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OPTIMIZING ADAPTABILITY AND RATIONAL CONTROL STRATEGIES FOR CYCLOGYRO SYSTEMS

The **cyclogyro**, *due to its potential applications in aviation and complex dynamic characteristics, has become the focus of our research. Although traditional PID control is effective in many cases, it may struggle in handling the complex nonlinear dynamics often encountered in cyclogyro systems. Therefore, the* **objective** *of this study was to design and implement a control system for the cyclogyro based on optimized strategies to improve the system stability and response speed. The proposed approach integrates mathematical modeling, optimization algorithms, real-time data analysis, and feedback mechanisms to predict and adjust the system behavior. The performance of traditional PID control was compared with that of Model Predictive Control (MPC) in a dual-target speed control system. The* **numerical simulation results** *demonstrated that the MPC-based optimized control significantly outperformed PID control, achieving higher stability and faster response speed when dealing with external disturbances and nonlinear dynamic changes, with the average response time reduced by 92.5% ($p < 1e-10$). This enhanced performance is due to the system's ability to dynamically adjust its control strategies in response to varying environmental conditions. The* **conclusions** *of this research highlight the substantial advantages of optimized control strategies for cyclogyro systems, offering new insights into the development of complex aviation control systems and demonstrating the potential of these strategies to enhance both performance and adaptability.*

Keywords: *Cyclogyro; Control System; PID Control; Model Predictive Control (MPC); Optimized Control Strategy; Nonlinear Dynamics; System Stability; Response Speed; Numerical Simulation; Adaptability.*

1. Introduction

1.1 Motivation

With the continuous development of low-altitude aircraft technology [1], the cyclogyro [2], as a new type of flying platform, is gradually demonstrating its application potential in various fields [3], especially in urban air mobility, drones, and military reconnaissance. Thanks to its unique rotating wing design [4], the cyclogyro can generate lift while also providing thrust, which enables it to perform exceptionally well in tasks such as vertical takeoff and landing (VTOL), low-speed flight, and hovering [5].

The semi-empirical analytical model proposed by Leger Monteiro J.A. et al. [6] provides more accurate structural and aerodynamic predictions for cyclogyro design. In practical aerodynamic design, optimizing the balance between thrust generation and power consumption is crucial. This balance enables the rotorcraft to quickly adjust thrust during rapid maneuvers, while minimizing excessive energy consumption and avoiding instability, critical factors for achieving high maneuverability in flight. Despite the promising advantages of cyclogyros in various mission scenarios, including their potential for exceptional maneuverability in complex environments, significant challenges persist in the design and implementation of their control systems. Du F. et al. [7] developed a cyclogyro featuring two circumferential propellers and a tail propeller. The two circumferential propellers, which rotate in the same direction, generate lift and control roll, while the tail propeller adjusts the pitch moment and also contributes to lift, as well as pitch and yaw control. However, flight tests with roll step inputs revealed that the cyclogyro exhibited poor stability and controllability.

In the design of a cyclogyro, especially in systems with two coaxial propellers rotating in the same direction, the gyroscopic effect [8] can be significant. Kou, H. et al. [9] established a rotor model considering rub-impact, geometric nonlinearity, local vibrations, and the gyroscopic effect, and analyzed the dynamic behavior of wide-chord blades under different operating conditions. They investigated the impact of rub-impact on rotor stability. By comparing with similar physical models, it can be drawled the conclusion that the gyroscopic effect generates additional torque during flight when the aircraft undergoes roll or other attitude changes, which can significantly affect the stability of the aircraft. Specifically, the gyroscopic effect refers to the phenomenon where the axis of rotation of a rotating object resists changes in direction, and its angular momentum remains fixed during

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high-speed rotation. To change the direction of its rotational axis, an external torque is required [10]. Therefore, when the aircraft undergoes attitude changes [11], such as rolling, pitching, or yawing, the rotating propellers generate a counteracting torque that resists the attitude change, thus affecting the aircraft's stability [12].

1.2. State of the art

Existing research indicates that the design of cyclogyro requires optimizing the balance between thrust generation and energy consumption to ensure rapid thrust adjustments during quick maneuvers while avoiding excessive energy expenditure and instability. Researchers have proposed various models and methods to analyze the dynamic behavior of cyclogyro, including considerations of gyroscopic effects, geometric nonlinearity, and local vibrations. While conventional PID control techniques are successful in numerous applications, their effectiveness is constrained in complex nonlinear dynamic environments, especially in scenarios involving rapid maneuvers and external disturbances.

In the application of cyclogyro, the gyroscopic effect is particularly prominent because two counter-rotating propellers generate coupled torques. When the aircraft performs rapid roll or aggressive maneuvers, the gyroscopic effect of the propellers can cause coupling between the roll [13], pitch, and yaw axes, thereby increasing the complexity of the aircraft’s control. This coupling effect [14] is especially significant during rapid control inputs and can lead to delayed or exaggerated responses, which negatively impacts flight stability. Dominik Saile et al. [15] found that the resonant frequency induced by the coupling effect appears to amplify the unfavorable fluctuations in the base region, thereby exacerbating the magnification of unstable loads, which in turn introduces significant stability issues during the flight process. In other word, when attempting a quick roll, the counteracting torque generated by the propellers may suppress the roll response, causing a lag effect [16]. This lag, particularly in complex flight environments, can exacerbate the aircraft's instability, leading to control responses that are not as expected, and thus affecting the aircraft's handling performance. In designing cyclogyro, factors such as the distribution of the aircraft's mass, the rotational direction and speed of the propellers, and other parameters influence the degree of the gyroscopic effect. Therefore, precise dynamic analysis is required to optimize the control system [17], ensuring that the aircraft maintains stable handling performance under various flight conditions.

In the process of optimizing control systems, reducing the response time of the system is crucial [18]. This not only helps to effectively compensate for adverse factors such as gyroscopic effects and lag effect, but also enhances the system's adaptability in complex flight environments. The response time of the control system directly affects the aircraft's ability to react to external disturbances, especially during high-speed flight or rapid attitude changes. The challenge lies in how to instantaneously adjust the control inputs to counteract the inertial effects caused by the gyroscopic effect and the delay effects due to control latency. By optimizing control strategies to reduce system lag and inertial effects, the stability and maneuverability of the aircraft can be significantly improved, ensuring efficient and precise control performance even under extreme flight conditions.

Aircraft are exposed to multiple external disturbances during flight, including changes in airflow, load variations, and environmental conditions. While traditional PID control [19] generally delivers effective control in most scenarios, its performance may be constrained in complex nonlinear dynamic environments. For example, Kim J.et al. [20] studied the shock-capturing strategy based on PID control and found that, although PID control can effectively capture and stabilize shock waves, it is highly dependent on the selection of parameters and may exhibit excessive sensitivity to high-frequency noise or delayed response when dealing with complex flow. One year later, they investigated the application of the PID-based SPID method in multidimensional compressible flows and found that PID faces challenges in selecting gain parameters, insufficient anti-windup mechanisms, and poor controller adaptability when capturing shock waves [21]. These issues can further lead to increased response delays and enhanced lag effects, ultimately resulting in a series of instabilities.

1.3. Objectives and the approach

Rational control [22] refers to the use of systematic and theoretical methods in control system design to optimize control strategies and achieve desired control objectives. It integrates mathematical modeling, optimization algorithms, real-time data analysis, and feedback mechanisms to precisely control the target by understanding system dynamics and environmental changes [23]. Rational control aims to predict and adjust system behavior, enhancing robustness, response speed [24], and adaptability. The ability to update control models and parameters in real time further improves system stability and reliability [25]. This real-time adaptability is crucial for complex, dynamic systems, where environmental conditions and system behaviors may change unpredictably. By continuously refining control strategies, rational control can mitigate performance degradation and reduce the impact of disturbances or uncertainties. Given these benefits, implementing rational control strategies in aircraft control systems is highly significant [26], as it ensures not only optimal performance under various conditions but also long-term system stability and safety in highly dynamic environments.

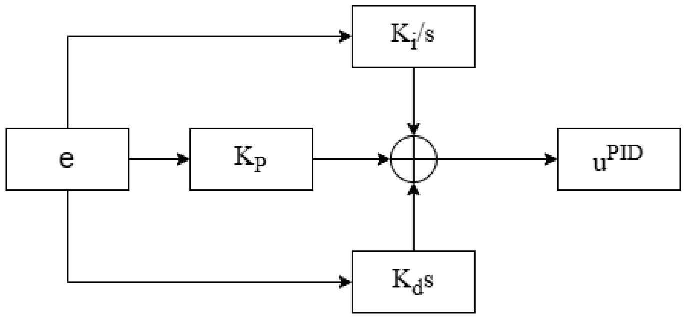

Fig. 1. Control block diagram of the PID controller

In complex nonlinear dynamic environments, such as cyclogyro control system design, traditional PID control methods, while effective in many applications, face limitations when confronted with high nonlinearity [27], time-varying characteristics [28], and factors like the gyroscopic effect and control delays in systems like cyclogyros. Particularly during fast maneuvers, external disturbances, and complex flight environments with multi-degree-of-freedom coupling [29], PID control often fails to provide sufficient accuracy and response speed [30], compromising stability and maneuverability. Therefore, a key challenge of this research is to overcome the limitations of traditional PID control and develop an optimized control strategy using rational methods. This strategy should enhance rotorcraft performance and improve response times. By leveraging advanced algorithms and real-time data processing, rational control can provide more precise and adaptive solutions, ensuring better system performance in unpredictable environments.

