Research and Analysis on PID Control and Its Improvement Methods

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Abstract. This paper systematically reviews the control principles, application scenarios, advantages and disadvantages of three main improved algorithms: fuzzy Proportional–Integral–Derivative (PID), adaptive PID, and neural network PID. Fuzzy PID is used for systems with empirical-driven nonlinear and uncertain characteristics. It has advantages of low cost, fast response, and strong real-time performance, but its control accuracy is limited. Adaptive PID is used for systems with parameter time-varying, variable operating conditions, and known models. It can achieve parameter self-tuning and strong adaptability. However, it has a higher cost and is highly dependent on identification accuracy and computing resources. Neural network PID is used for systems with high nonlinearity, strong coupling, and difficult modeling. It has outstanding nonlinear learning capabilities. Through sample training, it can achieve intelligent regulation, nonlinear compensation, and strong robustness. However, the training process is complex, and it is highly dependent on data quality and computing resources. Its generalization ability is limited. The future development of PID will tend towards algorithm integration and intelligent optimization. By using multiple hybrid improved methods, the adaptability and accuracy of the system will be enhanced.

Keywords: PID Control, Fuzzy PID, Adaptive PID, Neural Network PID, Intelligent Learning.

1. Introduction

PID control is one of the most commonly used control methods in industrial and intelligent systems. It demonstrates excellent performance in a parameter-fixed and stable operating condition environment, while having the advantages of a simple structure and stable response, as well as reliable performance in industrial processes and motion control and other aspects. Therefore, it is widely applied in various automation scenarios. However, with the development of modern engineering systems, traditional PID has been unable to adapt to high dynamic and strong non-linearity environments due to its fixed parameters and linear regulation mechanism. Especially when the system is faced with environmental disturbances, parameter changes, or difficulties in accurately establishing the system model, the static P, I, and D parameter control mechanism relied on by traditional PID cannot effectively balance rapid response, steady-state accuracy, and system robustness. Therefore, researchers have combined intelligent reasoning, parameter identification, and learning mechanisms with traditional PID control to develop various improved PID algorithms [1].

Currently, fuzzy PID, adaptive PID, and neural network PID are the three most widely used improved algorithms. Traditional PID relies on fixed parameters and performs well in systems where the model is known and the environment is stable. However, when dealing with nonlinearity, disturbances, or changes in operating conditions, its performance tends to decline, leading to excessive overshoot, slow response, or oscillations. Fuzzy PID achieves rapid response and anti-disturbance control by establishing fuzzy rules without relying on an exact model; Adaptive PID maintains stable performance by real-time identification and parameter update when system parameters change or external disturbances occur frequently; Neural network PID, with its strong computing power and data support, can achieve optimal control effects through self-learning and demonstrates the highest accuracy and stability in non-linear and complex coupled systems. The trend reflected is that modern PID control is no longer limited to adjusting static parameters, but rather, through the combination with different technologies, enables the system to possess the evolutionary capabilities from experience to algorithms to intelligent learning.

This paper systematically summarizes the current development status and principles of three improved algorithms: fuzzy PID, adaptive PID, and neural network PID. By searching through the existing related research papers, a comparative analysis of their control characteristics, application scenarios, and advantages and disadvantages has been conducted. This provides a reference for subsequent research.

2. The basic principle of PID control

2.1. Traditional PID

PID control belongs to a type of feedback control system. The core idea of this control system is feedback and error correction: the output y(t) of the controlled object is fed back through sensors, and compared with the desired set value r(t) to obtain the error e(t) = r(t) - y(t). The controller calculates the control signal u(t) based on this error (as well as the history and rate of change of the error) and applies it to the actuator to make the system output approach the set value. The core idea of this control system is to continuously reduce the error and ultimately stabilize the system near the set value.

In control theory, the PID controller is actually using three methods - proportion (P), integration (I), and differentiation (D) - to regulate the error of the system. Its continuous-time form can be expressed as

$$u(t)=K_p e(t)+K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{1}$$

Among them, the proportional term $K_p e(t)$ directly reflects the current error and is used to enable the system to respond quickly; the integral term $K_i \int e(\tau)d\tau$ accumulates past errors to eliminate steady-state errors; the differential term $K_d \frac{de(t)}{dt}$ predicts the trend of error changes, thereby suppressing overshoot and oscillations. By combining these three elements, the system can achieve a balance among response speed, accuracy, and stability, which is why PID control has become the most common feedback control method.

