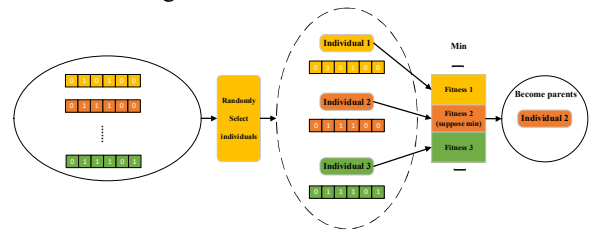


Fig. 2 Tournament selection process

Improved adaptive genetic algorithm process

This study introduces the speed error, the system overshoot, and the settling time into the fitness function of AGA and proposes an AGA based on the multi-objective fitness function. This algorithm can effectively regulate the speed of the centrifuge, meeting the requirement for rapid adjustment of working speed in daily operations. The specific process of AGA based on the multi-objective fitness function includes the following steps.

Step (1): Initialize algorithm parameters: population size N , upper and lower bounds of PID parameters L_b and U_b , upper and lower limits of adaptive crossover probability PC_{max} and PC_{min} , upper

and lower limits of adaptive mutation probability PM_{max} and PM_{min} ;

Step (2): Generate the initial population within the upper and lower bounds of PID parameters, and this population contains the required PID controller parameter information $[K_p, K_i, K_d]$;

Step (3): Evaluate the fitness of individuals and retain the individual with the best fitness:

Evaluate the fitness of each individual $fitness(x)$. Record the current best fitness (minimum fitness) $fitness_{min}$ and the corresponding individual $[K_{p,best}, K_{i,best}, K_{d,best}]$. Meanwhile, calculate the average fitness $fitness_{avg}$ and the maximum fitness $fitness_{max}$.

Step (4): Adaptively adjust the crossover rate and mutation rate (based on fitness variation):

Adjust the mutation rate $P_m(x)$; Adjust the crossover rate $P_m(x)$.

Step (5): Generate parent individuals using tournament selection to optimize the population:

Randomly select three individuals to form a tournament group; Calculate and compare the fitness of these three individuals. The individual with the lowest fitness wins and becomes one of the parent individuals; Repeat Step (5) until the population size reaches N .

Step (6): Perform genetic operations to create a new generation:

Perform crossover operation to generate offspring individuals $Child$; Perform mutation operation to generate mutated offspring individuals $Child_m$; Repeat Step (6) until the population size reaches N , producing a new population.

Step (7): Input the best fitness and the best PID parameters $[K_{p,best}, K_{i,best}, K_{d,best}]$ from the previous generation into the PID controller for speed feedback adjustment. Compare whether the adjusted speed error meets the condition of approaching zero. If not, repeat Steps (3) to (6); if yes, terminate the process.

For a more intuitive presentation, the specific process is shown in Fig. 3.

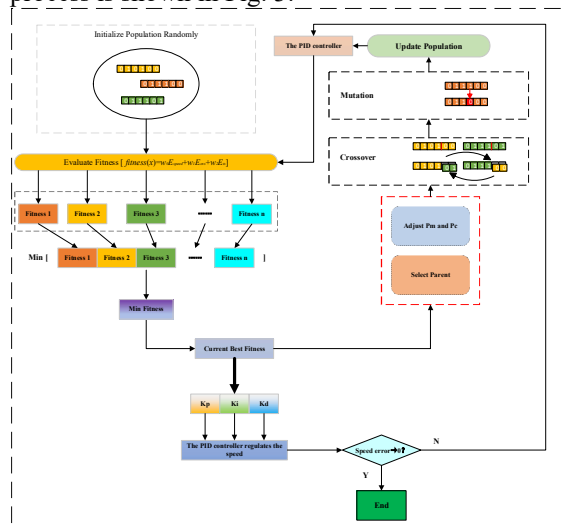


Fig. 3 Flowchart of improved adaptive genetic algorithm
Establishment of Real-Time PID gain coefficient

optimization system

Building on the implementation of AGA based on speed error, this study further meets the real-time requirements by using this algorithm to calculate the optimal PID gain coefficients in real-time and input them into the PID controller that controls the centrifuge speed to achieve optimal speed adjustment. Consequently, a centrifuge speed control system capable of real-time updating and optimizing PID gain coefficients is constructed. The construction process is shown in Figure 4, where the part within the red frame represents the real-time PID parameter adjustment module.