2. Rational control methods of cyclogyro

Rational control refers to the use of systematic and theoretical methods in control system design to optimize control strategies and achieve desired control objectives. It typically integrates mathematical modeling, optimization algorithms, real-time data analysis, and feedback mechanisms to precisely control the target by understanding system dynamics and environmental changes. Rational control emphasizes predicting and adjusting system behavior to enhance robustness and response speed [31].

Implementing rational control strategies in aircraft control systems is highly significant. Aircraft are exposed to multiple external disturbances during flight, including changes in airflow, load variations, and environmental conditions. While traditional PID control [32] generally delivers effective control in most scenarios, its performance may be constrained in complex nonlinear dynamic environments. Rational control enhances adaptability to changes through real-time updates of control models and parameters, thereby boosting system stability and reliability.

For the dual-target speed control system of cyclogyro, it expected the current velocities ω_c^1 and ω_c^2 to be regulated by the controller, progressively approaching or achieving the desired speeds. For each speed control system, the transfer function $G(s)$ of the PID controller is expressed as follows:

$$G(s)=K_p+\frac{K_i}{s}+K_v s\,. \qquad (1)$$

In this case, K_p represents the proportional gain, K_i represents the integral gain, and K_v represents the derivative gain.

In Fig. 1, the signal begins at the input error e on the left side, passes through the proportional controller K_P , and then flows into an addition node. At this moment, the outputs from the integral controller K_i/s and the derivative controller $K_d s$ also feed into the addition node, where all input signals are computed together. The final output signal is u^{PID} , which represents the system's control output.

Rational control significantly enhances robustness, allowing adaptive handling of uncertainties and external disturbances in the system, enabling the control system to remain stable under various complex environmental conditions. Additionally, by leveraging advanced optimization algorithms and real-time data analysis, rational control boosts system response speed, enabling quicker adaptation to changes, minimizing delays, and improving control accuracy. Rational control also features powerful adaptability, dynamically adjusting control strategies according to real-world conditions, adapting to shifts in system behavior, and enhancing the overall adaptability of the control system. Utilizing methods like Model Predictive Control (MPC) [33], rational control can predict future system behavior with higher precision, allowing proactive control adjustments to optimize system performance [34].

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The fundamental concept of MPC control is to predict the system output over a future time horizon and determine the control inputs using optimization algorithms. Assuming the prediction horizon is N, the optimization objective function can be formulated as:

$$J=\sum_{i=1}^{N}\left(y(t+i|t)-y_{target}\right)^2+\lambda\sum_{i=1}^{N}u(t+i|t)^2, \quad (2)$$

where $y(t+i|t)$ is the predicted output at future time step i from time t, y_{target} is the target output, and λ is the weighting coefficient of the control input.

The system receives two reference input signals $r_1(t)$ and $r_2(t)$, which represent the setpoint or desired state of the system at time t, forming the input signal vector $r(t)=\left[r_1(t) \quad r_2(t)\right]^T$.

The error signals $e_1(t)$ and $e_2(t)$ are determined by calculating the difference between the current reference inputs and the actual outputs:

$$e_1(t)=r_1(t)-\omega_1(t),$$
$$e_2(t)=r_2(t)-\omega_2(t).$$

These error signals constitute the error vector

$$e(t)=\left[e_1(t) \quad e_2(t)\right]^T.$$

The weighting matrix $\mathbf{W}$ is employed to regulate the weighting of each error signal to accommodate various control needs:

$$W=\begin{bmatrix} W_1 & 0 \\ 0 & W_2 \end{bmatrix}.$$

The weighted error signals are:

$$e_W(t)=We(t).$$

Perform PID control on the weighted error signals to derive the PID control signals $u_1^{PID}(t)$ and $u_2^{PID}(t)$

$$u_i^{PID}(t)=K_p e_i(t)+K_i\int_0^t e_i(\tau)d\tau+K_d\frac{de_i(t)}{dt}.$$

The MPC controller uses the system model for prediction and optimization, resulting in the calculation of MPC control signals $u_1^{MPC}(t)$ and $u_2^{MPC}(t)$. Generally, MPC derives the control signals by solving the following optimization problem [35]:

$$J=\sum_{k=0}^{N_p-1}\begin{pmatrix} e_W(t+k)^T Q e_W(t+k)+ \\ +u(t+k)^T R u(t+k) \end{pmatrix}, \quad (3)$$

where N_p is the prediction horizon length, Q is the error weighting matrix, and R is the control input weighting matrix. The control input vector is $u(t)=\left[u_1(t) \quad u_2(t)\right]^T$. Optimize this function to obtain the optimal solution $u(t)=\left[u_1^{MPC}(t) \quad u_2^{MPC}(t)\right]^T$ under constraints.

By integrating the PID control signals with the MPC control signals, the final control output is formed:

$$u_1(t)=\alpha u_1^{PID}(t)+(1-\alpha)u_1^{MPC}(t),$$
$$u_2(t)=\alpha u_2^{PID}(t)+(1-\alpha)u_2^{MPC}(t).$$

Where α represents the weighting factor for the combination of control signals.

The final control signal $u(t)=\left[u_1(t) \quad u_2(t)\right]^T$ acts on the system, generating outputs $\omega_1(t)$ and $\omega_2(t)$, with feedback creating the closed-loop control $\omega(t)=\left[\omega_1(t) \quad \omega_2(t)\right]^T$.

As shown in Fig. 2, the dual-objective aileron control block diagram illustrates a hybrid control strategy that combines the advantages of PID and MPC controllers, aiming for efficient control system design. The PID controller can respond quickly to error signals and make corrections, effectively reducing transient errors. In contrast, the MPC controller, utilizing the system's mathematical model, predicts future system states and optimizes current control inputs, considerably enhancing the system's steady-state performance and overall robustness. This hybrid control strategy offers key benefits, including fast response, optimized control, robustness, and flexible adjustment capabilities. The PID controller ensures rapid error correction, whereas the MPC controller enhances the control system's steady-state performance and its ability to handle complex operating conditions through future prediction and optimization. Moreover, by modulating the weighting of PID and MPC controllers in the overall control signal, the system can flexibly adapt to varying control demands.

In this hybrid control strategy, the essence of rational control is represented by the MPC controller. The MPC controller leverages the system model for prediction and decides on the optimal control inputs through solving optimization problems. This process encompasses several aspects, including predictive capability, optimization computation, and preventive adjustments. First, the MPC controller forecasts the

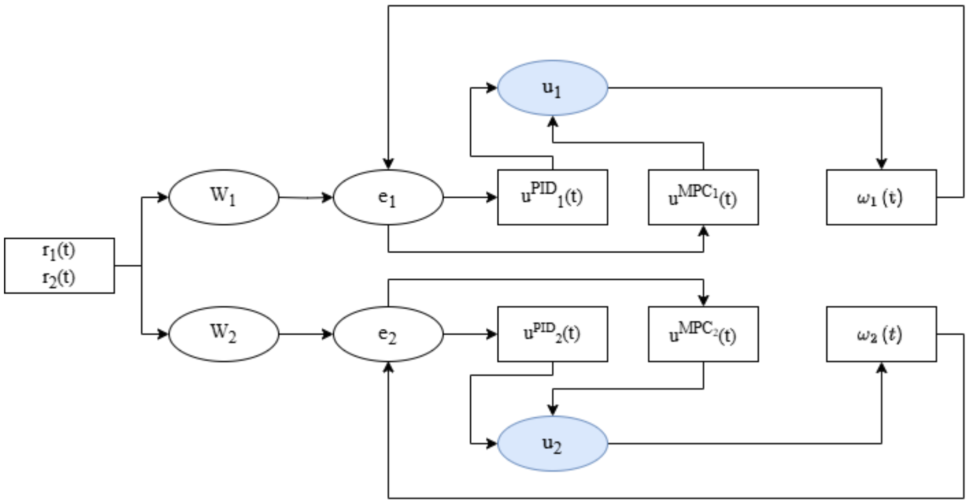

Fig. 2. Dual-degree-of-freedom control block diagram for cyclogyro

system behavior for a future time frame based on the system model and future reference trajectories, establishing an optimized control strategy. Secondly, the MPC controller ensures that the control inputs minimize errors while satisfying the physical system constraints by solving optimization problems with constraints. Finally, the MPC controller anticipates potential deviations and changes in the system, adjusting the control strategy in advance to minimize these deviations, thus demonstrating the superiority of rational control.

The cyclogyro system is a typical MIMO system [36] where precise control is critical for industrial and aerospace applications. The goal is to ensure that the two rotational speed variables track the reference signals quickly and accurately. To evaluate the performance of PID versus MPC control, had developed a case study comparing the control effectiveness of both PID and MPC for controlling the two rotational speeds in the cyclogyro system.The system is represented as a dual-input dual-output model consisting of two independent first-order systems, expressed as:

$$A=\begin{pmatrix} 1\text{-}Ts & 0 \\ 0 & 1\text{-}Ts \end{pmatrix}, \quad B=\begin{pmatrix} Ts & 0 \\ 0 & Ts \end{pmatrix}.$$

The sampling time is set to $Ts = 0.1s$, with the reference signals being $\omega_1=1$ and $\omega_2=2$, respectively. Two PID controllers have been designed to individually control the two target rotational speeds. For the first output, the PID controller parameters are set as: proportional gain $Kp_1=1$, integral gain $Ki_1=0.1$, and derivative gain $Kd_1=0.01$. For the second output, the PID controller parameters are set as: proportional gain $Kp_2=1.5$, integral gain $Ki_2=0.15$, and derivative gain $Kd_2=0.02$. When designing the MPC controller, the prediction horizon is set to $H=10$, meaning that the controller will predict the system behavior for the next 10-time steps. The state weighting matrix Q is set to I_H (a unit matrix of size $H\times H$), meaning that the state errors within the prediction horizon are penalized equally. The control weighting matrix R is set to $0.01I_H$, which is a unit matrix of size $H\times H$ multiplied by 0.01. This means that while changes in control input are penalized to maintain smooth control actions, the penalty applied is less significant than that for state errors. Consequently, the optimization places a higher priority on minimizing state deviations, allowing for more flexibility in control input adjustments without compromising overall system performance.

