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Research on the Integration of PID Controller and Intelligent Optimization Algorithm in the Field of Motor Control

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Abstract. The Proportional-Integral-Derivative (PID) controller is widely adopted in motor control due to its simple structure, high robustness, and ease of implementation. However, in the face of increasingly complex industrial environments and higher precision control requirements, traditional PID control encounters major challenge in terms of response speed of nonlinear systems, anti-interference ability and parameter adaptive adjustment. The paper reviews the integration of intelligent optimization algorithms, like reinforcement learning, genetic algorithms, and particle swarm optimization, with PID controllers, and examines their effects on DC motors, brushless DC motors (BLDCMs), and linear induction motors (LIMs). The results show that intelligent algorithms can effectively enhance dynamic response, trajectory tracking accuracy, and disturbance rejection via online PID parameter optimization.

Keywords: PID Control, Intelligent Optimization Algorithms, Nonlinear Motor Systems, Neural Networks, System-Level Intelligent Evolution

1. Introduction

Due to their simple structure, strong robustness, and ease of implementation, Proportional - Integral - Derivative (PID) controllers have long dominated motor control and are widely used for regulating speed, position, and torque. However, as industrial environments become increasingly complex and control precision requirements rise, traditional PID control often falls short in terms of nonlinear system response, disturbance rejection, and parameter adaptability. Traditional tuning methods like the Ziegler-Nichols method, trial-and-error, and model-based approaches often fail for multivariable, strongly coupled, or time-varying systems. Therefore, intelligent optimization algorithms, including genetic algorithms (GA), particle swarm optimization (PSO), and reinforcement learning-based deep deterministic policy gradient (DDPG), have been applied to PID parameter tuning, allowing online adaptive adjustment and improving dynamic response, trajectory tracking, and robustness. In addition, hybrid strategies like the PSO-gravity search algorithm (PSO-GSA) enhance motor control, while neural network-based sensorless control ensures precise operation at lower cost. Moreover, system-level methods, such as digital twins, co-simulation, and hardware-in-the-loop (HIL), support intelligent optimization and system evolution. This paper reviews recent advances in intelligent PID control for typical motor systems, covering single- and multi-algorithm optimization, nonlinear and sensorless control, and multi-condition disturbance rejection, and discusses the

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primary technical challenges and future directions. Thus, it highlights the significance of intelligent optimization and sensorless control in enhancing motor performance, accuracy, and operational efficiency.

2. Theoretical basis and limitations of PID controllers

2.1. Principles of PID control

In an automatic control system, the PID controller is a classical controller that operates by applying proportional, integral, and derivative actions to the error signal. The output $u(t)$ is composed of these three parts together, and its specific expression is as follows.

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

The proportional term (P) achieves a rapid response to the deviation by amplifying the error $e(t)$, improving the response rate of the system. However, it cannot fully remove steady-state error. As the system approaches the desired value, the decreasing error reduces the proportional output, which may cause the system to remain outside the target value. The integral term (I) accumulates the error over time, continuously driving the system toward the desired value and ultimately eliminating steady-state error. However, excessive accumulation in the initial response may cause overshoot or even instability. The derivative term (D) predicts the error trend based on its rate of change and adjusts the output in advance to suppress oscillations and smooth the response. Yet, the derivative term is highly sensitive to high-frequency noise, which can be mistaken for actual error changes, causing sharp fluctuations in the controller output and reducing control effectiveness. By utilizing the strengths of all three terms and properly adjusting the proportional, integral, and derivative gains, an effective balance between response speed, system stability, and control accuracy can be attained, leading to high-performance control.

2.2. Limitations of traditional tuning methods

Traditional PID tuning methods have significant limitations in practical applications, mainly due to their inherent shortcomings. The Ziegler-Nichols method determines parameters by identifying the critical state at which the system enters sustained oscillation. Although simple, it lacks robustness and tends to operate the system at the edge of stability, hence making it highly prone to instability under external disturbances or parameter variations. The trial-and-error method depends entirely on the engineer's experience and repeated adjustments, making it time-consuming and inefficient, particularly for multivariable or strongly coupled systems, and it seldom achieves globally optimal parameters, typically satisfying only local performance requirements. Model-based methods require an accurate mathematical model of the system. However, in industrial systems, particularly motors with nonlinear and time-varying characteristics, precise modeling is highly challenging, and model errors are inevitable. These errors directly affect tuning accuracy and control performance, limiting the applicability of such methods. These limitations have restricted traditional tuning methods in complex industrial settings, motivating the development of more adaptive, robust, and efficient PID tuning approaches. To satisfy the increasing requirements of modern industrial systems for control accuracy and fast response, new approaches frequently integrate intelligent algorithms with online adaptive mechanisms, boosting controller adaptability and robustness in dynamic conditions.