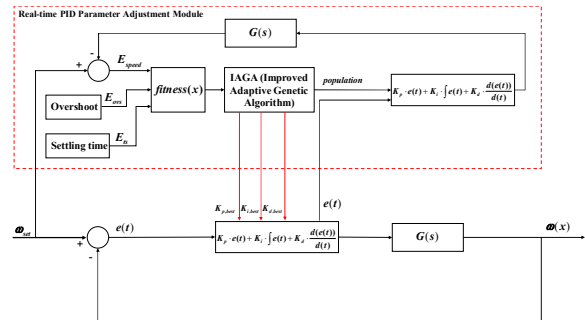


Fig. 4 Centrifuge speed control system

According to Fig. 4, the operational process of the entire system is as follows:

Step (1): Establish an initial population through AGA based on the speed error, the system overshoot, and the settling time.

Step (2): Input the initial population into the calculation module, which is identical to the current centrifuge model, to predict the speed adjustment results and obtain the adjusted speed of each individual in the current population.

Step (3): Calculate the fitness of each individual using the constructed fitness function equation and input it into AGA based on speed error for calculating the best fitness individual, followed by selection, crossover, and mutation operations based on the fitness function.

Step (4): Update the population based on the results and output the optimal solution in the current population as the current best PID gain coefficients.

Step (5): Input the optimal solution into the centrifuge model for speed adjustment calculation.

Step (6): If the speed has been adjusted to the target speed, terminate the process; if not, replace the initial population with the new population and repeat Steps (2) to (5).

SIMULATION EXPERIMENT

Experimental parameter settings

To investigate the influence of population size and the number of iterations on RT-PID-IAGA, three sets of experiments were designed with different configurations: a population size of 20 and 50 iterations, a population size of 100 and 200 iterations, and a population size of 400 and 800 iterations. The results are shown in Fig. 5.

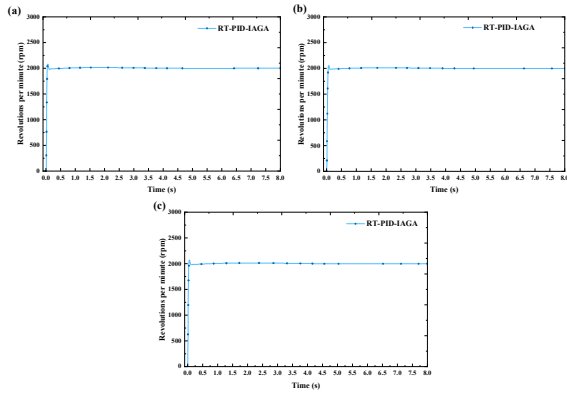


Fig. 5 Speed response curves at a target speed of 2000 rpm (a) a population size of 20 and 50 iterations (b) a population size of 100 and 200 iterations and (c) a population size of 400 and 800 iterations

Based on Fig. 5, it can be observed that increasing the population size and the number of iterations produces only minor changes in the speed regulation curve. However, a closer inspection of the plots reveals that when the population size is 100 and the number of iterations is 200, the speed regulation curve exhibits a smoother transition compared with the curve obtained with a population size of 20 and 50 iterations. In contrast, when the population size is set to 10, the simulation experiences an excessively long runtime. This is likely because a smaller population lacks sufficient search capability, making it difficult to identify suitable PID parameters within a limited number of iterations, which in turn prolongs the simulation. Therefore, to balance computational load and real-time requirements, this study selects a population size of 100 and 200 iterations.

To clearly demonstrate the performance of the centrifuge speed control system designed in this study, the simulation experiment conducted a comparative analysis of the simulation results of standard PID, standard GA, and RT-PID-IAGA. The parameters of the asynchronous motor used in the simulation experiment are shown in Table 1. In IAGA settings, the population size is set to 100 groups, the maximum number of iterations is set to 200, and the dimension is set to 3, corresponding to the three gain parameters of the PID controller: proportional (K_p), integral (K_i), and derivative (K_d). Considering that the common working speeds of the horizontal centrifuge is 2000 rpm, 3000 rpm, and 4000 rpm, this study sets these speeds as the target speed for speed adjustment experiments.

