

# Current Status of Quadcopter UAV Control Technology Based on PID and Related Methods

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**Abstract.** This paper summarizes the current quadcopter Unmanned Aerial Vehicle (UAV) control technology based on Proportional-Integral-Derivative (PID) and related methods status. Firstly, quadcopters' basic dynamics and kinematics are explained in detail, explicitly clarifying the underactuated and strongly coupled system features of quadcopters, to make a good foundation for the research of the method of control. Secondly, the key technologies of the control are summarized as follows: Traditional PID control is still the basic method for quadcopter attitude and position control because of its simple structure and high reliability, but it does not have the robustness when there is a strong external disturbance and nonlinear. Fuzzy PID control adjusts the parameters in real time according to the certain fuzzy rules, and improves adaptability in the occasion of fuzzy environment, but it also has the shortcoming of dependence on expert experience in the rule formulation. Particle Swarm Optimization-PID (PSO-PID) and Genetic Algorithm-PID (GA-PID) use intelligent algorithm to do the global parameter optimization. PSO-PID is good at optimization efficiency. GA-PID is good at global searching ability, but both of them have the slow late-iteration convergence, and GA-PID is also prone to local optima. Finally, the application scenario of each method is summarized, the future direction is summarized, and the reference is provided to do the optimization of quadcopter control technology.

**Keywords:** UAV, PID, particle swarm optimization algorithm, genetic algorithm.

## 1. Introduction

Quadcopter Unmanned Aerial Vehicles (UAV) are widely applied in power line inspection, spraying, and delivery because of the characteristics of vertical takeoff and landing, stable hovering, and flexible operation [1]. Xiangkai Xu's group designed a quadcopter UAV control system based on PID control algorithm for power line inspection [2]. Gatkal et al. tuned the operational parameters of UAV spraying system for sugarcane crops to improve the spraying efficiency and increase the accuracy of spraying coverage [3]. Zihao Zhou group designed model predictive control to enhance quadcopter UAV delivery capability [4]. However, the underactuated and strongly coupled dynamic characteristics of quadcopter drones and the problems of strong wind disturbance, load variation, and electromagnetic interference in the environment impose high requirements on control accuracy and robustness in practical applications.

Proportional-integral-derivative (PID) control technology has the advantages of simple structure, high reliability and low engineering implementation cost, the application field is very wide, and the PID control drone can keep the flight attitude in the disturbance environment. The attitude balance and hover of the drone were realized by adjusting the rotor speed through PID [5]. Optimized PID controllers can also regulate the motion and trajectories of the robotic arm to achieve high-precision path tracking. W. A. Shutnan's team proposed applying the clonal selection algorithm from artificial immune systems to optimize fractional-order PID controller parameters, addressing nonlinearity and uncertainty in robotic arms to enable high-accuracy path tracking [6]. When applied to motor control, it further enhances motor regulation precision and plays a vital role in medical devices and industrial settings. K. Joyo's team optimized the PID controller parameters for an upper-limb rehabilitation robot by integrating multiple algorithms, reducing overshoot issues in the robot [7]. J. Li's team employed fuzzy PID control to optimize the verticality control system of a rotary drilling rig, enhancing its dynamic response characteristics and control precision [8]. This paper investigates the

application of PID-related algorithms in quadcopter UAV to trace the technical evolution of PID, compare the advantages and disadvantages of various approaches, provide references for practical applications, and identify future optimization directions.

## 2. Theory of Quadcopter UAV

Research on the control of drones should first establish mathematical models for simulation. The spatial coordinate system and body coordinate system are involved in modeling. The body coordinate system is stationary relative to the body of the drone and moves with the motion of the drone. There are some parameters that need to be converted between the two coordinate systems during modeling. Rotation matrices act as both constraints and control targets [9]. They quantitatively describe rigid-body three-dimensional attitude rotation, describing the three-dimensional attitude of the body coordinate system with respect to the spatial coordinate system. Rotation matrix converts the lift of the aircraft to a drag force in the spatial coordinate system.