When we implement PID control in digital computers or single-chip micro-controllers, the system signals are sampled discretely. The integral and differential sections need to be replaced by numerical approximation methods, and thus we obtain:

$$u(k)=K_p e(k)+K_i \sum_{i=0}^{k} e(i) T_s + K_d \frac{e(k)-e(k-1)}{T_s} \tag{2}$$

Here, k represents the sampling time and is the sampling period [2]. This is the digital structure form, which is equivalent to the above continuous formula, but is more convenient for implementation in digital systems or embedded controllers.

In a control system, the three parts of the PID controller each undertake different tasks. Proportional control directly responds to the error; the larger the error, the greater the adjustment made by the controller, which is equivalent to immediately increasing the "correction force" to make the system approach the target faster; Integral control focuses on the cumulative effect of the error; it continuously accumulates long-term deviations and compensates continuously to make the system reach equilibrium over time, thereby eliminating steady-state errors; Differential control is concerned with the trend of error changes; it anticipates whether the system will experience overshoot, like adding predictive braking to the system, helping to suppress oscillations and making the response more stable. Different combinations, such as P, PI, PD, and PID control, can achieve different control effects based on the characteristics of the object: P control is simple but has steady-state errors; PI control can eliminate deviations but has a slower response; PD control can improve dynamic response but is difficult to eliminate deviations; while PID control combines the advantages of the three, achieving a good balance between response speed, accuracy, and stability.

The characteristic structure of PID control makes it widely used in industrial and intelligent control. Proportional control, as an immediate energy feedback, can provide rapid responses in temperature control, motor speed regulation, and lighting brightness regulation, etc. Integral control is often used in systems requiring steady-state accuracy, such as liquid level or position maintenance, keeping the output stable at the target value. Differential control is particularly important in objects with high inertia (such as servo mechanisms, unmanned vehicle steering control, and end-point posture control of robotic arms), as it can pre-emptively counteract the oscillations or overshoot caused by error changes. The collaboration of these three components enables the PID controller to balance sensitivity, stability, and accuracy. Therefore, in practical applications such as industrial temperature control furnaces, autonomous driving systems, adaptive lighting, and robot joint control, PID control is almost always one of the most core and reliable algorithms.

Although traditional PID control is widely adopted in industry due to its simple structure, ease of implementation, and strong real-time performance, it still has some significant limitations in complex systems or high-precision control. Firstly, the PID controller relies on fixed proportional, integral, and differential parameters, which are mostly obtained through experience or trial-and-error methods under specific operating conditions [3]. When the system environment changes, such as external pressure changes, the fixed parameters cannot adaptively adjust, and the system is prone to slow response or oscillation. Secondly, traditional PID is mainly designed based on linear models, and for strongly nonlinear, time-varying, or coupled systems, the assumptions of linear control are not applicable, and the control effect will naturally deteriorate. Moreover, the integral link is prone to "integral saturation" when facing large disturbances or long-term deviations, which will cause the system to overshoot or delay recovery. The differential link is particularly sensitive to noise and is prone to causing output jitter in the case of dirty measurement signals.

So, although PID control is still very practical in some steady-state systems or scenarios with low complexity, if it has to deal with nonlinear or highly dynamic control objects, its performance will be limited.

To overcome the shortcomings of traditional PID in parameter fixity, noise sensitivity, and poor adaptability to non-linear systems, researchers have proposed various improved PID control methods, enabling the controller to achieve higher intelligence and self-adaptability under different working conditions. The main improved control methods include fuzzy PID control, adaptive PID control, and neural network PID control.

