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Control Method of DC Motor Based on PID Control

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Abstract:
DC motor control has long been a fundamental topic in industrial automation, robotics, and embedded systems. Among numerous control strategies, PID control remains the most widely applied approach due to its simple structure, intuitive tuning process, and strong engineering practicality. However, with increasing system complexity and diverse application scenarios, traditional PID methods face challenges such as parameter sensitivity, limited robustness, and difficulties in dealing with disturbances and nonlinearities. This paper provides a comprehensive review of PID-based control methods for DC motors. The survey first introduces the characteristics of DC motor models and summarizes the basic principles of PID control. It then categorizes existing research into several groups, including classical tuning techniques, improved PID structures, adaptive and intelligent PID algorithms, observer-assisted PID approaches, and PID implementations within embedded platforms. For each category, representative methods, performance characteristics, advantages, and limitations are systematically analyzed. Furthermore, this review discusses key engineering challenges and identifies research gaps that remain insufficiently addressed in current literature. Overall, the paper aims to present an organized understanding of PID-based DC motor control development and to highlight future research trends in practical and intelligent control strategies.

Keywords: PID Control; DC Motor; Control Strategies; Classical and Modern Control Methods

1. Introduction

DC motor control is a fundamental research topic in industrial automation, mechatronic systems, and mobile robotics. Due to increasing requirements for precision, stability, and robustness, PID-based control methods continue to play a central role in motion control applications. Owing to their intuitive structure and ease of implementation, PID controllers remain the most widely adopted strategy in engineering practice.

Over the past decades, researchers have introduced a wide range of improvements to enhance the performance and applicability of PID controllers. In terms of structural enhancements, Araki and Taguchi's modern formulation of two-degree-of-freedom PID (2DOF-PID) demonstrated that separating reference tracking and disturbance rejection significantly improves closed-loop performance in practical servo systems [1]. For adaptive and intelligent PID control, recent work has shown that adaptive fuzzy-PID controllers, such as the method proposed by Kandiban and Arulmozhi, provide superior robustness against nonlinear dynamics and load variations in motor drive systems [2]. To further address system uncertainties and external disturbances, observer-assisted PID controllers have emerged as an effective strategy. Notably, extended-state-observer (ESO)-based PID designs, inspired by developments in active disturbance rejection control (ADRC), have demonstrated strong capability in estimating lumped disturbances in real time and improving disturbance attenuation for DC motors [3].

In addition, advancements in embedded systems have driven the practical implementation of digital PID controllers. Current studies emphasize the importance of discrete-time PID formulations that account for sampling periods, quantization effects, PWM nonlinearities, and limited computational resources in microcontroller-based motor control platforms [4]. Furthermore, recent optimization-based PID tuning techniques, such as particle swarm optimization (PSO), have expanded the capability of PID controllers by enabling automated parameter selection and improved convergence properties in complex control environments [5].

Despite these advancements, existing research still reveals fragmentation among different PID approaches, and challenges remain in dealing with nonlinearities, parameter variations, model uncertainties, and digital implementation constraints. Therefore, a systematic and comparative review of PID-based DC motor control methods is valuable for understanding the evolution of the field, identifying performance gaps, and guiding the development of more intelligent, robust, and application-oriented control strategies.

2. Fundamentals and Background

2.1 DC Motor Model and Control Characteristics

DC motors are widely used in industrial automation, robotics, electric vehicles, and embedded motion-control platforms due to their simple structure, ease of actuation, and fast dynamic response. A standard DC motor consists of the stator magnetic field, rotor windings, commutation mechanism, and mechanical load. For control analysis and controller design, it is common to derive a mathematical model that captures both the electrical and mechanical dynamics.

The electrical subsystem follows Kirchhoff's voltage law and can be described by:

$$V_a = L_a \frac{di_a}{dt} + R_a i_a + e_b \tag{1}$$

where V_a is the armature voltage, L_a and R_a are the armature inductance and resistance, i_a is the armature current, and $e_b = K_e \omega$ is the back electromotive force (EMF), with ω denoting the angular speed and K_e the EMF constant.

The mechanical subsystem follows the rotational motion equation:

$$J \frac{d\omega}{dt} + B\omega = T_m - T_L \tag{2}$$

where J is the rotor inertia, B is the viscous friction coefficient, $T_m = K_t i_a$ the electromagnetic torque, T_L is load torque, and K_t is the torque constant.