Taking the Z-Y-X clockwise Euler angle rotation matrix system [10].  $\phi$  is the angle of rotation of the nose about the corresponding coordinate axis in the body coordinate system,  $\theta$  is the angle of rotation of the nose about the right side of the fuselage, and  $\psi$  is the angle of yaw.  $R(\phi)$ ,  $R(\theta)$ , and  $R(\psi)$  are the rotation matrices around the Z, Y, and X axes, respectively. is called the composite matrix  $R_b^e$ . As shown in equation (1).

$$R_b^e = R(\psi)R(\theta)R(\phi) = \begin{bmatrix} \cos \theta \cos \psi & \cos \psi \sin \theta \sin \phi - \sin \psi \cos \phi & \cos \psi \sin \theta \cos \phi + \sin \psi \sin \phi \\ \cos \theta \sin \psi & \sin \psi \sin \theta \sin \phi + \cos \psi \cos \phi & \sin \psi \sin \theta \cos \phi - \cos \psi \sin \phi \\ -\sin \theta & \sin \phi \cos \theta & \cos \phi \cos \theta \end{bmatrix} \quad (1)$$

After the rotation matrix is built, the model can be divided into position and attitude models. These two models are further partitioned into dynamics and kinematics [10]. The position model regards the UAV as an entire system and models it in space.

In the dynamics section, Newton's second law is applied as follows, according to equation (2).  $mg$  represents the gravitational force of the UAV.  $\dot{V}_e$  represents the acceleration in the spatial coordinate system.  $f_b$  represents the lift of propeller in body coordinate system.  $R_b^e f_b$  represents the total thrust force in the body coordinate system transformed to the spatial coordinate system. Position coordinates in the kinematics are finally achieved by double integration of acceleration in the dynamics section.

$$m\dot{V}_e = mg - R_b^e f_b \quad (2)$$

The dynamic description of the attitude model addresses the relationship between torques acting on the UAV and the resulting airframe rotational motion, with its derivation strictly following rigid-body Euler rotation equations [11]. The relationship between angular acceleration  $\omega_b$  and applied torque  $\tau_b = [\tau_x \ \tau_y \ \tau_z]^T$  is shown in equations (3), where  $J$  denotes the rotational inertia tensor.

$$J\dot{\omega}_b = \tau_b - \omega_b \times (J\omega_b) \quad (3)$$

Establishing UAV attitude kinematics equations requires converting between instantaneous angular velocities (body frame,  $b$ ) and Euler rate of change (spatial frame,  $e$ ). The instantaneous angular velocity vector  $\omega_b = [\omega_{bx} \ \omega_{by} \ \omega_{bz}]^T$  (measured via gyroscopes) represents rotation rates about the three body axes. The Euler rate of change  $\dot{\Theta}_e = [\dot{\phi} \ \dot{\theta} \ \dot{\psi}]^T$  (spatial frame) corresponds to roll, pitch, and yaw rate changes, but it is the derivative of three rotation sequences rather than a direct angular velocity vector. Thus, a transformation matrix  $W$  in equation (4) is needed for conversion, with the Euler rotation rate expression given in equation (5).

$$W = \begin{bmatrix} 1 & \tan \theta \sin \phi & \tan \theta \cos \phi \\ 0 & \cos \phi & -\sin \phi \\ 0 & \sin \phi / \cos \theta & \cos \phi / \cos \theta \end{bmatrix} \quad (4)$$

$$\dot{\theta}_e = W \cdot \omega_b \quad (5)$$

### 3. Quadcopter UAV Control Method

The core of stable drone operation lies in the motor. Through the control signals sent to the motor, the system drives the motor to output corresponding power and rotational speed, thereby realizing the attitude control, i.e. roll, pitch and yaw, as well as cruise flight. The accuracy of the control signals has a direct impact on the flight accuracy and stability, so an appropriate control architecture is an important and critical technological means.

At present, PID control algorithm, because of its simple structure, strong robustness and fast dynamic response, has been widely used as main technical plan of UAV motor control as PID is applied in main module, such as motor speed regulation, attitude closed-loop control [2, 12, 13], and then provide technical guarantee for stable UAV.

#### 3.1. Traditional PID Control

PID obtains its output by adding proportional, integral and derivative parts according to the difference between setpoint and actual value as shown in equation (6).

$$\tau_d = K_{wp}e_w + K_{wi} \int e_w + K_{wd}\dot{e}_w \quad (6)$$

Damping ratio of second order system can be tuned. In here,  $K_{wp}$ ,  $K_{wi}$  and  $K_{wd}$  are proportional, integral and derivative coefficient, respectively that tunes the response of system together.  $\tau_d$  is desired torque of UAV.