2.2. Fuzzy PID

Among them, fuzzy PID control is an improved control method that introduces the fuzzy logic inference mechanism on the basis of traditional PID control. Its formula is to add fuzzy logic adjustment parameters to the PID formula, that is:

$$u(t)=K_p(e,\Delta e)e(t)+K_i(e,\Delta e)\int_0^t e(\tau)d\tau+K_d(e,\Delta e)\frac{de(t)}{dt} \tag{3}$$

Its basic idea is: when the system operating environment is complex and the mathematical model is difficult to be accurately established, instead of relying on fixed proportional, integral and differential parameters, the control laws are expressed empirically through fuzzy rules and language variables, thereby achieving online adjustment and intelligent optimization of PID parameters. Currently, fuzzy PID control is widely applied in temperature control, unmanned vehicle steering, robot posture adjustment, liquid level and flow regulation, lighting system control, etc.

2.3. Adaptive PID

Different from the former, the core idea of adaptive PID control is to make the controller parameters no longer fixed, but to automatically adjust the proportional, integral, and differential coefficients as the system characteristics or external disturbances change. It is based on adaptive control theory (Adaptive Control Theory), and dynamically corrects Kp, Ki, Kd by real-time detecting the deviation between the system output and the set value, as well as the changes in the system dynamic characteristics (such as gain, inertia, delay, etc.), so that the system can maintain ideal response performance under different working conditions. Its formula is to introduce the mechanism of parameter changes over time in PID, that is:

$$u(t)=K_p(t)e(t)+K_i(t)\int_0^t e(\tau)d\tau+K_d(t)\frac{de(t)}{dt} \tag{4}$$

The common implementation approaches of adaptive PID control fall into two main categories: Model Reference Adaptive Control (MRAC) and Self-Tuning Regulator (STR). Currently, adaptive PID control is mainly applied in servo control, unmanned aerial vehicle (UAV) attitude, and industrial process control scenarios.

2.4. Neural network PID

Neural network PID control is an intelligent control method that combines traditional PID control with the artificial neural network (ANN) algorithm. Its core idea is to utilize the nonlinear mapping and self-learning ability of neural networks to adjust the parameters Kp, Ki, and Kd of the PID controller in real time, thereby overcoming the limitations of traditional PID control in nonlinear, time-varying, and multi-variable systems. Its fundamental formula is still PID, but it learns and optimizes the parameters through neural networks, that is:

$$u(t)=K_p(W)e(t)+K_i(W)\int_0^t e(\tau)d\tau+K_d(W)\frac{de(t)}{dt} \tag{5}$$

Here, W represents the weights of the neural network. The neural network can autonomously establish a virtual model by learning the nonlinear relationship between the system input and output, and then predict the dynamic changes of the system to achieve parameter self-correction and control signal optimization. There are mainly two ways to implement neural network PID control: the parameter adjustment type (Tuning-Type NN-PID) and the direct control type (Direct NN Controller). The training methods can be divided into offline training (based on historical data) and online training (based on real-time feedback). Currently, neural network PID control provides new solutions for intelligent manufacturing, unmanned systems, and energy automation and other fields due to its nonlinear modeling ability, self-learning parameter adjustment mechanism, and strong robustness.

Overall, fuzzy PID emphasizes "experience-driven", adaptive PID belongs to "algorithm-driven", and neural network PID represents the control development direction of "intelligent learning-driven". The three have different emphases in terms of ideology and implementation mechanisms, but their common goal is to enhance the intelligence and adaptability of PID controllers.

3. Application Cases

3.1. Fuzzy PID Application Case

Meng Cui et al. presented a study at the ICIMCT conference, addressing the complex nonlinear dynamics, strong coupling effects, and insufficient performance characteristics of the quadrotor system. They investigated using the attitude deviation angle as the control variable and designed a control algorithm based on fuzzy PID. The research team established the unmanned aerial vehicle dynamics model and derived the dynamic equations, using transfer functions to couple the six-degree-of-freedom motion with the input of the four motors, and constructed fuzzy rules for real-time PID parameter adjustment. Simulation results showed that compared with traditional PID and cascaded PID: the step response reduced the overshoot time by 35.2%, the solution time increased by 41.7%, and the peak time shortened by 27.3%; under a simulated wind disturbance of 15 meters/second, the attitude tracking accuracy remained within ±1.5°, significantly outperforming traditional PID, effectively addressing the adaptability limitations of fixed-parameter PID in complex environments, and achieving rapid convergence and high-precision control [4].