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2.3. Key issues in motor control

The performance requirements of modern motor control are steadily increasing, with key challenges arising from continuously evolving application requirements. In terms of high-precision trajectory tracking, complex applications like the ball-and-plate (B&P) system require the ball to move strictly along a predefined path. And this requires the control system to provide real-time sensing, rapid response, and high-precision control, while ensuring trajectory stability under external disturbances and system nonlinearities to minimize deviations and maintain long-term tracking accuracy. This is crucial for the precise operation of robots and attitude control in aerospace. In sensorless control, reducing or even eliminating physical sensors has become a trend due to factors such as cost, reliability, and space limitations, for example, in brushless DC motors where the rotor position cannot be directly measured, To achieve precise control, indirect methods such as back electromotive force estimation or flux linkage observation are relied upon. These techniques simplify the hardware structure and enhance the adaptability and reliability of the system in harsh environments. In terms of resistance to parameter perturbation, the industrial operating environment is complex and variable, and motor parameters drift due to temperature changes, load fluctuations, and material aging. If the control system lacks sufficient robustness, performance will decline. To ensure that speed estimation accuracy and dynamic performance remain stable in the face of parameter changes and external disturbances. Thus, the improvement of trajectory tracking accuracy, the achievement of reliable sensorless control, and the enhancement of resistance to parameter perturbations have become key challenges in modern motor control, continuously driving innovation in advanced control algorithms and hardware technologies.

3. The application of intelligent optimization algorithm in PID parameter tuning

3.1. Single intelligent algorithm optimization strategy

Intelligent optimization algorithms provide powerful tools for PID parameter tuning, overcoming the tendency of traditional methods to get trapped in local optima. For example, genetic algorithms (GA) simulate the process of natural selection, using a fitness function to guide a population of parameters through selection, crossover, and mutation in a multidimensional solution space, thereby enhancing global search capability. In addition, GA demonstrates strong robustness and exploratory ability for complex multimodal problems. When applied to motor control, like trajectory tracking in the ball-and-plate system, GA optimization can reduce the integral absolute error (IAE) by about 40%, effectively eliminate system overshoot, and improve tracking accuracy and dynamic response performance [1]. Based on swarm intelligence, particle swarm optimization (PSO) guides the search direction of particles using the individual and global historical best positions, with the update formula as follows.

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \tag{2}$$

The PSO converges relatively quickly, and its parameter tuning is straightforward, while also providing a good balance between exploration and exploitation. In the optimization of motor PID parameters, PSO can effectively suppress torque fluctuations during dynamic operation, reducing their amplitude by up to 50% and significantly improving system stability and response smoothness [2]. Therefore, while GA emphasizes global search diversity, PSO accelerates convergence through

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collaborative mechanisms; both effectively overcome the limitations of traditional tuning methods and offer reliable support for motor PID optimization.

3.2. Multi-algorithm hybrid optimization strategy

To overcome issues such as slow convergence or susceptibility to local optima in single intelligent algorithms, hybrid optimization strategies that combine the strengths of multiple algorithms have become a research focus. For example, PSO-GSA combines the fast convergence of PSO with the strong global search capability of GSA. In this method, GSA models universal gravitation, making particles attract one another and directing the search process to efficiently bypass local optima. In motor control parameter optimization, PSO-GSA exhibits significant advantages. Prior studies have showed that controllers optimized using this hybrid algorithm shorten the motor's no-load startup response time from 0.35 seconds to 0.16 seconds, notably enhancing dynamic response. Moreover, when subjected to a sudden 2 N·m load disturbance, the motor speed deviation decreases sharply from 180 rpm to 42 rpm, greatly improving disturbance rejection [3]. As such, the PSO-GSA hybrid algorithm utilizes combined strengths to accelerate system response and markedly improve stability and robustness under complex dynamic and high-disturbance conditions, highlighting the practical value of multi-algorithm hybrid optimization in high-performance motor control.

3.3. Intelligent control for nonlinear systems

For motor systems with pronounced nonlinear characteristics, such as dead zones, saturation, and friction, particularly BLDCMs, traditional PID control and model-based optimization methods often struggle to achieve effective control. As a solution, fuzzy PID control utilizes fuzzy logic reasoning to dynamically adjust PID parameters based on the real-time error (e) and its rate of change (e_c). It does not rely on an exact mathematical model, but instead uses a fuzzy rule base constructed from expert knowledge, allowing flexible handling of system nonlinearity and uncertainty. This adaptive tuning mechanism makes fuzzy PID particularly suitable for complex nonlinear systems such as BLDCM. Practical applications show that fuzzy PID can effectively reduce the speed fluctuation of BLDCM by approximately 30% compared to traditional PID with fixed parameters, improving the stability and accuracy of the control system to a certain extent [4]. This effect is mainly due to the fact that the fuzzy controller compensates for the system's nonlinear dynamics in a timely manner, ensuring performance under a wide range of operating conditions. From this, it can be seen that fuzzy PID control, as an intelligent control strategy for nonlinear motor systems, effectively compensates for the shortcomings of traditional methods through rule-driven parameter adaptation, providing strong technical support for high-performance motor control [3].