In terms of control performance, the PID controller demonstrates slower response speed and considerable steady-state error (Fig. 3). The PID1 controller rises quickly but fails to reach the target reference value within 20 seconds, showing poor steady-state performance. Although PID1 responds quickly, it does not eliminate steady-state error, resulting in long-term deviation. In comparison, PID2 has a faster dynamic response than PID1 but also experiences overshoot and steady-state error within about 25 seconds, indicating shortcomings in both dynamic performance and steady-state control. Overall, the PID controller struggles to maintain high-precision control, with non-negligible error.

Compared to the PID controller, the MPC controller demonstrates significant advantages in dynamic response (Fig. 4). The MPC1 controller outperforms the PID controller in the speed of approaching the target reference value. Although it does not fully stabilize within 20s, its dynamic performance is clearly better. MPC1's control signal can quickly follow the changes in the reference

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value, reflecting its strong dynamic response ability, although there are still some limitations in steady-state accuracy. However, the MPC2 controller exhibited the best performance, stabilizing rapidly and maintaining a steady control signal throughout the entire process, suggesting that it not only has a faster response speed but also surpasses other controllers in both stability and steady-state accuracy. Through optimized control of the system, MPC2 minimizes steady-state error and fluctuations to the greatest extent, further improving the system's control performance.

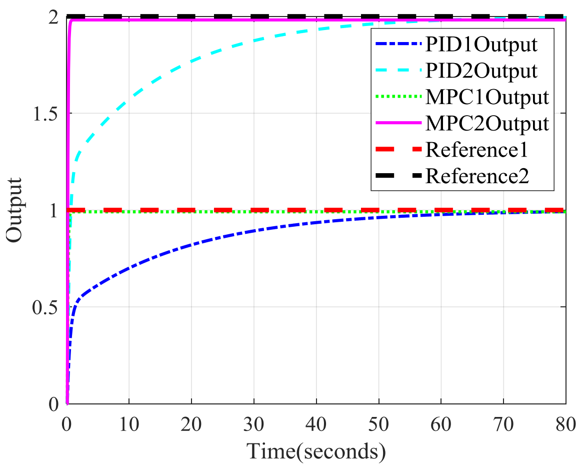

Fig. 3. Output vs Time (seconds)

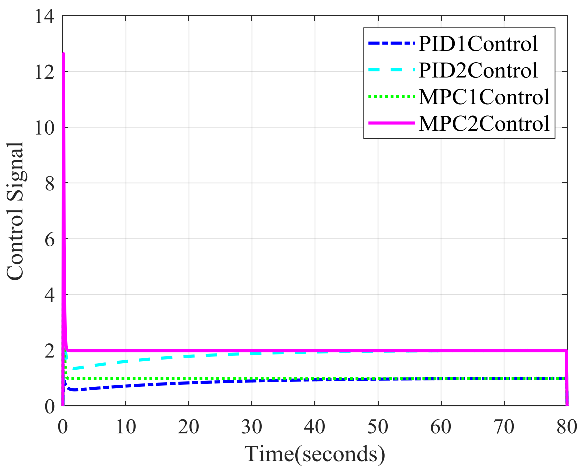

Fig. 4. Control Signal vs Time (seconds)

In terms of error performance, the MPC controller outperforms the PID controller, especially in terms of error convergence speed and steady-state accuracy (as illustrated in Fig. 5). The errors in PID1 and PID2 controllers are initially large and converge slowly. Although they eventually decrease, considerable residual error remains during the steady-state phase, limiting system performance during prolonged control. In contrast, the MPC controller has a smaller initial error and significantly faster convergence speed. Particularly for the MPC2 controller, it maintains near-zero error throughout the entire control process, showing its exceptional steady-state accuracy and rapid error convergence ability. MPC2 not only effectively suppresses the accumulation of errors but also maintains extremely small steady-state error, showcasing its advantages in precise control and efficient response.

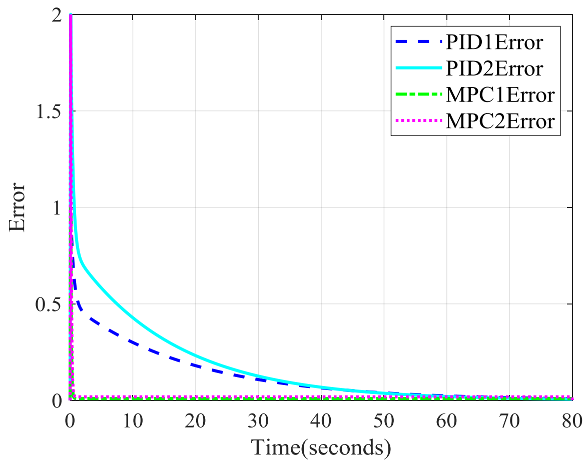

Fig. 5. Error vs Time (seconds)

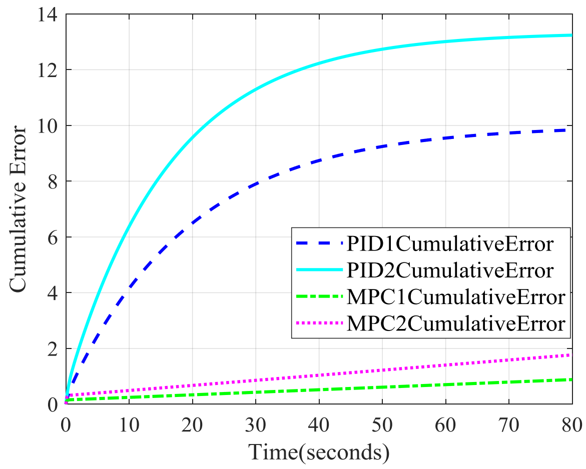

Fig. 6. Cumulative Error vs Time (seconds)

From the perspective of accumulated error (as illustrated in Fig. 6), the PID controller shows larger cumulative error over long-term operation, especially in PID1 and PID2 controllers. Although the error decreases gradually, significant residual error remains during the steady-state phase. This suggests that while the PID controller can offer relatively fast response in the short term, its error may progressively accumulate in long-term steady-state control, ultimately impacting the overall system performance. In comparison, the MPC controller has considerably smaller accumulated error during long-term operation, particularly MPC2, which is capable of maintaining an error close to zero for an extended period, showing more stable and precise control performance. Therefore, the MPC controller, especially MPC2, demonstrates stronger competitiveness within the entire control system, owing to its superior dynamic response, steady-state accuracy, and error suppression capability.

Overall, the MPC controller outperforms the PID controller in all aspects, particularly in dynamic response, steady-state accuracy, and error convergence, with MPC2 being undoubtedly the best choice. While the PID controller has some advantages in the short term, its long-term performance is constrained by steady-state and accumulated errors, making it challenging to fulfill high-precision and stability demands.

The average response time [37] for PID and MPC control can be calculated as:

$$\bar{T}_{PID} = \frac{1}{n_{PID}} \sum_{i=1}^{n_{PID}} T_{PID,i} \,,$$

$$\bar{T}_{MPC} = \frac{1}{n_{MPC}} \sum_{i=1}^{n_{MPC}} T_{MPC,i} \,,$$

where $\bar{T}_{PID}$ and $\bar{T}_{MPC}$ represent the average response time for PID and MPC control, respectively, and n_{PID} and n_{MPC} are the sample sizes for each group. $T_{PID,i}$ and $T_{MPC,i}$ represent the individual response times for each sample.

The average reduction [38] in response time R is calculated as:

$$R=\frac{\bar{T}_{PID}-\bar{T}_{MPC}}{\bar{T}_{PID}}\cdot 100\% \,. \quad (4)$$

The confidence interval M [39] is the range in which the true value of the parameter is included. For the PID control system response time:

$$M_{PID}=\bar{T}_{PID} \pm z \times \frac{\sqrt{\frac{1}{n_{PID}} \sum_{i=1}^{n_{PID}} (T_{PID,i}-\bar{T}_{PID})^2}}{\sqrt{n_{PID}}}.$$

For the confidence interval of the MPC control system response time:

$$M_{MPC}=\bar{T}_{MPC} \pm z \times \frac{\sqrt{\frac{1}{n_{MPC}} \sum_{i=1}^{n_{MPC}} (T_{MPC,i}-\bar{T}_{MPC})^2}}{\sqrt{n_{MPC}}}.$$

The results presented in Fig. 3 - 6 indicate a significant advantage of MPC over PID control in terms of stabilization time. Specifically, with the error threshold set to 0.05, both PID1 and PID2 achieved system stabilization in 45.1s. In stark contrast, MPC1 and MPC2 managed to stabilize the system in a mere 0.6s. This observation demonstrates a substantial reduction in stabilization time for MPC, with a remarkable decrease of 44.5s for PID1 compared to MPC1 and 44.4s for PID2 compared to MPC2. Consequently, the average reduction in stabilization time for MPC relative to PID is calculated to be an impressive 99.7%. This highlights the superior efficiency of MPC in rapidly achieving system stabilization, making it an effective control strategy. These findings underscore the potential of MPC for applications requiring fast and precise control responses, enhancing the performance, efficiency, and reliability of control systems.