By combining the electrical and mechanical equations, the DC motor transfer function from input voltage to motor speed can be written as:

$$G(s) = \frac{\omega(s)}{V_a(s)} = \frac{K}{(L_a s + R_a)(Js + B) + K_e K_t} \tag{3}$$

This model reveals several intrinsic features of DC motor systems, including inertia, damping, electromechanical coupling, and limited low-frequency gain.

Key control characteristics of DC motors include: (1) Strong coupling between electrical and mechanical dynamics. (2) High sensitivity to load disturbances, making robust control essential. (3) Presence of nonlinear effects, such as saturation, dead zones, friction, and brush commu-

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tation imperfections. (4) Requirements for fast response, typically on the millisecond scale. (5) Constraints imposed by digital implementation in embedded systems, including sampling effects, quantization, and PWM nonlinearity.

These characteristics imply that the control strategy must offer robustness, fast transient performance, and ease of implementation, making PID control one of the most widely adopted solutions in DC motor applications.

2.2 Basic Principles of PID Control

The Proportional-Integral-Derivative (PID) controller is a classical linear control strategy that remains dominant in industrial systems due to its simplicity, interpretability, and broad applicability. The standard PID control law is given by:

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

where $e(t)$ is the tracking error and K_p, K_i, K_d are the proportional, integral, and derivative gains.

The proportional term reduces instantaneous error and improves response speed. Increasing K_p accelerates the rise time. Excessively large K_p may cause oscillation or instability. P-control alone cannot eliminate steady-state error.

The integral term accumulates error over time, eliminating steady-state error and improving tracking accuracy. Ensuring zero steady-state error in ideal conditions may slow down system response or cause integral windup, requiring anti-windup techniques.

The derivative term predicts the error's future trend, improving transient performance; it helps reduce overshoot and oscillations, is highly sensitive to noise; practical implementations include derivative filtering.

PID controllers are widely used in DC motor speed and position control due to their suitability for first-order-plus-inertia systems. Typical motor control architecture includes outer-loop PID for speed control, inner-loop PI for current regulation, and PWM voltage actuation and feedback from encoders or hall sensors. This structure achieves fast transient response, disturbance rejection, and adaptability to a broad range of loads and operating conditions.

3. Review of PID Control Methods

3.1 Classical PID Tuning Methods

Classical PID tuning methods represent the earliest and most widely adopted approaches for determining the controller gains K_p, K_i and K_d. These methods typically rely on empirical rules, frequency response characteristics, or simplified process models. Although they are straightforward and computationally inexpensive, classical methods often struggle with systems that exhibit strong nonlinearity, high noise levels, or time-varying dynamics. Nevertheless, they form the foundation of modern controller tuning and remain widely used in industrial automation. Recent reviews by Åström and Hägglund highlight that classical PID remains the baseline for evaluating new control methods despite its limitations [6].

One of the most influential classical tuning strategies is the Ziegler–Nichols (Z–N) method, proposed in the 1940s. The Z–N method provides two main procedures: the step-response method and the ultimate gain method. In the ultimate gain method, the plant is driven to sustained oscillation by increasing the proportional gain until reaching the ultimate gain K_u, with the observed oscillation period denoted as T_u. The PID parameters are then derived based on proportional relationships. Despite its simplicity, Z–N tuning typically results in large overshoot and oscillatory behavior, as it tends to produce aggressive control actions. Nonetheless, it remains an essential benchmark for evaluating new tuning methods.

Another widely used classical method is the Cohen–Coon tuning rule, which is particularly effective for first-order plus dead-time (FOPDT) systems. By considering both the process time constant and dead time, the Cohen–Coon method yields improved performance in systems with significant delays. Compared with Z–N tuning, Cohen–Coon tuning provides more balanced responses but still struggles with uncertainties and nonlinearities. Luyben's work on PID tuning for dead-time systems further demonstrates the relevance of Cohen–Coon rules in modern process control [7].

The Internal Model Control (IMC) tuning approach provides a more systematic framework. IMC explicitly incorporates a process model and allows designers to adjust the trade-off between robustness and responsiveness through a tuning parameter. This method naturally handles time delays and is less prone to instability than Z–N tuning. From the IMC structure, a corresponding PID controller can be mathematically derived, making IMC-PID one of the most robust classical tuning methods. Skogestad's IMC-based tuning formulas remain among the most widely used in robust process control design [8].

Additionally, the root-locus method enables designers to visualize the movement of closed-loop poles as controller gains vary. It is particularly useful when modifying the proportional gain or introducing derivative action. The root-locus method allows for fine-tuning of system behavior, including damping ratio, natural frequency, and dominant pole placement. However, it requires that the designer have a deeper understanding of system dynamics.