Actually, Yejin Wi et al. proposed a hierarchical control structure in which an inner-loop velocity PID controller and an outer-loop altitude proportional controller are employed to satisfy the attitude, position, and velocity control objectives of six-degree-of-freedom UAVs [12]. Xiangkai Xu's group proposed a quadcopter control system in which image, velocity, and angular velocity are integrated into a three-level PID algorithm for autonomous power grid inspection, and their solution can be applied to the control of drones in electrical inspection [13].

Traditional PID controllers play a vital role in drone control due to the following advantages: the balance between the computational complexity and the performance in routine situation. The traditional PID is an old algorithm, which has less computation demand, no need for advanced hardware, and easy to be applied into engineering, and it has a satisfactory performance in routine situation and can meet the requirements of attitude stabilization and position tracking. The disadvantages of the traditional PID are two folds: on one hand, the parameter tuning needs human experience and there is no universal method; on the other hand, the traditional PID performs badly in complex situation and high precision requirement, which causes the bad performance in high performance UAV application.

#### 3.2. Fuzzy PID Control

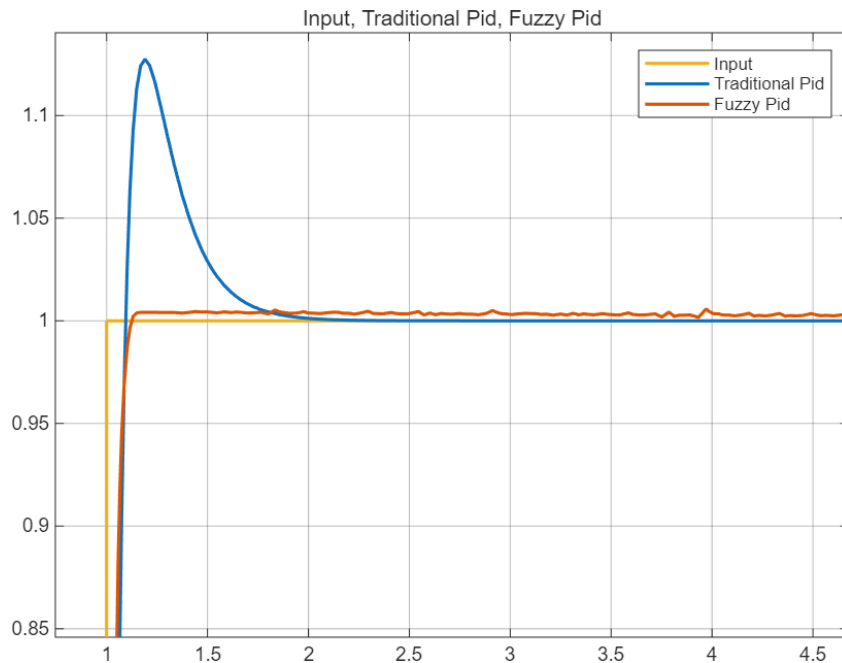
It is based on multivalued logic, extended with fuzzy set methods for investigating fuzzy thinking, linguistic terms and their underlying concepts. In order to overcome the disadvantages of conventional PID control, rules are used to tune the parameters of both controllers. In the conventional PID control, the proportional (P), integral (I) and derivative (D) parameters are constant during the entire control action after tuning. On the other hand, fuzzy PID allows the PID controller parameters to be optimized and adjusted during the operation, which is better suited for nonlinear and time varying systems, and the overshoots are lowered to work in face of more complex and dynamic system conditions [14].

In the simulation design, fuzzy controller is used to online analyze the system error  $e$  and the rate of change of system error  $ec$ .  $e$  and  $ec$  use Gaussian membership functions as inputs, and the curve results are more reasonable. The output is  $K_p$ ,  $K_i$ , and  $K_d$ . The expressions of self-adjusting three coefficients are shown as equations (7-9). A simple control model is selected to better demonstrate the optimization effect. Figure.1 shows a comparison between fuzzy PID and traditional PID controllers simulated in Simulink.

$$K_p(t) = K_p(t - 1) + \Delta K_p \left( e(t), \frac{de(t)}{dt} \right) \quad (7)$$

$$K_i(t) = K_i(t - 1) + \Delta K_i \left( e(t), \frac{de(t)}{dt} \right) \quad (8)$$

$$K_d(t) = K_d(t - 1) + \Delta K_d \left( e(t), \frac{de(t)}{dt} \right) \quad (9)$$