3. Comparison of PID and MPC control systems with disturbances

The study of the comparison between PID and MPC control systems in the presence of disturbances is essential for understanding how these two control strategies perform under real-world conditions, where disturbances are inevitable. While PID controllers are widely used for their simplicity and ease of implementation, their effectiveness diminishes when confronted with large or time-varying disturbances, particularly in complex systems with multiple variables. MPC, with its ability to predict and optimize, offers a more robust solution but requires careful tuning and reliable system models. Investigating this comparison is crucial for selecting the most appropriate control strategy for a given application, especially in dynamic environments where disturbances can significantly affect performance. This analysis also helps identify potential trade-offs between simplicity and precision in control design.

Consider a discrete-time linear time-invariant (LTI) system [40] described by the following equations:

$$\begin{cases} x(k+1)=Ax(k)+Bu(k)+Ed(k) \\ y(k)=Cx(k)+Du(k)+n(k) \end{cases}, \quad (5)$$

where $x(k)$ denotes the state vector at time step k. $u(k)$ is the control input. $y(k)$ is the system output. $d(k)$ represents the disturbance signal. $n(k)$ is the measurement noise. $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}, \mathbf{E}$ are system matrices of appropriate dimensions.

3.1. PID Controller

PID controller is defined by the following control law (see Fig.1):

$$u_{PID}(k)=K_p e(k)+K_i \sum_{i=0}^{k} e(i)+K_d \left(e(k)-e(k-1)\right),$$

where: $e(k)=r(k)-y(k)$ is the control error, with $r(k)$

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being the reference signal; K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively.

3.2. Model Predictive Controller (MPC)

MPC optimizes control action by solving a finite horizon optimization problem at each time step. The optimization problem can be formulated as:

$$\min_{U(k)} \sum_{i=1}^{N} \begin{bmatrix} \left(y_p(k+i|k)-r(k+i)\right)^T \times \\ Q\left(y_p(k+i|k)-r(k+i)\right)+ \\ +\Delta u(k+i-1)^T R \Delta u(k+i-1) \end{bmatrix},$$

where: $y_p(k+i|k)$ is the predicted output at time $k+i$ based on information available at time k. $U(k)=[\Delta u(k),\Delta u(k+1),\cdots,\Delta u(k+N-1)]^T$ represents the sequence of future control input changes. $\Delta u(k)=u(k)-u(k-1)$ denotes the change in control input. Q and R are weighting matrices for the output error and control effort, respectively. N is the prediction horizon.

3.3. Impact of Disturbances

The impact of disturbances on control systems [41] refers to the effect that external or internal disruptions have on the performance of a system and its ability to maintain desired outputs. Disturbances can arise from various sources, such as environmental changes, sensor noise, modeling errors, or unanticipated system dynamics. These disturbances can cause deviations from the intended trajectory, leading to performance degradation, instability, or even system failure if not properly managed.

Disturbances $d(k)$ can be either known or unknown signals affecting the system's state and output in Eq.(5). During control, disturbances $d(k)$ and noise $n(k)$ influence the system output $y(k)$, thereby affecting the control error $e(k)$. Both PID and MPC controllers adjust their control actions based on the current error and system model to minimize this error and achieve the control objective.

According to natural statistical laws, external disturbance $d(k)$ and measurement noise $n(k)$ are typically independent Gaussian white noise [42]:

$$d(k) \sim N(0,\sigma_d^2),$$
$$n(k) \sim N(0,\sigma_n^2),$$

where: $N(0,\sigma_d^2)$ denotes a Gaussian distribution with a mean of 0 and a variance of σ_d^2. $N(0,\sigma_n^2)$ denotes a Gaussian distribution with a mean of 0 and a variance of σ_n^2.

3.4. Cumulative Error

To evaluate the performance of the controllers over the simulation period, compute the cumulative error [43] denoted as e_C, defined by:

$$e_C = \sum_{k=0}^{T} e(k)^2 \sqrt{2} \qquad (6)$$

where T is the total simulation duration; $e(k)$ is the control error.

The error variance of the MPC controller is significantly smaller than that of the PID controller, especially for the MPC2 controller, whose error variance shows almost no fluctuation, demonstrating excellent stability and precision (Fig. 7). In contrast, the error variance of the PID controller fluctuates more significantly, especially in the PID1 controller, where the fluctuation range reaches 0.02 to 0.04, indicating system instability. The error variance fluctuation range of the PID1 controller is from 0.02 to 0.04, showing substantial variability and indicating significant instability in the system.

Especially in the early stages, the controller fails to effectively reduce the error, and the system response exhibits strong oscillations. Although the error variance gradually decreases to some extent, the fluctuation amplitude remains large, reflecting the limitations of the PID controller in handling disturbances. Compared to the PID1 controller, the error variance of the PID2 controller is reduced, with a fluctuation range from 0.015 to 0.035. Although the fluctuation amplitude has decreased, the error variance remains large, indicating that the PID2 controller still has significant deficiencies in system stability. In particular, when tracking the target value, the PID2 system shows significant overshoot and slower convergence, failing to effectively achieve the ideal steady-state performance. This indicates that although the precision of the PID2 controller has improved, its overall performance is still inferior to that of the MPC controller.

In the case of the MPC1 controller , the error variance fluctuation is small, ranging from 0.01 to 0.02. The MPC1 controller effectively suppresses error fluctuations, with its fluctuation amplitude significantly lower than that of the PID controller, showing better stability. This indicates that the MPC controller, when facing disturbances, can effectively maintain stable operation of the system through model prediction and optimization control strategies, with more precise control of error fluctuations. The MPC2 controller shows the smallest error variance, with a fluctuation range of only 0.005 to 0.015, exhibiting almost no fluctuation and demonstrating outstanding stability and precision. This suggests that the MPC2 controller has a clear advantage in system stability and accuracy, effectively suppressing error accumulation and fluctuations during system operation, thus showing the best control performance.

Furthermore, MPC demonstrates better stability and accuracy in tracking the reference value (Fig. 8). The output of the MPC2 controller consistently follows the target value closely, with very small errors and almost no fluctuation. In contrast, the PID controller, especially PID1, fails to effectively track the target value, showing significant deviation and instability. For the PID1 controller , its output fluctuates within a range of 0.5 to 1.0 when tracking the target value, failing to stabilize at the target value. This indicates that the PID1 controller has significant deviation and instability in tracking the target value, and the system fails to adjust promptly to reduce errors, showing poor tracking accuracy and stability. The output of the PID2 controller fluctuates within a range of 1.0 to 1.8 and frequently overshoots the target value, showing significant overshoot and instability. This indicates that the PID2 controller has significant deviation during the tracking process, and the system is more sensitive to disturbances, failing to stabilize near the target value.

Although the performance of PID2 has improved compared to PID1, its accuracy and stability are still poor. In contrast, the output of the MPC1 controller fluctuates within a range of 0.8 to 1.0, which is relatively close to the target value, with smaller fluctuation, indicating good tracking accuracy and stability. The MPC1 controller is able to quickly adapt to system changes during tracking and effectively adjust control signals, ensuring the system output remains stable near the target value, demonstrating good control performance. The output of the MPC2 controller fluctuates within a range of 1.8 to 2.2, closely tracking the target value, demonstrating outstanding steady-state performance and minimal error. The MPC2 controller experiences almost no fluctuation when tracking the target value and can maintain stable output under disturbances, demonstrating extremely high control accuracy and good adaptability. Compared to the PID controller, MPC2 can track the target value more accurately, showing a more ideal control performance.

The MPC controller effectively mitigates error accumulation (Fig. 9). Both MPC1 and MPC2 maintain cumulative errors below 0.1, with MPC2 demonstrating almost negligible error accumulation. In contrast, the PID controller shows increasing cumulative errors over time. PID1 reaches an error of 0.5 after 30 seconds, while PID2 reaches 0.7, with the latter exhibiting more significant error fluctuations. The cumulative error of PID1 increases steadily without effective correction, indicating a failure to adjust and prevent error accumulation during long-term operation, resulting in poor steady-state performance. PID2 has a cumulative error peak of 0.7, with substantial fluctuation, showing slight improvement over PID1 but still experiencing significant error accumulation. The control performance of PID2 is severely impacted by system disturbances, leading to sustained error accumulation. In the MPC1 controller , the cumulative error is consistently maintained around 0.1, demonstrating good error control capabilities. The MPC1 controller can relatively stably keep the error within a low range and effectively reduce error accumulation during long-term operation, demonstrating excellent error suppression ability. The cumulative error of the MPC2 controller is below 0.05, with almost no error accumulation, showing outstanding precision and stability. This controller can achieve almost error-free control during operation, demonstrating extremely high control precision and strong error correction ability, making it the most outstanding among all controllers.