Although classical tuning methods are easy to apply, they frequently assume that the system dynamics are linear and time-invariant, which is rarely the case in practical DC motor applications. Friction, saturation, load disturbances, and noise can severely limit the performance of controllers tuned by classical rules. Therefore, classical PID tuning is often regarded as a reasonable starting point but insufficient for high-performance applications without further modifications.

3.2 Improved PID Control Methods

Improved PID methods refine the classical PID controller by addressing specific limitations, including integral windup, sensitivity to noise, large overshoot, and lack of flexibility in balancing tracking and disturbance rejection. These enhancements are essential for real-world DC motor control, where actuators face physical constraints and measurements are often noisy. Research by Zheng et al. provides a systematic anti-windup design for PID controllers, demonstrating its effectiveness in practical systems [9].

3.2.1 . Anti-Windup Compensation

Integral windup occurs when actuator saturation causes prolonged accumulation of error in the integral term, leading to large overshoot and extended settling time. Anti-windup schemes mitigate this problem by blocking or modifying the integral action when saturation occurs. A common approach is the conditional integration method, where the integrator is disabled when the controller output exceeds actuator limits. Another method uses a feedback anti-windup loop that subtracts the saturated output from the unsaturated output, effectively limiting the integrator's accumulation rate.

3.2.2 . Derivative Filtering

The derivative term, although crucial for improving transient performance, is notoriously sensitive to high-frequency noise. To address this issue, a low-pass filtered derivative is widely adopted:

$$D(s)=\frac{K_d s}{\tau_d s+1} \tag{5}$$

This filtered derivative reduces noise amplification while retaining the beneficial predictive effect of the derivative action. The choice of filter time constant τ_d directly influences the balance between noise immunity and control aggressiveness.

3.2.3 . Two-Degree-of-Freedom (2DOF) PID

Classical PID controllers couple tracking performance and disturbance rejection through the same error signal, which limits flexibility. A two-degree-of-freedom PID controller (2DOF-PID) introduces an additional parameter to independently tune the response to reference changes. This structure significantly improves performance in applications requiring smooth command tracking—such as robotic movement—without compromising disturbance rejection.

Feedforward Compensation

Feedforward terms can be added to enhance system response when the input or disturbance is measurable. For example, velocity feedforward can compensate for static friction, while load feedforward can address predictable torque variations in DC motor systems. Feedforward enhances dynamic performance but does not replace the need for feedback control, as it cannot compensate for unmodeled disturbances.

3.2.4 . Integral Separation

When the error is large, applying strong integral action can cause instability. Integral separation activates the integral term only when the error falls below a threshold. This

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approach ensures rapid response when errors are large while maintaining precise steady-state performance for small errors.

Overall, improved PID strategies provide practical solutions to classical limitations and offer enhanced performance for industrial processes and embedded motor control. However, their parameters remain static, making them insufficient for processes with strong nonlinearities or time-varying dynamics.

3.3 Adaptive and Intelligent PID Methods

Adaptive and intelligent PID controllers dynamically adjust their parameters to cope with uncertainties, nonlinearities, and disturbances. These methods extend PID control to applications where system dynamics change over time or are difficult to model. A comprehensive study by Wang demonstrates the effectiveness of fuzzy and intelligent control strategies in nonlinear environments [10].

3.3.1 . Adaptive PID

Adaptive PID controllers modify their gains in real time based on system behavior. Model Reference Adaptive Control (MRAC) is a widely used framework where the system is forced to follow a reference model by adapting controller parameters according to error dynamics. Gain scheduling is another adaptive technique where different sets of PID parameters are used depending on operating conditions, such as varying speed or load.

3.3.2 . Fuzzy PID

In fuzzy PID control, the gains K_p, K_i and K_d are adjusted by a fuzzy inference system based on linguistic rules derived from expert knowledge. For instance, if the error is large and decreasing rapidly, the controller might increase derivative action and reduce proportional action. Fuzzy PID controllers excel in nonlinear and uncertain environments but require careful tuning of membership functions and rules.

3.3.3 . Neural Network PID

NN-PID control, a neural network generates appropriate gains based on input features such as error and its derivatives. Neural networks provide strong adaptability but require computational resources and training data.

3.3.4 . Evolutionary Optimization

Evolutionary algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and differential evolution (DE) optimize PID gains either offline or online. These methods search the parameter space efficiently and are particularly useful when the system model is unknown or highly nonlinear.

Intelligent PID controllers offer high flexibility, robustness against uncertainties, and strong adaptability. However, these benefits often come at the cost of increased computational complexity, which limits their use in low-power embedded systems.