Table 1. Main parameters of the asynchronous motor

Main parameters	Numerical values	Tolerance / range
rated power P	90 kW	total losses +15%
rated voltage U	400 V	380-420 V ($\pm 5\%$)
number of pole pairs p	2	-
stator resistance R_s	0.01956 Ω	0.01956-0.02725 Ω
stator self-inductance L_s	0.02 H	0.016-0.022 H
magnetizing inductance L_m	0.018 H	0.0126-0.0198 H

fluid resistance coefficient C_d	$2.97 \times 10^{-3} \text{ N} \cdot \text{m} / (\text{rad} / \text{s})^2$	$1.49 \times 10^{-3} - 4.46 \times 10^{-3} \text{ N} \cdot \text{m} / (\text{rad} / \text{s})^2$
equivalent moment of inertia J	1.30 $\text{kg} \cdot \text{m}^2$	1.17-1.43 $\text{kg} \cdot \text{m}^2$
viscous damping coefficient B	0.65 $\text{N} \cdot \text{m} \cdot \text{s} / \text{rad}$	0.39-0.91 $\text{N} \cdot \text{m} \cdot \text{s} / \text{rad}$

Comparison and analysis of three methods

Through tuning, the gain coefficients of Standard PID are $K_p=1.2$, $K_i=0.2$, and $K_d=0.05$, while those of Standard GA are $K_p=5.236$, $K_i=9.265$, and $K_d=2.848$. Subsequently, simulation analysis was performed to obtain the centrifuge speed response curves under the three methods. Fig. 6 illustrate the speed response characteristics of the centrifuge under the three methods at different set speeds.

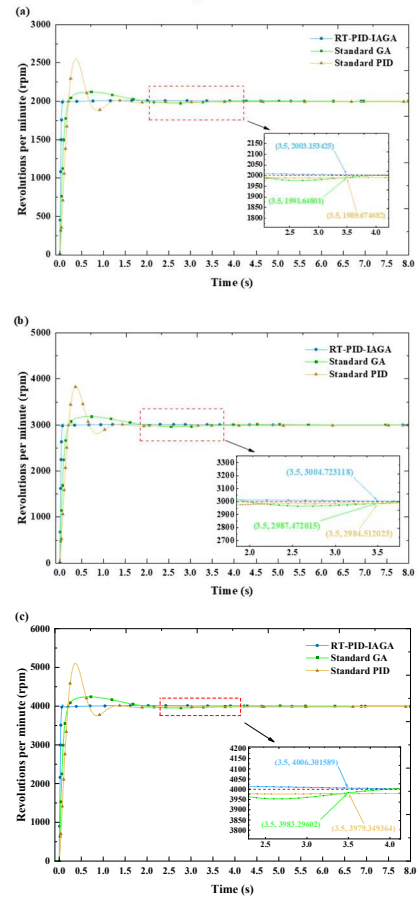


Fig. 6 The speed regulation process of the three methods under the static model (a) 2000 rpm (b) 3000 rpm and (c) 4000 rpm

As shown in Fig. 6(a), RT-PID-IAGA responds rapidly at approximately 0.2 s, rising to around 2050 rpm and converging near 2000 rpm at approximately 0.3 s. A magnified view of the figure shows that it fully converges to around 2003 rpm at approximately 3.5 s. Standard GA reaches about 2125 rpm at approximately 0.6 s and then gradually begins to converge, approaching 2000 rpm after 2 s. From the magnified data, it can be seen that it converges to around 1991 rpm after 3.5 s. Standard PID rises to approximately 2500 rpm at around 0.5 s, then drops to about 1800 rpm at approximately 0.9 s, indicating a large