Then, although the MPC controller requires higher control effort, especially MPC2, its precision and stability far exceed those of the PID controller (Fig. 10). The PID2 controller shows greater fluctuations in control effort, indicating that its control system is unstable and requires more adjustments. The cumulative control effort of PID1 controller ranges from 20 to 30, indicating that the controller requires less control effort and remains relatively stable during system operation. Although the control signal fluctuates significantly, overall, the PID1 controller's control effort is relatively low, and the system stability is good. The cumulative control effort of PID2 controller fluctuates significantly, ranging from 45 to 55, indicating larger system fluctuations and a marked increase in control effort. This reflects PID2’s instability, which requires higher control effort to compensate for system fluctuations, thus increasing the system’s burden. The cumulative control effort of MPC1 is concentrated around 30, indicating lower control effort while maintaining good stability. Although MPC1’s control effort is slightly higher than PID1, it demonstrates clear advantages in control precision and stability, achieving better performance with relatively low effort. The cumulative control effort of MPC2 ranges from 55 to 60, with higher values reflecting stronger control strategies that achieve higher precision and smaller errors. Although MPC2 demands more control effort, it compensates for system fluctuations effectively, showing significant advantages in stability and precision.

The MPC controller demonstrates rapid adjustments in the initial phase, ensuring stable control (Fig. 11). Although the control signals for MPC1 and MPC2 are initially substantial, they quickly stabilize within a narrower range, indicating superior adaptability