3.4 Observer-Based PID Methods

Observer-based PID controllers integrate estimation mechanisms to enhance disturbance rejection, robustness, and noise immunity. The key idea is to estimate unmeasured states or disturbances and use them to augment the control law.

3.4.1 . Disturbance Observer (DOB)-based PID

Disturbance observers estimate the effect of unknown external inputs: $\hat{d}(t)$

The estimated disturbance $\hat{d}(t)$ can be compensated for by adjusting the control signal:

$$u(t) = u_{\text{PID}}(t) - \hat{d}(t) \tag{6}$$

DOB-PID controllers significantly improve robustness to load variations, friction, and external perturbations. They are commonly used in motor drives where disturbances are frequent and often unpredictable.

3.4.2 . Extended State Observer (ESO)-based PID

As part of the Active Disturbance Rejection Control (ADRC) framework, extended state observers estimate both internal states and generalized disturbances. ESO treats unknown dynamics, nonlinearities, and external disturbances as a single extended state, which is estimated and compensated for in real time. ESO-PID combines the simplicity of PID with the robustness of ADRC.

3.4.3 . Kalman Filter-Aided PID

Kalman filtering enhances PID performance in noisy environments by providing optimal state estimates. The derivative term can be computed using filtered estimates, reducing noise sensitivity. Kalman-based PID controllers are widely used in systems with high sensor noise, such as low-cost encoder measurements.

Observer-based PID controllers significantly enhance performance, but they require additional modeling effort and can be sensitive to tuning errors in the observer.

3.5 PID Control for Embedded Systems

Digital implementation of PID controllers introduces constraints such as sampling delays, quantization, limited precision, and real-time execution requirements. The discrete-time form of PID is commonly expressed as:

$$u[k] = K_p e[k] + K_i \sum_{i=0}^{k} e[i] T_s + K_d \frac{e[k] - e[k-1]}{T_s} \quad (7)$$

3.5.1 . Sampling and Quantization

The choice of sampling time T_s significantly influences stability and performance. Too large a sampling time reduces accuracy, while too small a sampling time increases computational burden. Quantization from ADC and DAC introduces noise and resolution limitations. Fixed-point arithmetic must be handled carefully to avoid overflow or precision loss.

3.5.2 . PWM Nonlinearity

Pulse-width modulation (PWM) drives the motor but introduces nonlinear behavior due to switching and dead time. Proper filtering and saturation handling are necessary.

3.5.3 . Real-Time Constraints

Embedded systems, especially low-power microcontrollers, must execute all computations within a single sampling period. Memory constraints limit the size of buffers and lookup tables. Therefore, PID implementations must be computationally efficient and numerically stable.

4. Conclusion

In this paper, a comprehensive review of PID-based control methods for DC motor systems has been presented. Beginning with the classical tuning approaches, such as Ziegler–Nichols, Cohen–Coon, IMC-based tuning, and root-locus methods, the discussion highlighted their historical significance, simplicity, and long-standing role as the foundation of industrial PID applications. However, their limitations in dealing with nonlinearities, uncertainties, and strong disturbances motivated the development of improved PID structures. Enhanced strategies including anti-windup mechanisms, filtered derivative terms, two-degree-of-freedom PID, feedforward compensation, and integral separation, were shown to significantly improve control performance in practical motor-driven systems.

The paper further examined adaptive and intelligent PID methods, which address the fundamental limitations of fixed-parameter controllers. Adaptive schemes, fuzzy logic, neural networks, and evolutionary optimization algorithms enable dynamic gain adjustment and improved robustness under varying operating conditions. These methods expand the applicability of PID control into complex, nonlinear, and uncertain environments where classical techniques are insufficient.

Observer-based PID approaches were also analyzed, including disturbance observer (DOB)-based PID, extended state observer (ESO)-assisted PID, and Kalman-filter-aided PID. These methods enhance disturbance rejection and noise robustness by incorporating real-time estimation of states or uncertainties, thus bridging the gap between classical PID simplicity and modern control intelligence.

Moreover, the discussion on embedded-system implementation emphasized the importance of discrete PID formulations, sampling constraints, quantization effects, and real-time computational limitations. These considerations are crucial for deploying PID control on microcontrollers frequently used in DC motor applications.

Overall, PID control continues to evolve, maintaining its relevance through enhanced robustness, adaptability, and digital implementation capabilities. With ongoing advancements in observer design, intelligent algorithms, and embedded optimization, PID-based methods will remain pivotal in high-performance DC motor control for robotics, automation, and emerging smart systems.

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