overshoot and significant fluctuations. The magnified view shows that it approaches around 1989 rpm after 3.5 s, demonstrating a slower convergence rate. As shown in Fig. 6(b), RT-PID-IAGA responds rapidly within approximately 0.2 s, rising to around 3080 rpm and converging near 3000 rpm at approximately 0.3 s. A magnified view of the figure shows that it converges to around 3004 rpm at 3.5 s. Standard GA reaches about 3250 rpm at approximately 0.6 s and then gradually begins to converge, approaching 3000 rpm after 2 s. From the magnified data, it can be seen that it converges to around 2987 rpm at 3.5 s. Standard PID rises to approximately 3800 rpm at around 0.5 s and then drops to about 2700 rpm at approximately 1 s, indicating a large overshoot and significant fluctuations. The magnified view shows that it approaches around 2984 rpm at 3.5 s, demonstrating a slower convergence rate. As shown in Fig. 6(c), RT-PID-IAGA responds rapidly at approximately 0.2 s, rising to around 4100 rpm and converging near 4000 rpm at approximately 0.3 s. A magnified view of the figure shows that it converges to around 4006 rpm within 3.5 s. The standard GA reaches about 4300 rpm at approximately 0.75 s and then gradually begins to converge, approaching 4000 rpm after 2 s. From the magnified data, it can be seen that it converges to around 3983 rpm after 3.5 s. The standard PID rises to approximately 5100 rpm at around 0.5 s and then drops to about 3700 rpm at approximately 0.9 s, indicating a large overshoot and significant fluctuations. The magnified view shows that it converges to around 3979 rpm after 3.5 s, demonstrating a slower convergence rate.

Table 2 presents the classical performance indices of the three methods during the regulation process, including steady-state error, overshoot, and settling time. From Table 2, it can be observed that RT-PID-IAGA achieves the optimal values for all three indices, demonstrating lower overshoot and faster convergence, while the smaller steady-state error indicates higher control accuracy. Standard GA exhibits a low steady-state error and a moderate overshoot, but the longer settling time implies higher regulation accuracy with slower convergence. Standard PID shows both larger steady-state error and overshoot. Although its settling time is shorter, the regulation accuracy is comparatively lower.

Table 2. Performance indices of the regulation results for the three methods (stable model)

Speed (rpm)	Method	Steady-state error (rpm)	Overshoot (%)	Settling time (s) (bandwidth, $\pm 2\%$)
2000	RT-PID-IAGA	0.1	2.8	0.1
	Standard GA	0.1	6.0	1.6
	Standard PID	6.6	27.6	1.1
3000	RT-PID-IAGA	0.1	2.8	0.1
	Standard	0.1	6.0	1.6

	GA			
	Standard PID	13	27.6	1.1
4000	RT-PID-IAGA	0.2	2.8	0.1
	Standard GA	0.1	6.0	1.6
	Standard PID	10	27.5	1.1

To analyze the influence of motor parameter uncertainties on the proposed method, the Monte Carlo method was employed to randomly sample the parameters of the transfer function. Overshoot, settling time, and steady-state error were then used as performance metrics for the uncertainty analysis. Taking 2000 rpm as an example, the resulting uncertainty histograms are shown in Fig. 7.

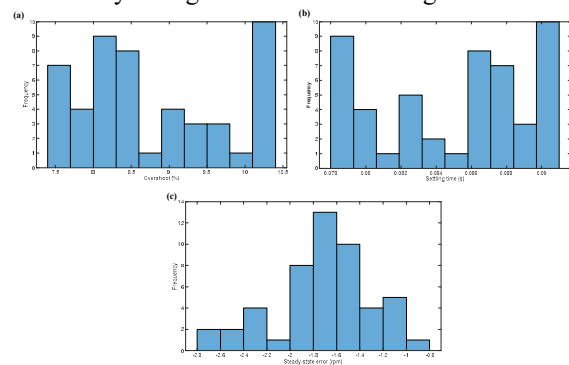


Fig. 7 Distribution of performance indices in 50 simulations at 2000 rpm (stable model) (a) overshoot (b) settling time and (c) steady-state error

From Fig. 7(a), it can be observed that for the steady-state model, the overshoot ranges from 7.5% to 10.5%, with the highest frequency occurring near 10.5%, followed by a concentration between 7.5% and 8.5%. Overall, the variation in overshoot is small, indicating good robustness, although a certain degree of uncertainty remains. From Fig. 7(b), it can be seen that the settling time ranges from 0.078 s to 0.09 s, with the highest frequency observed near 0.09 s, followed by concentrations around 0.078 s, 0.086 s, and 0.088 s. Overall, the variation in settling time is small, indicating good robustness; however, the distribution is relatively scattered, suggesting some uncertainty. From Fig. 7(c), it can be seen that the steady-state error ranges from -2.8 rpm to -0.8 rpm, with the highest frequency near -1.8 rpm and most values concentrated between -2 rpm and -1.4 rpm, again reflecting good robustness. In summary, RT-PID-IAGA demonstrates strong overall regulation performance and high robustness, making it suitable for speed regulation in various centrifuges. Nonetheless, a certain level of uncertainty remains, which may limit its applicability in high-precision centrifuge systems.