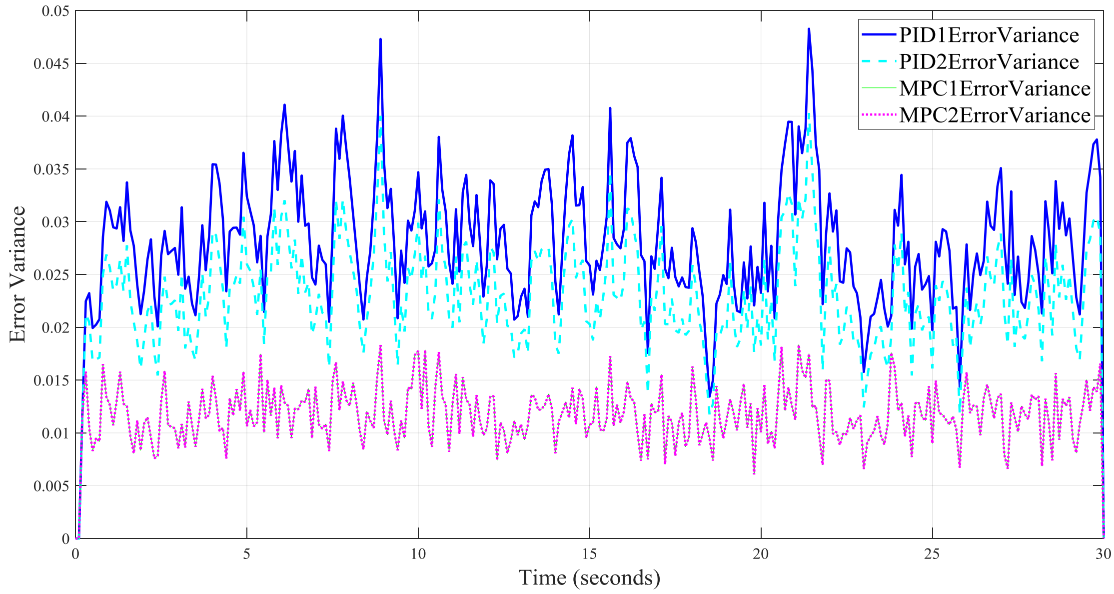

Fig. 7. Output Responses

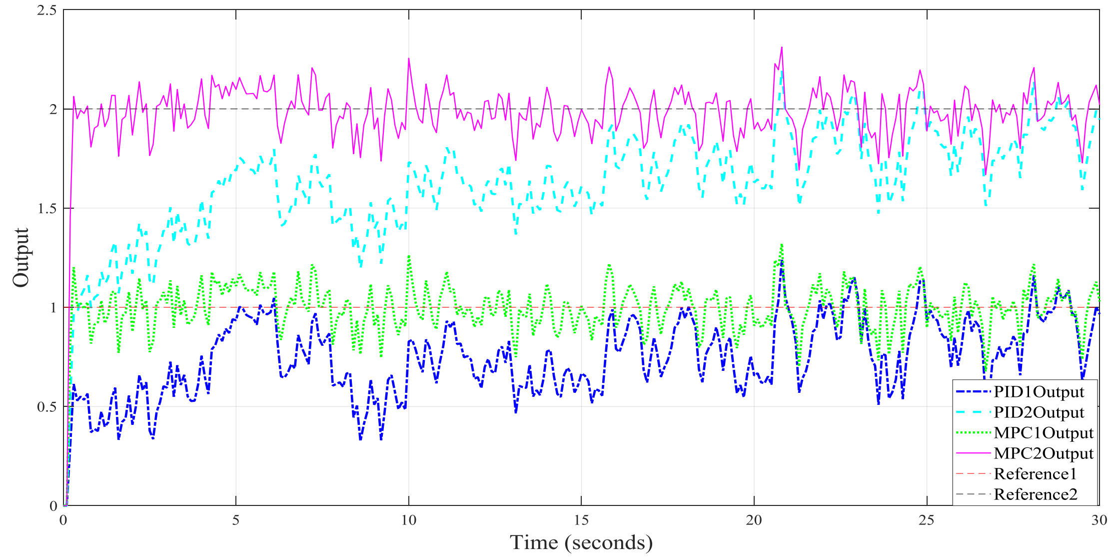

Fig. 8. Control Errors

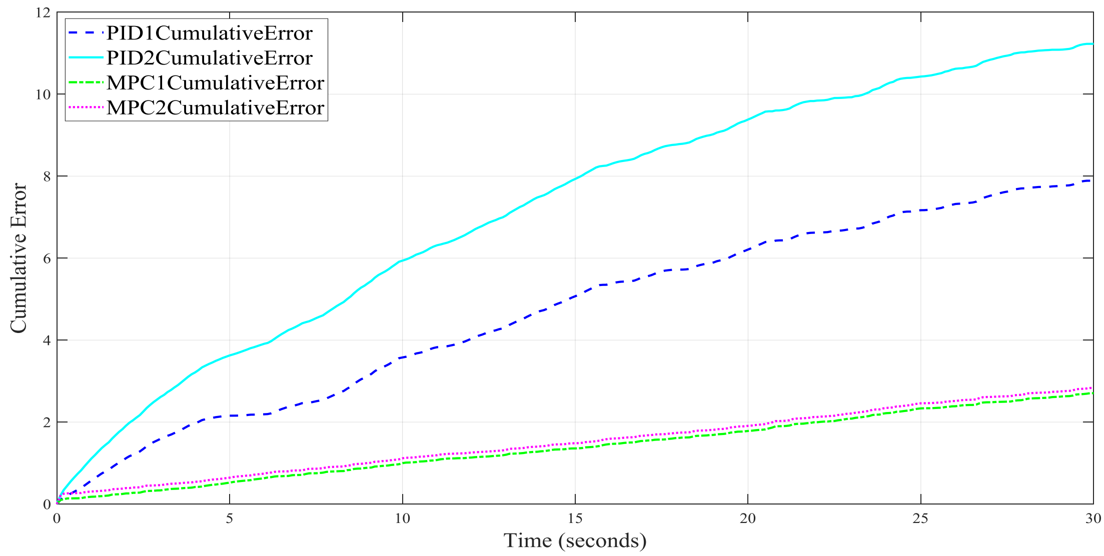

Fig. 9. Cumulative Errors

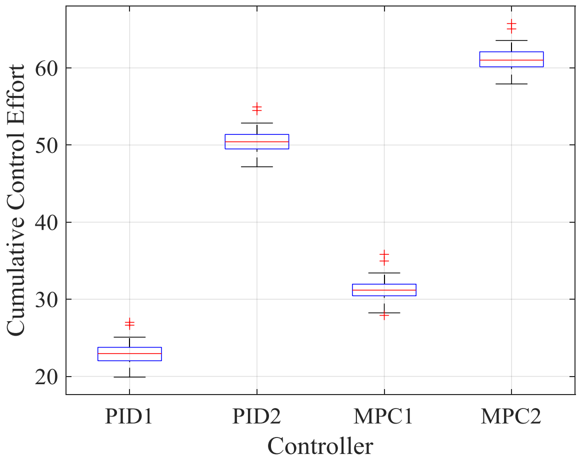

Fig. 10. Control Signals

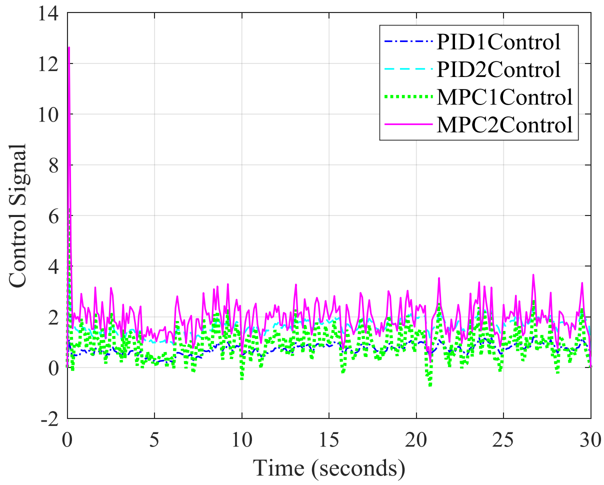

Fig. 11. Cumulative Errors

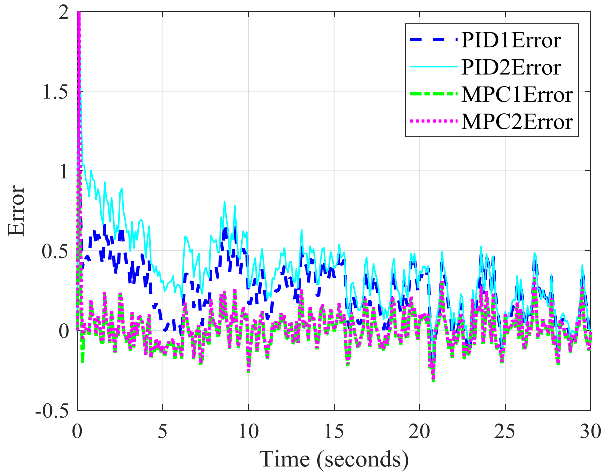

Fig. 12. Cumulative Errors

and control precision. In contrast, the Proportional-Integral-Derivative (PID) controller, particularly PID1, exhibits a smaller initial control signal but suffers from poor system stability and significant fluctuations. The control signal for PID1 oscillates between 0 and 2, reflecting lower control effort yet better stability. However, due to considerable errors in the PID1 control strategy, the signal fails to adjust effectively, leading to a large steady-state error. The PID2 controller starts with a high initial value of approximately 12, which rapidly decreases and stabilizes around 2. This controller necessitates larger initial adjustments to address system disturbances, but it ultimately adapts over time. Nevertheless, the instability of the system requires PID2 to maintain a higher initial control signal for stability. The MPC1 controller shows a rapid initial increase in the control signal, stabilizing between 1 and 2, demonstrating strong adaptability and minimal fluctuations. The MPC2 controller begins with a higher initial control signal of around 12, stabilizing between 2 and 3. While MPC2 requires a larger initial adjustment, it exhibits lower fluctuations post-stabilization, indicating enhanced stability and precision. Overall, MPC2 effectively stabilizes in later stages and responds adeptly to disturbances.

The MPC controller shows a clear advantage in error variation (Fig. 12). The error of the MPC2 controller remains between 0 and 0.2, with almost no fluctuation, showing optimal precision and steady-state performance. In contrast, the error of the PID controllers fluctuates more, especially in PID1, where the error fluctuates between 0.5 and 1.0, indicating poor precision. After prolonged operation, the PID1 controller accum-showing a large error deviation. The data shows that, after 100s, the error deviation of the PID1 controller reaches 0.035, which is significantly higher than the stable values of the other controllers. At this stage, the system fails to control error accumulation, leading to significant long-term errors.

Further analysis reveals that the PID1 controller does not respond quickly enough to external disturbances, exhibiting noticeable oscillations during adjustment, which prevent it from converging effectively to the target value. In contrast, PID2 shows some improvement with a reduced error deviation. At 100 seconds, the error deviation of PID2 is 0.025, lower than PID1 but still higher than the MPC controller. Despite this improvement, PID2 still exhibits some overshoot. When disturbances are present, PID2 has a slower response and a slower error convergence rate, preventing it from reaching the ideal steady-state value. The MPC1 controller shows the best performance (Fig. 12), maintaining a stable, small error deviation over a long period. The data indicates that after 100 seconds, the MPC1 error deviation is 0.015, demonstrating high precision and minimal error accumulation. This advanced controller exhibits superior robustness in disturbed environments, effectively suppressing error fluctuations and showing no significant overshoot during adjustments, indicating a strong dynamic response. Compared to MPC1, MPC2 offers a slight improvement in error control, with error deviation stabilizing at 0.012

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after 100 seconds of operation. This shows minimal error accumulation and enhanced stability, suggesting MPC2 optimizes performance through more accurate predictions, reducing long-term errors and enhancing system reliability and efficiency.

The comparison between the PID and MPC control systems shows notable differences in both cumulative errors and settling times. For cumulative errors, PID1 has a value of 8.7532, PID2 is 11.787, MPC1 is 2.8101, and MPC2 is 3.0101, indicating that MPC controllers generally achieve lower cumulative errors than PID controllers. Regarding settling times, PID1 has a settling time of 7.3 seconds, and PID2 takes 16.2 seconds, whereas MPC1 settles in 0.7 seconds and MPC2 in just 0.5 seconds. This shows that MPC controllers are significantly faster in achieving stability compared to PID controllers.

To compare the settling times of the PID and MPC control systems, firstly calculate the average settling time for each. For PID, the average settling time is 11.75s, while for MPC, the average settling time is 0.6 s. Applying the formula for relative improvement in settling time

$$R=\frac{11.75-0.6}{11.75}\times 100\% \approx 94.9\% .$$

MPC control achieves a 94.9% improvement in settling time over PID control, reducing stabilization from 11.75s to just 0.6s. This significant reduction demonstrates MPC's superior ability to respond quickly to disturbances and system changes. The faster response is essential in applications where real-time stability and performance are critical. By anticipating future states and adjusting control inputs accordingly, MPC handles disturbances more effectively, making it ideal for systems requiring rapid, precise control. MPC control not only offers improved settling time but also enhances system stability by minimizing overshoot, ensuring that the system reaches its desired state without excessive fluctuations.

4. Reliability of PID and MPC

The purpose of studying the reliability of PID and MPC control systems is to evaluate their performance, stability, and adaptability across various applications. The research compares response time, steady-state error, disturbance rejection, and tracking accuracy, while also assessing each method's ability to maintain stability under disturbances or uncertainties. Additionally, the study examines the scalability, resource consumption, and implementation complexity of both methods, with a focus on the feasibility of deploying MPC in computationally demanding applications. Ultimately, the goal is to guide the selection of the most suitable control strategy based on system requirements.

The Monte Carlo simulation [44] proceeds by generating multiple random realizations of the uncertain parameters θ . For each realization, the system's dynamics are simulated over a given time horizon, and the control input is computed either using the PID or MPC controller. The random variables are sampled from predefined probability distributions that reflect the inherent uncertainties in the system [45].

Let the set of uncertain parameters be denoted by θ_i , where $i=1,2,\cdots,M$ represents the number of Monte Carlo trials. For each trial i , the corresponding system trajectory $x_i(t)$ and control input $u_i(t)$ are computed as:

$$x_i(t)=f(x_i(t),u_i(t),\theta_i) .$$

For example, the average steady-state error across M simulations can be computed as:

$$\mu_{RT}=\frac{1}{M}\sum_{i=1}^{M}RT_i ,$$

$$\sigma_{RT}^2=\frac{1}{M}\sum_{i=1}^{M}\left(RT_i-\mu_{RT}\right)^2 ,$$

where RT_i is the response time of the system in the i-th trial.

Likewise, the tracking accuracy over the simulation trials can be evaluated using the root mean square error (RMSE):

$$RMSE=\sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(r(t)-x_i(t)\right)^2} ,$$

where $r(t)$ is the reference trajectory and $x_i(t)$ is the output of the system for the i-th simulation.

Monte Carlo simulations are computationally intensive, particularly when evaluating large-scale systems or using long prediction horizons in the case of MPC. The computational cost grows with both the number of Monte Carlo trials M and the complexity of the system model. Therefore, a key aspect of this evaluation is to analyze the scalability and resource consumption of both control strategies.

For MPC, the computational load is higher due to the optimization problem solved at each time step, requiring solving a quadratic programming problem over the prediction horizon. In contrast, PID controllers are simpler to implement and less demanding, making them more suitable for real-time applications with limited resources. Conducted simulations to analyze the performance of PID and MPC control algorithms. The following section provides a description of response time, disturbance rejection, steady-state error, tracking accuracy, computation time, and performance scores for both algorithms. Each chart presents performance metrics and compares PID1, MPC1, PID2, and MPC2, highlighting the strengths and weaknesses of each algorithm. These results are based on Monte Carlo simulations with repeated trials to account for variations in system behavior, providing statistical averages for understanding performance under different conditions.

Through 100 trials, verified the reliability and validity of each algorithm's performance. The calculation results are shown in Figure 13-18. First, with regard to steady-state error (Fig. 13), the MPC algorithm demonstrates a significant advantage. Specifically, the median steady-state errors for the PID controllers are 0.15 and 0.14, while the median steady-state errors for the MPC controllers are notably lower, around 0.08 and 0.09. This result indicates that, under the experimental conditions employed, the MPC algorithm outperforms the traditional PID algorithm in reducing steady-state error.