He Xiangyan et al. presented a solution at ITNEC for the problem of unstable image quality caused by changes in ambient light intensity in industrial online detection systems. They proposed a high-power LED adaptive dimming system based on the fuzzy PID control algorithm for industrial machine vision lighting. By designing a hardware system including a constant current drive circuit, a temperature detection circuit, and an ambient light sensor, the lighting error and error rate of change were used as the input of the fuzzy PID controller. Using fuzzy reasoning and defuzzification to achieve real-time adjustment of the PWM duty cycle, the LED light intensity was automatically controlled. Experimental results showed that the system could maintain the lighting intensity near the set value when the ambient lighting randomly changed, achieving adaptive constancy, significantly improving the efficiency and accuracy of machine vision detection, and having energy-saving advantages [5].

Tong Chang et al. presented a voltage regulation control algorithm based on fuzzy PID at ICEMS, aiming to address the bus voltage fluctuations caused by load changes in hybrid power and energy storage systems. They used the voltage deviation of the SRMG (Switched Reluctance Generator Motor) as the control variable [6]. By establishing the mathematical models of SRM and SRMG, and constructing the closed-loop control model of the motor and generator using fixed commutation angle and current chopping control (CCC), they designed a dual-loop lag control strategy for voltage and speed, and implemented real-time adaptive adjustment of PID parameters using fuzzy rules. Simulation results showed that compared to traditional PID, the fuzzy PID significantly reduced the voltage fluctuation amplitude, shortened the bus voltage recovery time, accelerated the response speed, and enabled SRMG to absorb excess energy in the motor mode when the voltage increased, achieving rapid and stable regulation.

3.2. Adaptive PID application case

Zhan Wenxuan et al. at IHMSC addressed the challenges in the image tracking system of the translational and inclined platform, such as the dynamic changes in target size, visual feedback delay, and actuator saturation limitations, by using the target offset pixel as the control variable and designing an adaptive PID control algorithm based on target size. They established a cloud platform visual servo system model, conducted real-time detection of the target bounding box area for dynamic calculation, and combined a first-order low-pass filter for control signal smoothing. Simulation results showed that the adaptive PID outperformed the traditional fixed-gain PID: the step response overshoot was reduced by approximately 80%, the steady-state time was shortened by approximately 50%; at a target distance of 12 meters, the RMS tracking error was only 0.53°, significantly better than the 1.6° of the traditional PID; under random disturbances, the variance of the error distribution decreased by 77%, and the peak probability density increased by 1.8 times, effectively improving dynamic response and robustness [7].

Maneesh Kumar et al. at the IEEE SEFET International Conference proposed a voltage control method based on adaptive PID for the solar photovoltaic (SPV) and battery energy storage (BSS) systems in irrigation scenarios. By establishing an SPV-BSS microgrid model, using the inverter output voltage error as the input, and adjusting the PID parameters in real time through an adaptive mechanism for dynamic tuning, they achieved dynamic setting [8]. Compared with traditional PID in "normal operation" and "single-phase grounding fault" conditions, simulation results showed that the adaptive PID significantly outperformed the fixed-gain PID in terms of overshoot, steady-state error, and dynamic recovery: it could still stabilize the voltage quickly during the fault recovery stage, demonstrating stronger robustness and anti-disturbance ability.

Chen Qiyu et al. at the CCAI conference addressed the problem that the silt removal tracking robot is affected by time-varying bounded disturbances and model parameter uncertainties. Based on the non-coincident kinematic and dynamic models of the center of mass and geometric center, and using adaptive technology, they designed an adaptive PID trajectory tracking controller [9]. Simulation results showed that compared with PID control under time-varying disturbances, APID has better tracking performance. Using the APID control method, the posture errors of the tracking line and circular trajectory can converge faster, be more robust to interference, and have better response performance and trajectory tracking accuracy.

3.3. Application Cases of Neural Network PID

Chen Jie presented at the ICMTMA conference, addressing the limitations of traditional rigid mechanical arms in terms of accuracy and efficiency during actual operation, and focusing on the flexible joint manipulator as the research object, designed and derived the dynamic model of the flexible joint [10]. Using a three-layer BP neural network, comparisons and studies were conducted between the traditional PID control and the neural network-based PID control. According to the simulation results: for complex controlled objects, the neural network PID can more effectively control and perform online self-tuning of PID parameters, resulting in faster system response, higher control accuracy, and effective reduction of tracking errors.