To demonstrate the robustness of RT-PID-IAGA, a single pulse disturbance with an amplitude of 200 is introduced during the simulation. This approach is used to evaluate the disturbance rejection capability of the method. Fig. 8 illustrates the speed regulation

process of the three methods under the influence of the impulse disturbance. As shown in Fig. 8, it is evident that in the disturbance rejection tests conducted at rotational speeds of 2000, 3000, and 4000 rpm, RT-PID-IAGA adjusts the speed more rapidly after being subjected to the disturbance compared with the other two methods. At 2000 rpm, the system converges to the target speed in approximately 3 s, while at 3000 and 4000 rpm, the convergence occurs in about 3.5 s. These results demonstrate that RT-PID-IAGA exhibits strong robustness in the speed regulation of the centrifuge.

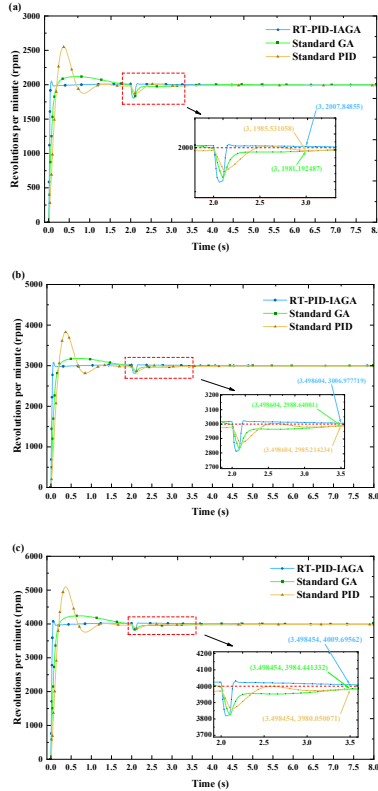


Fig. 8 The speed regulation process of the three methods under the influence of the impulse disturbance (a) 2000 rpm (b) 3000 rpm and (c) 4000 rpm

To investigate the regulation performance of RT-PID-IAGA under the time-varying model. In this study, time-varying damping is introduced to enhance the model, expressed as $B[1+0.2 \sin(t)]$. The simulation test results of the modified model are shown in Fig. 9. The classical performance indicators, including steady-state error, overshoot, and settling time, for the three methods with the introduction of time-varying damping are summarized in Table 3.

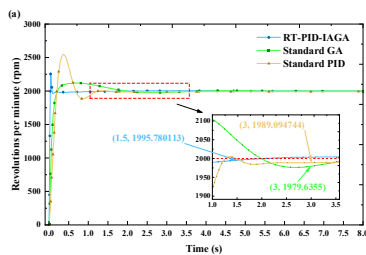
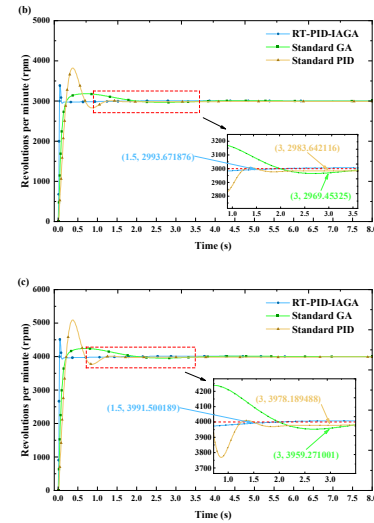


Fig. 9 The speed regulation process of the three methods under the time-varying model (a) 2000 rpm (b) 3000 rpm and (c) 4000 rpm