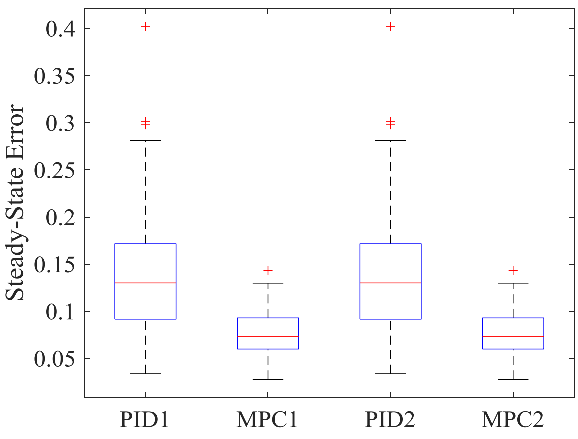

Fig. 13. Steady-State Error Statistics

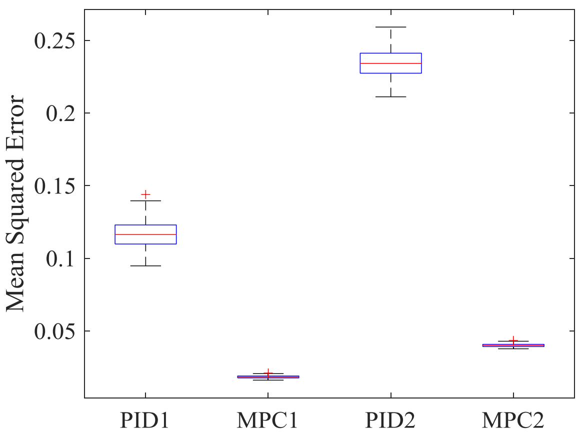

Fig. 14. Tracking Error Comparison

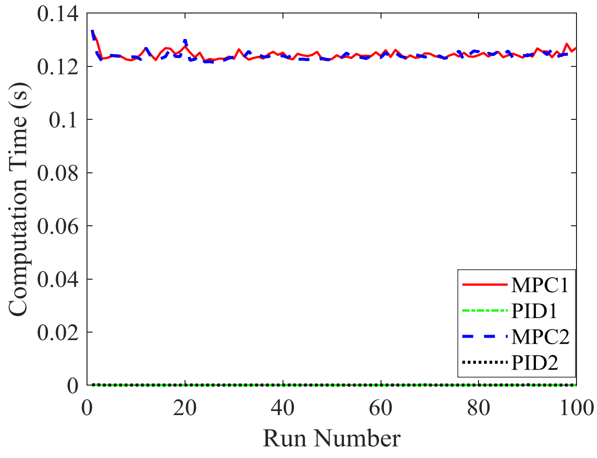

Fig. 15. Computation Time of PID and MPC

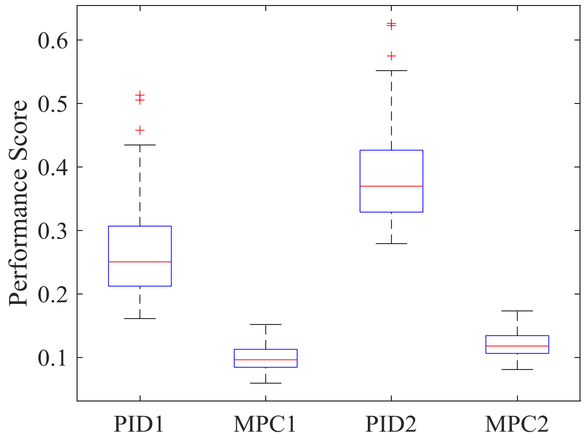

Fig. 16. System Performance Comparison

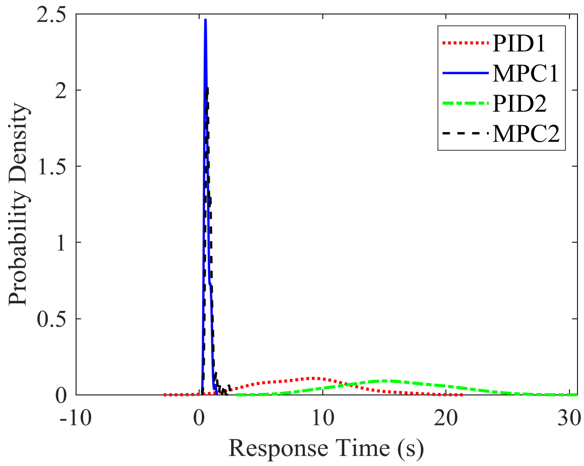

Fig. 17. Response Time Distribution of Different Control Algorithms

The MPC controller, by predicting the system's future behavior and optimizing control inputs, is able to adjust the system output more accurately, thereby effectively suppressing the accumulation of steady-state error. Furthermore, the adaptive capability of the MPC algorithm allows it to maintain relatively stable control performance under varying operational conditions.

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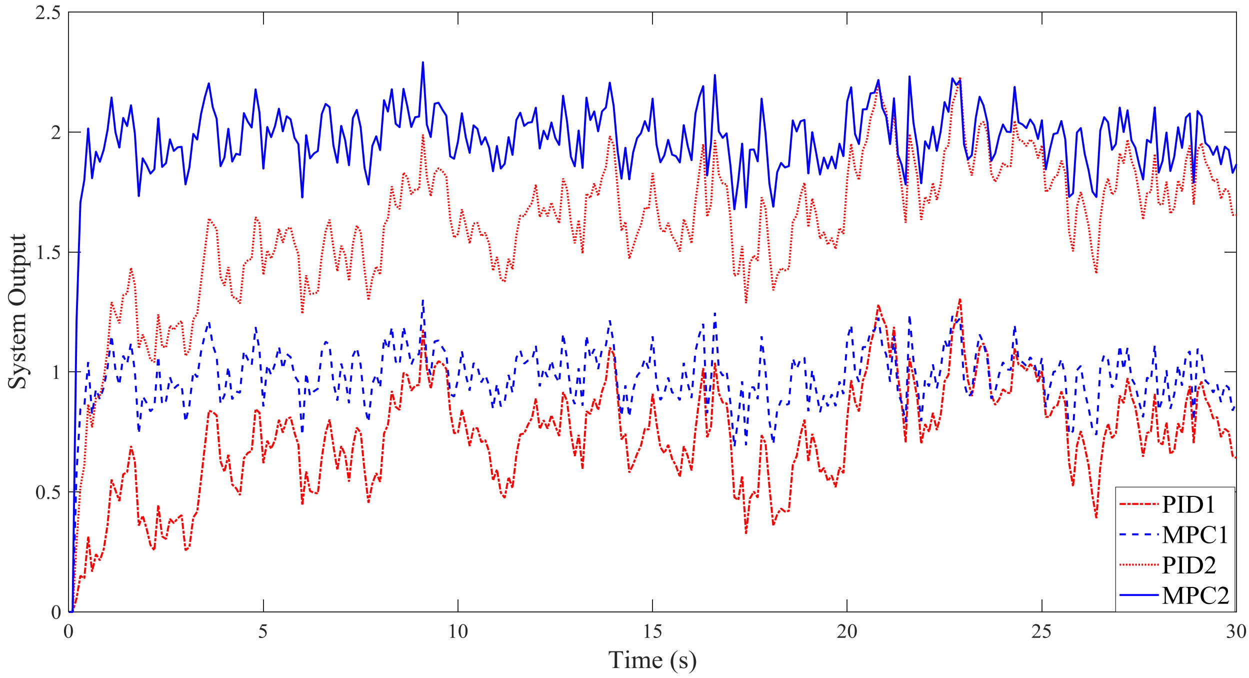

Fig. 18. Distubance Rejection Comparison

In contrast, although the PID algorithm is simple and easy to implement, its steady-state performance is typically affected by parameter tuning and system nonlinearity.

Next, in terms of Mean Squared Error (MSE) performance (Fig. 14), the MPC algorithm again exhibits superior performance. Specifically, the MSE values for PID1 and PID2 are 0.12 and 0.23, whereas the MSE values for MPC1 and MPC2 are 0.05 and 0.04, respectively. This result clearly shows that the MPC control algorithm has a significant advantage in terms of system tracking accuracy. Notably, MPC2 achieves the lowest MSE, nearly a quarter of the error observed with the PID algorithm, further confirming the potential and effectiveness of MPC in precise control. By incorporating a system model for prediction and optimization, the MPC algorithm can make decisions based on the current state and future behavior at each time step, thus effectively reducing the accumulation and fluctuations of control errors. In contrast, the traditional PID controller relies on simple error feedback, and its adjustment method is limited by a simplistic estimate of the system dynamics, making it difficult to achieve the same level of accuracy in complex or time-varying systems. Therefore, MPC is better suited to handle nonlinear, constrained, or multivariable control problems, providing more precise and stable control performance.

However, there is a difference in terms of computational cost. Firstly, regarding computation time (Fig. 15), the PID algorithms maintain a nearly constant computation time, ranging between 0 and 0.01 seconds. This indicates that PID algorithms have low computational complexity, allowing them to complete tasks in a short time, making them suitable for real-time control applications. In contrast, the MPC algorithms have longer computation times, fluctuating between 0.08 and 0.12 seconds, suggesting that MPC algorithms are relatively more complex in terms of computation. This longer computation time may pose a limitation in certain real-time systems, especially in scenarios with high-frequency control demands. However, it is important to note that MPC typically excel in control precision and system stability, particularly when dealing with multivariable and constrained optimization problems.

In terms of performance scores (Fig. 16), the PID algorithms demonstrate superior performance in control tasks. The median performance score for PID1 is 0.25, while for PID2 it is 0.35, indicating that both PID algorithms can achieve high control precision within a short computation time. In comparison, the median performance scores for the MPC algorithms are lower, with MPC1 at 0.10 and MPC2 at 0.12. Although they may exhibit high precision in specific control tasks, such as in the case of cyclogyro system, their higher computational complexity and longer computation times may hinder their ability to fully leverage their advantages.

Additionally, from the comparison of response times (Fig. 17), the MPC algorithm clearly demonstrates superior performance. The response times for MPC1 and MPC2 are concentrated around zero seconds, with a high peak probability density, indicating that these controllers can react swiftly, exhibiting high response speed and accuracy. In contrast, the response times for the PID controllers are more dispersed, with slower response speeds and greater variability, indicating some instability. This suggests that MPC can adapt more rapidly to system changes, ensuring precise control, while PID is slower to respond to complex system disturbances and is more susceptible to external influences.