4. Intelligent PID control applications in typical motor systems

4.1. Applications of intelligent control in nonlinear motor systems

In motor control, complex nonlinearities and strong coupling bring major difficulties. For instance, in the ball-and-plate (B&P) system, the ball's position is closely linked to the plate's tilt, while in linear induction motors (LIMs), parameter variations influence speed estimation. Traditional linear control methods like fixed-parameter PID struggle to meet the requirements for trajectory tracking accuracy and robustness in speed estimation, notably when the system model cannot be precisely defined. To achieve B&P trajectory tracking, PID parameters are tuned via the deep deterministic

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policy gradient (DDPG) algorithm using reinforcement learning, where the agent interacts with the environment to learn optimal control strategies. The reward function is defined as follows.

$$R_i = 10 - (e(t)^2 + u(t)^2) \tag{3}$$

Meanwhile, both the tracking error $e(t)$ and the control input $u(t)$ are minimized. In circular trajectory tracking, DDPG-optimized PID reduces the error by 35% relative to GA-optimized PID, significantly enhancing control performance in nonlinear systems [5]. For LIM speed estimation, a dual-phase-locked loop (DPLL) structure incorporating pre-filtering, amplitude normalization, and a dual-loop configuration efficiently mitigates harmonic interference and the impact of parameter variations. In comparison with standard single-phase-locked loops (SRF-PLL), it markedly reduces steady-state error and enhances the precision and reliability of speed estimation. Existing studies have indicated that DPLL exhibits strong disturbance rejection under complex operating conditions [6]. Thus, DDPG and DPLL serve as intelligent control approaches for nonlinear trajectory tracking and speed estimation, respectively, boosting system control effectiveness and adaptability amid model and parameter uncertainties.

4.2. Neural networks and sensorless control techniques

Traditional brushless DC motor (BLDCM) control typically relies on Hall sensors to detect rotor position, which increases cost and reduces reliability. Sensorless control techniques based on BP neural networks leverage their strong nonlinear mapping and learning capabilities to directly predict commutation signals $\mathrm{g_y(k)}$ from the motor's phase voltages (u_a, u_b) and phase currents (i_a, i_b). The mapping can be expressed as:

$$\mathrm{g_y}(k) = f(u_a(k), u_b(k), i_{a(k)}, i_b(k); \theta) \tag{4}$$

where θ denotes the neural network parameters, including weights and biases. This approach no longer relies on physical Hall sensors; the processed neural network output can directly drive the power switches to perform commutation. This technique greatly reduces system cost and complexity while enhancing interference resistance, as the neural network can reliably extract position information from noisy signals. Besides, the network possesses learning capabilities, allowing it to adapt to variations in motor parameters and operating conditions. Related studies have shown that this method performs well in practical applications, providing an economical, reliable, and intelligent sensing solution for BLDCMs [7].

4.3. Multi-condition disturbance control for DC motors

In complex working conditions, DC motors often encounter sudden disturbances and parameter changes. Traditional PID control faces difficulties in balancing response speed and robustness. To address this issue, the PSO-gravity search hybrid algorithm, also known as PSO-GSA, It combines the fast convergence feature of particle swarm optimization (PSO) with the global search ability of gravity search algorithm (GSA) to achieve efficient global optimization of PID parameters [6]. This fusion strategy effectively overcomes the limitations of a single algorithm and enhances the adaptability and stability of the controller. Studies have shown that PSO-GSA-optimized PID controllers have no overshoot at no-load startup, and the response time has been reduced from the traditional 0.35 seconds to 0.16 seconds. Facing the sudden addition of a 2 N·m load, Speed

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deviation was significantly reduced from 180 revolutions per minute to 42 revolutions per minute, and torque fluctuation was greatly reduced to 0.05 N·m at 2500 revolutions per minute, which is better than the traditional method of 0.09 Newton-meters [8]. The PSO-GSA hybrid algorithm enhances the system's dynamic response and anti-disturbance performance, and also improves the operational stability of the DC motor under multiple operating conditions, demonstrating the key value of intelligent hybrid optimization in complex industrial applications [9].