**Figure 1.** Comparison between fuzzy PID and traditional PID controllers in Simulink (Picture credit: Original)

Figure 1 shows the response results of traditional PID and fuzzy PID to a step signal under a simple UAV model. The parameters of the traditional PID were tuned empirically by the author, primarily to achieve a faster response time for the UAV. As shown in Figure 1, the settling time of the fuzzy PID is 1.8s faster than that of the traditional PID, and the overshoot is 1.1 lower than that of the traditional PID. The regulation effect is significantly better than that of the traditional PID.

Nelson Gatica. Z. 's team countered disturbances with fuzzy PID in the design of quadcopter hover control and obtained satisfactory results with the indoor hovering in limited space [15]. Sairoel Amertet's team used hybrid fuzzy PID in agricultural quadcopter drones to suppress disturbances in agricultural environment and the faster deviation correction showed that the fuzzy PID has better performance in more environment [16].

Although fuzzy PID inherits the strengths of traditional PID and fuzzy logic, its rule base is based on expert experience and therefore is limited with regard to the operational coverage. After the parameterization of the fuzzy controllers has been optimized, local optima occur. Furthermore, convergence slow down or even fail with an increase in dimensionality. When implemented on real UAVs, the inference operations are too complex to meet the real-time requirements. Additionally, the interference resistance of the fuzzy controllers is weak, and the controllers are very sensitive to noise. Therefore, it is hard to fulfill the requirements with respect to high-frequency responses.

### 3.3. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is mainly finding optimal solutions by cooperation and communication between the individuals in a swarm. The design of the PSO is inspired by the flocks of birds while foraging in nature, which means that the natural phenomenon is transferred into an algorithm. Each possible solution is represented by a particle and all particles move in the solution space. The particles update their positions by following the two best solutions: the best solution obtained by each particle, called Personal Best (*pbest*) and the best solution discovered by the entire swarm, called Global Best (*gbest*). Taking the PSO into the PID control, the appropriate PID parameters can be quickly found and the manual tuning process is avoided. In addition, the control performance of the system in the presence of varying operating conditions is improved [17].

The corresponding method is designed to apply the PSO algorithm to PID control, and the parameter encoding is implemented. Three PID parameters  $K_p$ ,  $K_i$ , and  $K_d$  are mapped to the position of a particle, where each particle represents a set of candidates PID parameter combinations, denoted as  $X_i$ , as shown in equation (10). The velocity of the particle  $V_i$  in equation (11) represents the direction and step size of parameter adjustment. Through iterative cycles, each particle updates its velocity and position based on its historical individual optimal position and the global optimal position of the entire swarm while calculating its fitness value using a predefined objective function (e.g., integral of the time-weighted absolute error, ITAE). During the iteration process, the individual optimal and global optimal solutions are continuously updated until either the maximum number of iterations is reached or the minimum fitness threshold is satisfied. The velocity and position update equations for particles are given in equation (12) and equation (13), where  $\omega$  denotes the inertia weight to balance global and local search,  $c_1$  and  $c_2$  are learning factors adjusting the weight of the particle's movement toward *pbest* and *gbest*, respectively, and  $r_1$  and  $r_2$  are random numbers uniformly distributed within [0, 1] to maintain the algorithm's search randomness to mitigate the risk of falling into local optima.