Finally, in the disturbance response analysis (see Fig. 18), the MPC algorithm significantly outperforms the traditional PID control algorithm. Specifically, between 0 and 30 seconds, the system output for MPC1 and MPC2 shows a much smoother trend, with the system state remaining at a stable level. In contrast, the system output for PID1 and PID2 exhibits noticeable fluctuations and more intense responses. This difference clearly indicates that the MPC algorithm is more effective in mitigating system oscillations in response to external disturbances, avoiding the excessive responses and stability issues that the PID algorithm is prone to. Therefore, the MPC algorithm demonstrates superior performance in disturbance suppression and system stability, especially in complex dynamic environments, providing more reliable control outcomes.

Despite the challenges that MPC algorithms face regarding computation time in certain applications, this does not imply that their prospects in real-time systems are limited. By optimizing the solving process of the MPC algorithm, such as employing real-time optimization techniques, like fast gradient methods [46] or heuristic algorithms [47], parallel computing, or utilizing hardware acceleration, like GPUs [48] or FPGAs [49]. It is possible to effectively reduce computation time and enhance their feasibility in real-time control. Additionally, model simplification and dynamic adjustment of the prediction horizon are also effective methods to alleviate computational burdens.

Overall, the MPC algorithm performs excellently in control systems requiring precision and adaptability. It can effectively reduce errors and improve stability. Although it has higher complexity, MPC remains the superior choice for demanding scenarios.

5. Discussion and recommendations

This research demonstrates the substantial benefits of optimized control in cyclogyro systems. Through comparative analysis of PID controllers and Model Predictive Control (MPC), have identified key performance differences under various disturbance conditions. PID controllers, recognized for their simplicity and ease of implementation, exhibit limitations when dealing with large or time-varying disturbances, especially in systems with multiple variables. Conversely, MPC shows superior performance in terms of control accuracy, disturbance rejection, and response speed due to its predictive and optimization capabilities. However, MPC's high computational demands present a notable challenge, requiring further research into optimization techniques.

Here are some recommendations for future research:

- Enhanced Computational Efficiency: Future research should prioritize the development of methods to reduce the computational burden of MPC. This can include algorithmic improvements, hardware acceleration, and efficient coding practices to ensure real-time applicability;

- Robust System Modeling: Accurate and reliable models are crucial for the effectiveness of MPC. Efforts should be directed towards improving model accuracy and robustness, particularly in dynamic and complex environments;

- Hybrid Control Strategies: Exploring hybrid control strategies that combine the simplicity of PID with the predictive power of MPC could offer a balanced approach, leveraging the strengths of both methods;

- Application-Specific Tuning: Given the varying requirements of different applications, tailored control strategies should be developed. This involves fine-tuning control parameters specific to the operational context of the cyclogyro systems;

- Field Testing and Validation: Extensive field testing under real-world conditions is essential to validate the theoretical advantages of optimized control strategies. This will help in understanding practical limitations and refining the control systems accordingly.

Through these recommendations, aimed to accelerate the development of more efficient, adaptive, and resilient control systems specifically designed for cyclogyro applications. By integrating advanced control strategies, our goal is to improve their responsiveness, accuracy, and robustness, enabling better performance under a wide range of operating conditions. This will ultimately enhance the reliability and functionality of cyclogyros in complex, dynamic, and challenging environments.

6. Conclusion

This work compares the performance of MPC with traditional PID controllers in terms of dynamic response, steady-state accuracy, error convergence speed, and disturbance rejection in application of cyclogyro.

In terms of dynamic response, MPC demonstrates superior adaptability compared to PID. It can maintain faster response speeds when dealing with complex and rapidly changing systems, effectively addressing multivariable control problems. While PID exhibits a quicker initial response, MPC shows greater precision and stability when dealing with complex dynamic behaviors, allowing for more accurate tracking of setpoints and preventing excessive oscillations.

MPC also holds a clear advantage in steady-state accuracy. Since MPC relies on system mathematical models to predict future states, it effectively suppresses steady-state errors, ensuring that the system maintains precise control during long-term operation. In contrast, PID controllers often experience small, persistent errors at steady-state, which can affect the long-term stability and control accuracy of the system, especially in complex or nonlinear systems where PID struggles to achieve perfect tracking.

Error convergence speed is another key area where MPC outperforms PID. MPC can rapidly reduce system error to near-zero, especially in the presence of disturbances or changes in system parameters, demonstrating strong robustness and adaptability. By performing real-time optimization, MPC predicts and adjusts control inputs to eliminate errors. In comparison, PID controllers often require frequent parameter adjustments and have slower error convergence, particularly when disturbances are significant, which can lead to system instability.

MPC's ability to handle complex, multi-variable control problems through predictive modeling allows it to maintain optimal performance and quickly correct errors, ensuring system stability and efficiency. This advanced control strategy continuously evaluates the future impact of current control actions, making it exceptionally proficient at managing dynamic and unpredictable environments. Consequently, MPC is often the preferred choice for applications requiring high precision and rapid error correction, outperforming traditional PID controllers in both robustness and adaptability.

MPC's adaptability allows it to anticipate future dis turbances by leveraging its predictive model, adjusting c ontrol actions proactively to maintain optimal performa nce. Furthermore, its ability to handle multi-variable sys tems and constraints makes MPC a superior choice in co mplex industrial applications where precise disturbance rejection is critical. In contrast, PID controllers, with the ir reactive nature, often struggle to cope with dynamic c hanges and interactions in such scenarios, leading to sub optimal control and increased maintenance efforts. Addi tionally, MPC's ability to incorporate system constraints and optimize control inputs over a defined horizon allo ws for more efficient and robust responses to disturbanc es, ensuring minimal performance degradation even in c hallenging operating conditions.

Although MPC shows significant advantages in terms of accuracy, stability, error convergence speed, and disturbance rejection, especially in the control of complex, nonlinear, and multivariable systems, its computational burden in real-time control remains a challenge. MPC requires real-time system modeling and optimization calculations, which increase computation time. This can create performance bottlenecks in high-frequency real-time control applications. Therefore, improving the computational efficiency of MPC is a major direction for future work. Techniques such as fast gradient methods and heuristic algorithms can effectively shorten computation time and reduce computational load. Additionally, parallel computing and hardware acceleration (such as GPUs or FPGAs) are widely used in real-time MPC control. These methods can significantly improve real-time response capabilities and computational efficiency while maintaining accuracy.

Future research in Model Predictive Control (MPC) should concentrate on optimizing its application in controlling complex systems to enhance real-time control performance in high-precision and high-demand environments. Despite its substantial benefits, such as high control accuracy, robust disturbance rejection, and fast response times, the computational burden remains a significant challenge. This complexity hinders MPC's widespread use in real-time applications. To address this, future studies should focus on developing advanced optimization techniques for both hardware and software. Hardware acceleration, like specialized processors or parallel computing, could reduce the time for solving MPC optimization problems. Software improvements, such as more efficient algorithms and model reduction techniques, are also crucial. Additionally, researchers should explore MPC's broader applicability in fields like robotics, energy systems, aerospace, and autonomous vehicles to unlock new possibilities and drive innovation.

Contributions of the author: conceptualization, methodology, formulation of tasks, analysis, development of model, software, verification, analysis of results, visualization, original draft preparation, writing – review and editing –**Sibei WEI**.

Conflict of Interest

The author declares that there is no conflict of interest in relation to this research, whether financial, personal, in authorship, or otherwise, that could affect the research and its results presented in this paper.

Financing

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Data Availability

The work has associated data in the data repository.

Use of Artificial Intelligence

The author confirms that he did not use artificial intelligence methods while creating the presented work.

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The author has read and agreed to the published version of this manuscript.

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ОПТИМІЗАЦІЯ АДАПТИВНОСТІ ТА РАЦІОНАЛЬНІ СТРАТЕГІЇ КЕРУВАННЯ ДЛЯ ЦИКЛОГІРОСКОПІЧНИХ СИСТЕМ

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Циклогіроскопічна система, завдяки своїм потенційним застосуванням в авіації та складним динамічним характеристикам, стала об'єктом нашого дослідження. Хоча традиційний PID-регулятор ефективний у багатьох випадках, він може мати труднощі з обробкою складної нелінійної динаміки, яку часто зустрічають у циклогіроскопічних системах. Тому **метою** цього дослідження було спроектувати та реалізувати систему керування для циклогіроскопічної системи на основі оптимізованих стратегій, щоб поліпшити стабільність системи та швидкість реакції. Запропонований підхід інтегрує математичне моделювання, алгоритми оптимізації, аналіз даних у реальному часі та зворотні механізми для прогнозування та коригування поведінки системи. Порівняли ефективність традиційного PID-регулятора з моделлю прогнозуючого контролю (MPC) в системі контролю швидкості з подвійною метою. **Результати** числових симуляцій продемонстрували, що оптимізоване керування на основі MPC значно перевершує PID-регулятор, досягаючи вищої стабільності та швидшої реакції при обробці зовнішніх збурень та нелінійних динамічних змін, з середнім часом реакції, зменшеним на 92,5% ($p < 1e\text{-}10$). Ця підвищена продуктивність зумовлена здатністю системи динамічно коригувати свої стратегії керування у відповідь на змінювані умови навколишнього середовища. **Висновки** цього дослідження підкреслюють суттєві переваги оптимізованих стратегій керування для циклогіроскопічних систем, пропонуючи нові погляди на розвиток складних авіаційних систем керування та демонструючи потенціал цих стратегій для підвищення як продуктивності, так і адаптивності.

Ключові слова: циклогіроскоп; система керування; PID-регулятор; модель прогнозуючого контролю (MPC); оптимізована стратегія керування; нелінійна динаміка; стабільність системи; швидкість реакції; числове моделювання; адаптивність.

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