Speed (rpm)	Method	Steady-state error (rpm)	Overshoot (%)	Settling time (s) (bandwidth, $\pm 2\%$)
2000	RT-PID-IAGA	0.4	12.9	0.1
	Standard GA	0.1	6.0	1.6
	Standard PID	6.6	27.3	1.1
3000	RT-PID-IAGA	0.7	12.9	0.1
	Standard GA	0.1	6.0	1.6
	Standard PID	9.9	27.3	1.1
4000	RT-PID-IAGA	0.8	12.9	0.1
	Standard GA	0.1	6.0	1.57
	Standard PID	13.1	27.3	1.1

From Fig. 9, it can be observed that under the time-varying model, RT-PID-IAGA exhibits superior regulation performance for the three target rotational speeds of the centrifuge compared with the other two methods. The rotational speed converges to the vicinity of the target speed at approximately 1.5 s, with the smallest steady-state error. In contrast, both Standard GA and Standard PID approach convergence at around 3 s, yet their speed errors remain relatively large. From Table 3 it can be concluded that for all three target rotational speeds, the speed regulation curves under RT-PID-IAGA achieve smaller steady-state errors and shorter settling times. Although its overshoot is moderate among the three methods, its overall performance is superior, demonstrating high robustness. The speed regulation curves under Standard GA present smaller steady-state errors and overshoot but require a longer settling time, resulting in overall performance inferior to RT-PID-IAGA. Standard PID produces larger steady-state errors and overshoot, and although the settling time is moderate,

its overall performance is poor. Combining the results from Fig. 9 and Table 3 confirms that RT-PID-IAGA maintains excellent regulation performance under the time-varying model, thereby verifying its strong robustness.

To analyse the uncertainty of the time-varying model, this study employs the Monte Carlo method to randomly sample the parameters of the transfer function. The uncertainty analysis is then carried out using overshoot, settling time, and steady-state error as performance metrics. Taking 2000 rpm as an example, the resulting uncertainty histograms are shown in Figs. 10.

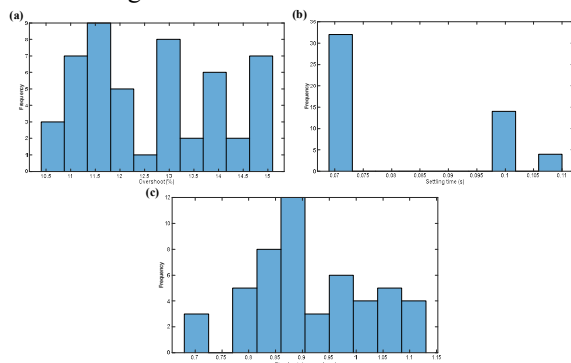


Fig. 10 Distribution of performance indices in 50 simulations at 2000 rpm (time-varying model) (a) overshoot (b) settling time and (c) steady-state error

As shown in Fig. 10(a), the system overshoot ranges from 10.4% to 15.1%, with the highest frequency occurring around 11.5%. Most values fall between 11% and 13%, while a few samples reach nearly 15%, indicating some deviation. Overall, the method demonstrates a certain degree of robustness in handling overshoot under time-varying models, though some uncertainty remains and high overshoot risks cannot be fully ruled out. According to Fig. 10(b), the settling time varies between 0.07 s and 0.11 s, with the highest frequency observed near 0.07 s. A smaller number of samples appear around 0.1 s and 0.11 s. This indicates good robustness and fast response speed in terms of settling time under time-varying models. Fig. 10(c) shows that the steady-state error falls within the range of 0.7 rpm to 1.1 rpm, with the highest frequency near 0.9 rpm. Some samples appear around 0.85 rpm. The method exhibits a certain level of robustness regarding steady-state error under time-varying models, although the distribution is relatively dispersed, suggesting some degree of uncertainty. In summary, the method provides good stability and effective performance in overall regulation, but a degree of uncertainty still exists.

In summary, compared to the other two methods, RT-PID-IAGA demonstrates faster response speed, smaller overshoot, and quicker convergence, further validating its superior performance and excellent control effectiveness in regulating the centrifuge speed. In addition, the robustness and regulation performance of the proposed method are further validated through pulse disturbance tests, time-varying model tests, and

uncertainty analyses.

To further verify the real-time adaptive adjustment capability of RT-PID-IAGA for the proportional, integral, and derivative parameters, taking the stable model as an example, Fig. 11 present the real-time variations of these three parameters throughout the entire simulation process. As shown in Fig. 11, the three parameters change dynamically over time, ensuring that the proportional, integral, and derivative parameters used in each feedback loop are always in their optimal state.