$$X_i = (Kp_i, Ki_i, Kd_i) \quad (10)$$

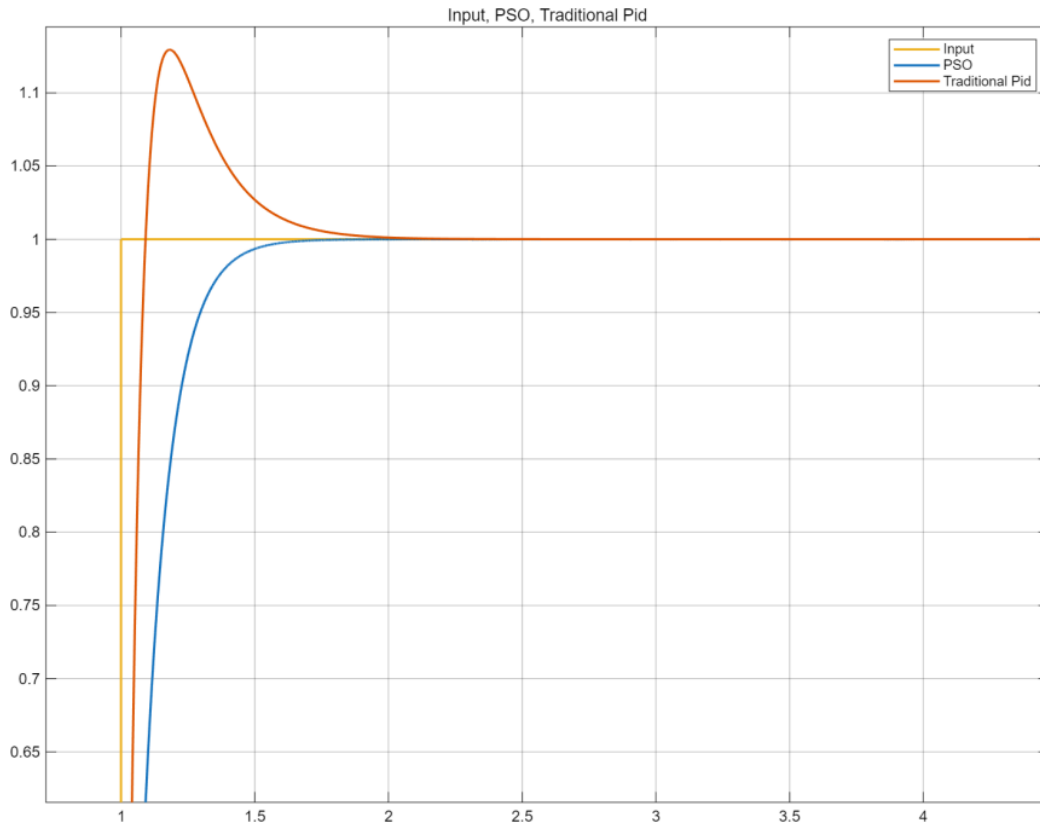
$$V_i = (v_{Kp_i}, v_{Ki_i}, v_{Kd_i}) \quad (11)$$

$$v_{ij}(t + 1) = \omega \cdot v_{ij}(t) + c_1 \cdot r_1 \cdot (pbest_{ij} - x_{ij}(t)) + c_2 \cdot r_2 \cdot (gbest_j - x_{ij}(t)) \quad (12)$$

$$x_{ij}(t + 1) = x_{ij}(t) + v_{ij}(t + 1) \quad (13)$$

Figure.2 shows an example of the simulation results using the particle swarm optimization algorithm in MATLAB. A simple UAV controller model was selected, where the parameters of the traditional PID ensure a fast response time for the UAV. Owing to the simplicity of the model, the particle swarm achieved excellent results after only five iterations, whereas the traditional PID parameters were set based on experience. This demonstrates that the particle swarm optimization algorithm can effectively reduce overshoot and accelerate adjustment time.

Yazid, E. and his team improved the tracking accuracy and response speed of quadcopter drones along multiple trajectories by optimizing the proportional coefficient ( $K_p$ ) and derivative coefficient ( $K_d$ ) of the controller using an adaptive particle swarm optimization (APSO) algorithm [18]. Meanwhile, Nur Hayati, S. et al. verified in a simulated quadcopter dynamics model that the PSO-PID controller outperforms the traditional PID controller in terms of system stability, trajectory tracking precision, and disturbance rejection capability [19].



**Figure 2.** Comparison of PSO and Traditional PID Performance After Parameter Tuning (Picture credit: Original)

The PSO algorithm has a tendency to become stuck in the local optima. When the parameter optimization range is fixed and the controller model is simple, increasing the iteration count (from five to ten) leads to becoming trapped in the local optima. Therefore, when the parameter dimensions increase or the objective function becomes complex, finding the global optimum becomes challenging. In addition, the convergence speed is easily affected by parameter settings, and convergence stagnation often occurs in later stages, prolonging the optimization time.