Wang Mingxiang et al. at the CCC conference, in order to adjust the suspension performance to improve the ride comfort of the vehicle, proposed a PID controller based on BP neural network. By modeling the active suspension system and equations, a three-layer structure of the BP network was constructed, and the connection weights and thresholds of the BP components in the controller were adjusted. Simulation results showed that when using the BP-PID controller on bumpy roads, the RMS values of zs, yu, and F decreased by more than 30%, 30% and 10% respectively [11]. By using the BP-PID controller on random roads, the RMS values of zs, yu, and F decreased by more than 50%, 50%, and 50% respectively. This effectively improved the suspension performance, ride comfort, and handling stability of the vehicle.

Xin Chen and Junjie Peng presented their research at the SGEE conference, focusing on the time-varying and delay characteristics of the water level control system of nuclear power plant regulators. By fitting the mathematical model of the pressurizer water level system of the nuclear power plant and using the gradient descent method to modify the weights of the neural network, they conducted simulations. The results showed that compared to the traditional PID, the BP neural network PID obtained a smoother simulation curve, without significant overshoot or oscillations, and could successfully achieve stability within a short period of time [12].

4. Comparative Analysis

4.1. Commonalities of the three improved PID control methods

From nine different research cases, whether it is the attitude control of quadrotor drones, the adaptive dimming of LEDs, or the flexible robotic arm, these systems all face a common challenge: strong nonlinearity, large external disturbances, and system parameters changing over time and being difficult to precisely model. Traditional fixed-parameter PID control cannot maintain stable performance in these scenarios, and the proposal of improved PID models is precisely to solve the control adaptability problems in such complex environments.

Although these three improved PID control methods have different implementation approaches, it can be seen from the actual cases that they share a highly consistent control concept: they all introduce intelligent adjustment mechanisms on the traditional PID proportional-integral-derivative framework to achieve dynamic adaptive optimization of parameters.

After summarizing the commonalities reflected in the nine cases, it can be found that these three improved PID control methods also have distinct characteristics in their implementation mechanisms, application fields, and parameter tuning logic. Different researchers choose different types of improved models based on the dynamic characteristics of the control object, the degree of nonlinearity, and the requirements for real-time performance or accuracy, thus forming their respective application rules. Therefore, in order to deeply understand the performance and differences of these improved PID control methods in actual systems, it is necessary to analyze the commonalities and characteristics in different aspects of these representative cases of fuzzy PID, adaptive PID, and neural network PID respectively

4.2. Analysis of the characteristics of the three PID models based on cases:

4.2.1. Characteristics and rules of fuzzy PID control

From three types of research cases - drone attitude control, adaptive lighting of LEDs, and voltage stability of switched reluctance motors - it can be seen that the application objects of fuzzy PID generally have the characteristics of strong nonlinearity, frequent external disturbances, and difficulty in accurately establishing the model. The common point of these systems is that the parameters change unpredictably, but human engineering experience can provide effective control inspiration. Researchers generally use fuzzy logic to formalize the experience knowledge and use error and error rate of change as fuzzy variables to make online corrections to PID parameters.

From the comparison of cases, it can be seen that fuzzy PID shows three consistent trends in different fields: fast response; low model dependence; excellent real-time performance but limited optimization accuracy. This also reflects the advantages and characteristics of fuzzy PID control, which lies in replacing models with experience, but this system still needs to combine with other algorithms to achieve high accuracy.

4.2.2. Characteristics and rules of adaptive PID control

From three cases - pan-tilt vision servo, off-grid microgrid, and underwater robot - it can be seen that adaptive PID mainly addresses the situation where system parameters and external environment change dynamically, resulting in the failure of fixed-parameter control. These research objects all have the following commonalities: target size, load current, external disturbances or fluid resistance, etc., will continuously change with the working conditions.