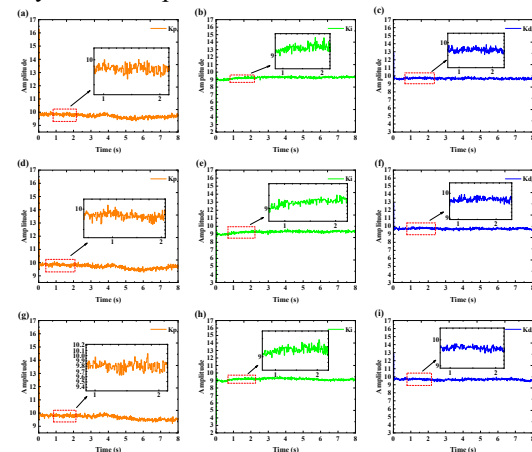


Fig. 11 The variation process of three parameters at a target speed (a) Kp at 2000 rpm (b) Ki at 2000 rpm (c) Kd at 2000 rpm (d) Kp at 3000 rpm (e) Ki at 3000 rpm (f) Kd at 3000 rpm (g) Kp at 4000 rpm (h) Ki at 4000 rpm and (i) Kd at 4000 rpm

CONCLUSIONS

RT-PID-IAGA aims to improve the speed regulation performance of the centrifuge during operation. It ensures that the centrifuge quickly reaches the desired speed while maintaining stable operation, thereby reducing energy consumption to some extent. Based on simulation analysis, the following conclusions can be drawn:

RT-PID-IAGA demonstrates faster response speed, smaller overshoot, and quicker convergence compared to the other two methods, significantly enhancing control performance. Although RT-PID-IAGA performs well in speed control of the centrifuge, the target speed is currently set manually. To further enhance adaptability, a humidity feedback loop can be introduced in the future. This loop would dynamically adjust the target speed according to the real-time moisture content of the produced sludge, achieving adaptive target speed adjustment.

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NOMENCLATURE

Symbol	Definition
F_c	the centrifugal force acting on the solid particles
m	the mass of the particles
ω	the angular velocity of the rotor
r	the radial distance of the particles from the rotation axis
RCF	Relative Centrifugal Force
g	the gravitational acceleration at the Earth's surface
u_d	the stator d-axis voltage
u_q	the stator q-axis voltage
R_s	the stator winding resistance
i_d	the stator d-axis current
i_q	the stator q-axis current
ψ_d	the stator d-axis flux linkage
ψ_q	the stator q-axis flux linkage
ω_e	the electrical angular velocity
u_{dr}	the rotor d-axis voltage
u_{qr}	the rotor q-axis voltage
R_r	the rotor winding resistance
i_{dr}	the rotor d-axis current
i_{qr}	the rotor q-axis current
ψ_{dr}	the rotor d-axis flux linkage
ψ_{qr}	the rotor q-axis flux linkage
ω_r	the mechanical angular velocity
L_s	the stator self-inductance
L_r	the rotor self-inductance
L_m	the main magnetizing inductance
p	the number of pole pairs
T_e	the electromagnetic torque
B	the viscous damping coefficient
$B\omega_r$	the viscous damping term
C_d	the fluid resistance coefficient
$C_d\omega_r^2$	the slurry fluid resistance term
J	the equivalent moment of inertia
ω_{set}	the target speed
$\omega(x)$	the actual speed
x	an individual in the population
E_{speed}	the speed error
$\omega(x)_{max}$	the maximum output
E_{ovs}	the magnitude of the overshoot
$0.02\omega_{set}$	the bandwidth threshold

τ	all later time instants starting from time t
$\omega(\tau)$	the speeds at all later time instants
E_{ts}	the settling time
$w0$	the weight of the speed error
$w1$	the weight of the overshoot magnitude
$w2$	the weight of the settling time
$fitness(x)$	the fitness function
$fitness_{min}$	the minimum fitness
$fitness_{max}$	the maximum fitness
$fitness_{avg}$	the average fitness
PC_{max}	the upper limit of the crossover rate
PC_{min}	the lower limit of the crossover rate
PM_{max}	the upper limit of the mutation rate
PM_{min}	the lower limit of the mutation rate