### 3.4. Genetic Algorithm

Genetic Algorithm (GA)-based PID Parameter Optimization (GA-PID) advantages in control engineering are very prominent. Its strong global optimization ability is one of its strong points that can well overcome the weak points of traditional PID parameter tuning. Because GAs have taken the biomimetic iterative process of chromosome selection, crossover and mutation to effectively solve the problem of local optimum. Especially when the multidimensional cooperative optimization of PID parameters ( $K_p$ ,  $K_i$ , and  $K_d$ ) is needed, GAs can effectively cross the parameter space to accurately locate the global optimum and avoid the problem of control instability caused by the deviation of initial value.

Zareb, M. and his team optimized parameters of hybrid control architecture which combined fuzzy controllers and PID controllers by using GA. They proposed a new kind of Bi-Genetic Algorithm to automatically adjust the own parameters of GA (such as crossover rate, mutation rate). The UAV equipped with the optimized control architecture can adapt to the indoor and outdoor flight environment and has less energy consumption and control error than traditional PID scheme [20].

The core of GA-PID achieves optimal parameter search for PID controllers through biomimetic iteration of GA. Continuous  $K_p$ ,  $K_i$ , and  $K_d$  parameters are mapped to chromosomes encoded as binary real numbers. Let the chromosome length be  $L$ , with the three parameters encoded as  $L_1$ ,  $L_2$ , and  $L_3$  ( $L = L_1 + L_2 + L_3$ ), respectively, forming the initial population. Control-system performance metric as fitness function, generally use error integral indicator in equation (14), where  $e(t)$  is

system error. The function value of PID parameters corresponding to each chromosome is calculated, and the lower value represents the more approximate parameter.

In genetic operation, select the chromosome according to the roulette wheel as shown in equation (15).

$$ISE = \int_0^{\infty} e^2(t) dt \quad (14)$$

$$p(x_i) = f(x_i) / \sum_{j=1}^N f(x_j) \quad (15)$$

Select the chromosome to crossover randomly (such as single-point crossover) to produce offspring. At the same time, real value is perturbed with small probability  $P_m$  to keep population diversity. The iteration continues until the optimal  $K_p$ ,  $K_i$ , and  $K_d$  parameters corresponding to optimal chromosome are obtained and then take the GA-PID optimal control parameter.

The shortcoming of GA-PID is that the iteration is very time consuming if the population size is large. This results in inefficient optimization and premature convergence that may result in suboptimal global solutions.

## 4. Conclusion

PID and related improved methods have been a focus area for quadcopter drone control for a long time. As a typical feedback control regulation algorithm, traditional PID has the advantages of simple structure and high reliability and is widely used in the attitude and position control of low altitude and low speed drone. However, PID is weak in the face of strong disturbance and nonlinear flight condition. Fuzzy PID optimizes parameters through fuzzy rules and improves the adaptability of drones to the environment. The shortcomings of fuzzy PID are dependence on expert experience and rule-set redundancies. PSO-PID and GA-PID use intelligent optimization algorithms to realize the global optimization of parameters and avoid the problem of manual trial-and-error tuning. PSO-PID has high optimization efficiency, and GA-PID has stronger global searchability. However, both of them have the shortcoming of slow convergence in the next iteration.

The application of PID and related algorithms on UAVs can be enhanced through three approaches: Hardware Optimization, Introducing Deep Learning, and Algorithm Advantage Integration. By integrating relevant hardware devices and incorporating sensor information technology into the UAV's PID control loop, more detailed data can be obtained. Simultaneously, combining multi-source data from Inertial Measurement Units (IMUs), visual sensors, and other sources while designing appropriate filters to eliminate noise provides precise feedback for the PID system. Deep learning methods can be applied to optimize UAV PID parameters. By collecting massive data on factors such as attitude, wind speed, and payload during quadcopter flight, Long Short-Term Memory (LSTM) or transformer models can be trained to predictively adjust PID parameters. This enables the model to output adapted parameters in shorter timeframes, significantly enhancing the response speed and stability under extreme conditions, such as strong convection or low-altitude turbulence. The integration of multiple algorithms to enhance UAV PID control also offers significant advantages. For instance, combining the dynamic optimization capabilities of fuzzy logic with the search characteristics of PSO enables the precise tuning of fuzzy PID controllers by optimizing fuzzy controller parameters via PSO. Similarly, integrating the global search capabilities of GA with the adaptive properties of fuzzy PID achieves precise tuning of fuzzy PID parameters.

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