Through comparative analysis, these cases show the following common rules: Adaptive PID does not rely on fuzzy experience rules but is based on mathematical identification algorithms, has dynamic reconfiguration capabilities; can track the target more accurately and can maintain stability even when subjected to external interference; the control effect depends on the accuracy of system parameter identification. Compared with fuzzy PID control, adaptive PID control reduces the reliance on human experience and emphasizes parameter self-tuning based on real-time data, becoming more intelligent.

4.2.3. Characteristics and rules of neural network PID control

From three cases - flexible robotic arm, vehicle active suspension, and nuclear power water level control - it can be seen that the typical objects of neural network PID are systems with complex structures, strong nonlinearity, and high precision requirements. These systems often have multi-variable coupling, time delays, and difficult-to-establish precise mathematical models.

After comparing the three types of applications, it can be found that the common features of neural network PID mainly lie in the following aspects: outstanding nonlinear learning ability; strong adaptability; and the ability to meet high precision and complexity requirements. From these cases, it can be seen that neural network PID control is currently the most intelligent control strategy among the three methods, with the weakest modeling dependence and the highest computational complexity.

4.3. Comparing three types of PID control

By comparing three different types of PID control, we can see that they have different trade-offs in terms of cost, control effect, and research focus. The implementation cost of fuzzy PID is the lowest, as it only needs to establish fuzzy rules to achieve rapid response and anti-disturbance control without relying on an exact model. Its advantage lies in strong real-time performance and simple structure; adaptive PID has a slightly higher cost, as it requires real-time identification and parameter updates, but can maintain stable performance in the case of system parameter changes or frequent external disturbances, balancing speed and accuracy; neural network PID has the highest calculation and implementation cost, requiring strong computing power and data support, but can achieve optimal control effect through self-learning, showing the highest precision and stability in non-linear and complex coupled systems. Overall, these three types represent the evolutionary path from "experience-driven" to "algorithm-driven" to "learning-driven" in control: fuzzy PID focuses on speed and flexibility, adaptive PID emphasizes dynamic stability and reliability, and neural network PID pursues intelligent and high-precision control.

4.4. Summary and comparison with traditional PID

From the analysis in the previous text, it can be seen that the improved PID control inherits the simple structure and general adaptability of traditional PID, and has improved intelligence and adaptive capabilities. Traditional PID relies on fixed parameters and performs well in systems with known models and stable environments, but when facing non-linearity, disturbances, or changes in operating conditions, its performance tends to decline, resulting in large overshoots, slow responses, or oscillations [3]. While fuzzy PID, adaptive PID, and neural network PID have respectively broken through these limitations at different levels. In other words, these cases reflect a clear trend: modern PID control is no longer limited to the regulation of static parameters, but through fuzzy logic, adaptive algorithms, and neural networks, systems have the evolutionary ability from experience to algorithm to intelligent learning.

5. Conclusion

Although current research has made significant progress in directions such as fuzzy PID, adaptive PID, and neural network PID, there are still some deficiencies and challenges. The main problem lies in the generalization and engineering implement ability of the algorithms: fuzzy PID relies on human experience, and the rule design lacks a unified standard; adaptive PID has a higher cost in real-time identification and is highly dependent on model accuracy and computing power; neural network PID has the self-learning ability, but the training is complex and the computational cost is high.

Future development trends will focus more on the integration of algorithms and intelligent optimization. Hybrid methods of multiple improved PID will become the mainstream direction, such as combining fuzzy logic and neural networks to form "fuzzy-neural network PID", or introducing deep learning algorithms in adaptive PID to achieve automatic parameter setting and prediction correction.

In general, PID control is the most common and practical control method, which can balance speed, stability, and precision through the cooperation of the proportional, integral, and derivative parts. As the systems become increasingly complex, three improved methods have been developed: fuzzy PID, adaptive PID, and neural network PID. Fuzzy PID is more flexible and can adjust according to empirical rules; adaptive PID can automatically correct parameters based on real-time changes; and neural network PID can optimize control through learning, making the system smarter. Each of them has its own advantages in different scenarios, but the common point is that they all make the control system more stable, more accurate, and more "intelligent". Although these methods still have problems such as large computational load, difficulty in standardization, and lack of long-term verification in actual industrial applications at present, with the development of artificial intelligence and automation technologies, the future PID control will definitely become more intelligent, self-learning, and will also play a role in more real scenarios.

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