5. Technical challenges and future directions

5.1. Algorithm performance and deployment constraints

Although intelligent optimization algorithms have achieved some success in motor control, there are still key bottlenecks. One of them is the lack of real-time performance, which limits the practical application of complex algorithms, such as deep deterministic policy gradients, or DDPG, which takes a long time to train, mostly more than 400 seconds per training session, making it difficult to adapt to low-cost control hardware [10]. How to improve training and operation efficiency to meet the requirements of resource-constrained environments is an urgent problem to be solved. Second, the generalization ability of the algorithm is limited. It is an urgent issue to enhance training and runtime efficiency so as to satisfy the demands of resource-constrained environments. Second, the generalization ability of the algorithms is restricted. For instance, many optimization strategies are tailored for specific systems or operating conditions, and their performance deteriorates markedly when the parameters are used to other environments. This reflects the limitations of current methods in adapting to variable systems. In addition, hardware dependency increases system complexity. For instance, the Dual Phase-Locked Loop (DPLL) has a multi-stage filtering structure, which enhances the precision of speed estimation but also imposes a heavier computational burden on the Digital Signal Processor (DSP), restricting its use in resource-constrained devices [4]. Thus, real-time bottlenecks, limited generalization, and hardware complexity are the key challenges for intelligent optimization algorithms in motor control, requiring breakthroughs through algorithm simplification, cross-platform design, and hardware co-optimization.

5.2. Scenario adaptation and generalization capabilities

Future motor control development will center on boosting intelligence, efficiency, and adaptability to tackle varied application scenarios and complex industrial needs. First, lightweight intelligent algorithms will be a key direction. Tailored to the characteristics of embedded systems with limited resources, techniques like knowledge distillation can be used to compress neural network models. This approach can significantly reduce computational requirements while maintaining performance, thus promoting the widespread application of intelligent control algorithms on low-cost hardware. Second, cross-domain transfer learning provides a novel approach to boost algorithm generalization. By leveraging pre-trained models and fine-tuning them in new systems, parameter tuning time can be notably reduced, enabling efficient transfer between different motor control tasks. For example, the transfer of a DDPG model trained in a ball and plate system to robotic arm control effectively enhances adaptation speed and control performance. Moreover, the need for multiple performance metrics in practical applications is addressed by multi-objective collaborative optimization. The use of approaches such as the Pareto frontier seeks the optimal balance among response speed, energy consumption, and noise, enabling efficient motor control.

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5.3. System-level collaboration and intelligent evolution

To meet the rising performance demands of future motor control systems and overcome the limits of traditional point-by-point optimization, the focus must shift to system-level collaborative design and intelligent evolution. Firstly, a multi-objective collaborative optimization framework should be established. By utilizing intelligent techniques such as multi-objective evolutionary algorithms and reinforcement learning, it aligns competing targets like dynamic response, precision, efficiency, and robustness at the system level, pursuing global optimality. Secondly, digital twin technology builds high-accuracy multiphysics models, thus enabling offline tuning and online adjustment. This allows real-time adaptive tuning of PID parameters and system configuration, supporting ongoing system performance enhancement. Meanwhile, high-precision co-simulation drives system development, validating the overall performance and feasibility of the "PID + intelligent optimization" solution in the electromechanical control loop at an early stage, thus ensuring a seamless connection between theoretical achievements and practical applications. By combining hardware-in-the-loop (HIL) and rapid control prototyping (RCP) platforms, hierarchical barriers are broken to form a closed loop of perception, decision, and action, facilitating iterative virtual and physical integration. Future efforts should move from algorithmic details to developing adaptive optimization systems that enable deep collaboration and continuous intelligent evolution, leveraging digital twin and system simulation technologies to enhance motor control systems' intelligence, robustness, and overall performance.

6. Conclusion

This paper reviews the integration of intelligent optimization algorithms and PID control in motor systems, dissects the key mechanisms that can enhance control performance, and finds that swarm intelligence algorithms like genetic algorithms and particle swarm optimization, due to their strong global search capabilities, break through the limitations of traditional fixed-parameter PID control in complex conditions, and the speed and accuracy of parameter optimization have been enhanced. In addition, reinforcement learning methods and deep deterministic policy gradients have endowed PID controllers with online adaptive capabilities, achieving near-zero overshoot high-precision control in nonlinear trajectory tracking and improving system stability and response speed. Hybrid intelligent algorithms such as PSO combined with gravitational search algorithms have enhanced perturbation resistance and multi-condition adaptability in complex environments. While intelligent optimization algorithms have been effective, there are deficiencies in real-time performance, generalization ability and hardware adaptation. Future efforts should be targeted at the lightweight algorithm design, cross-domain transfer learning, and holistic system optimization, in conjunction with digital twin and edge computing technologies. To advance intelligent PID control toward efficiency, stability, and adaptability, and support the intelligent upgrade of motor drive systems.

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