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Review

Review of Servo Systems Towards High-Performance Manufacturing: Identification, Tuning, and Advanced Control

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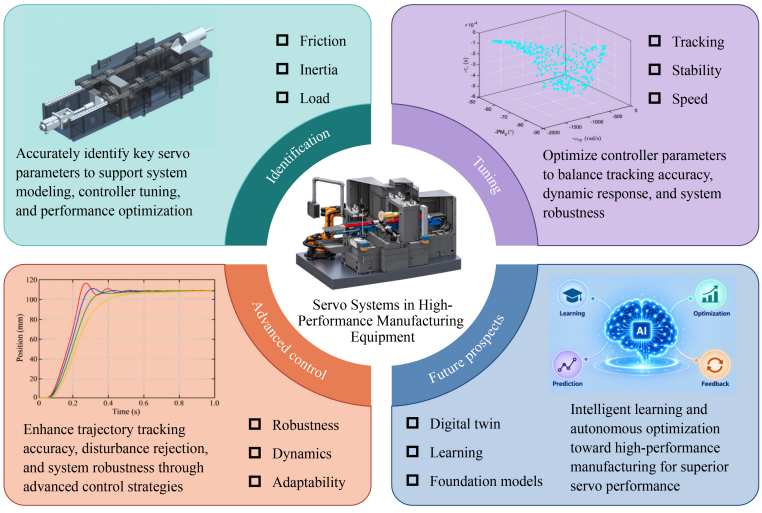
GRAPHICAL ABSTRACT



HIGHLIGHTS

- A unified review framework integrates servo identification, tuning, and advanced control of servo systems.
- Servo system performance is linked to manufacturing accuracy and product quality.
- Friction, inertia, and load identification, and parameter tuning methods of servo systems are reviewed.
- Robust, disturbance-rejection, predictive, and learning-based control are compared.
- AI-enabled identification, autonomous tuning, and intelligent control are envisioned towards high-performance manufacturing.

ABSTRACT Servo systems are critical enabling components of high-performance manufacturing equipment, and their performance directly determines motion accuracy, manufacturing quality, and production efficiency. With the rapid development of high-performance manufacturing technologies, servo systems are required to achieve higher precision, faster dynamic response, and stronger adaptability under increasingly complex operating conditions. However, nonlinear dynamics, time-varying parameters, transmission uncertainties, and external disturbances remain major challenges for achieving high-performance servo systems in practical manufacturing environments. This paper presents a comprehensive review of servo systems technologies enabling high-performance manufacturing, focusing on three key aspects: system identification, parameter tuning, and advanced control strategies. The mathematical modeling and nonlinear characteristics of servo systems are first introduced, followed by a systematic review of recent advances in friction, inertia, and load identification methods. Subsequently, classical tuning approaches and optimization-based strategies are discussed with respect to their roles in improving servo performance. Furthermore, advanced control technologies, including robust control, disturbance rejection control, predictive control, and learning-based intelligent control, are reviewed in terms of their capabilities for enhancing motion accuracy, robustness, and adaptability under complex manufacturing conditions. Finally, future research directions toward intelligent and high-performance manufacturing are

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discussed. The integration of various artificial intelligence technologies with servo systems is expected to drive the evolution of servo systems toward intelligence, self-optimization, and high reliability. This review provides comprehensive insights into the evolution of servo technologies and their potential to support next-generation high-performance manufacturing equipment.

KEYWORDS Servo systems; High-performance manufacturing; System identification; Parameter tuning; Advanced control

1 Introduction

Servo systems are fundamental execution components of high-performance manufacturing equipment, serving as the critical bridge between digital manufacturing instructions and physical motion generation. Their performance directly determines achievable motion accuracy, dynamic capability, process stability, and operational reliability. With the rapid development of high-performance manufacturing technologies, including aerospace manufacturing, semiconductor fabrication, precision engineering, and intelligent production, manufacturing equipment is required to achieve higher precision, faster dynamic response, and stronger adaptability under increasingly complex operating conditions. In this context, improving servo system performance has become a fundamental approach for enhancing the overall capability of high-performance manufacturing equipment.

Among various high-performance manufacturing platforms, computer numerical control (CNC) machine tools represent one of the most important applications of servo technologies [1–8]. As the core motion component of CNC systems, servo drives determine the positioning accuracy, contouring capability, and dynamic machining performance of feed axes. The machining quality of complex components, such as aerospace structural parts and precision molds, strongly depends on the ability of servo systems to accurately follow high-speed and high-precision trajectories. Industrial robots [9–21] also rely heavily on servo systems to achieve flexible and coordinated motion control in applications such as automated assembly, precision manufacturing, and intelligent production lines. Furthermore, advanced manufacturing equipment [22–46], including semiconductor processing platforms and ultra-precision positioning systems, requires servo systems with sub-micron positioning capability and extremely low vibration characteristics. Additive manufacturing equipment [47–54] also relies on high-performance servo systems to achieve precise toolpath tracking, accurate layer positioning, and stable material deposition processes, which are essential for improving manufacturing quality and process consistency. As illustrated in Fig. 1, servo technologies provide essential motion support across diverse manufacturing platforms.

However, achieving high-performance servo control remains challenging because practical manufacturing systems exhibit complex nonlinearities, time-varying parameters, transmission uncertainties, and external disturbances. Time-varying inertia caused by changing loads and operating conditions may alter servo dynamics, while nonlinear factors such as Stribeck friction, backlash, dead zones, and mechanical compliance introduce additional uncertainties. Cutting-force variations, structural vibrations, and other external disturbances further deteriorate motion accuracy. These factors are often strongly coupled and cannot be effectively addressed simply by increasing controller gains, thereby requiring systematic modeling, estimation, optimization, and compensation.

System identification provides key information on friction, inertia, loads, and other uncertain dynamics for modeling and compensation, with recent research shifting from offline methods toward online, adaptive, and data-assisted approaches. Parameter tuning determines closed-loop tracking, dynamic response, and stability, and is increasingly moving from classical empirical methods toward online and optimization-based strategies. Advanced control further addresses nonlinearities, disturbances, constraints, and repetitive errors through robust, disturbance-rejection, predictive, and learning-based methods. These three areas form an interconnected optimization loop: identification supplies dynamic information, tuning maps it into controller parameters, and advanced control uses both to achieve the desired performance, while operating data feed back to support re-identification and retuning.

This review primarily focuses on electromechanical servo systems used in high-performance manufacturing equipment, with particular emphasis on permanent magnet synchronous motor (PMSM)-based servo drives because of their widespread application in precision motion control. The reviewed identification, parameter-tuning, and advanced-control methods are therefore discussed mainly within this electromechanical servo framework. Nevertheless, the underlying principles are applicable to a broader range of manufacturing platforms, including CNC machine tools, industrial robots, semiconductor manufacturing equipment, and additive manufacturing systems, although their implementation priorities differ according to mechanical structure, operating conditions, disturbance characteristics, and manufacturing-performance requirements.

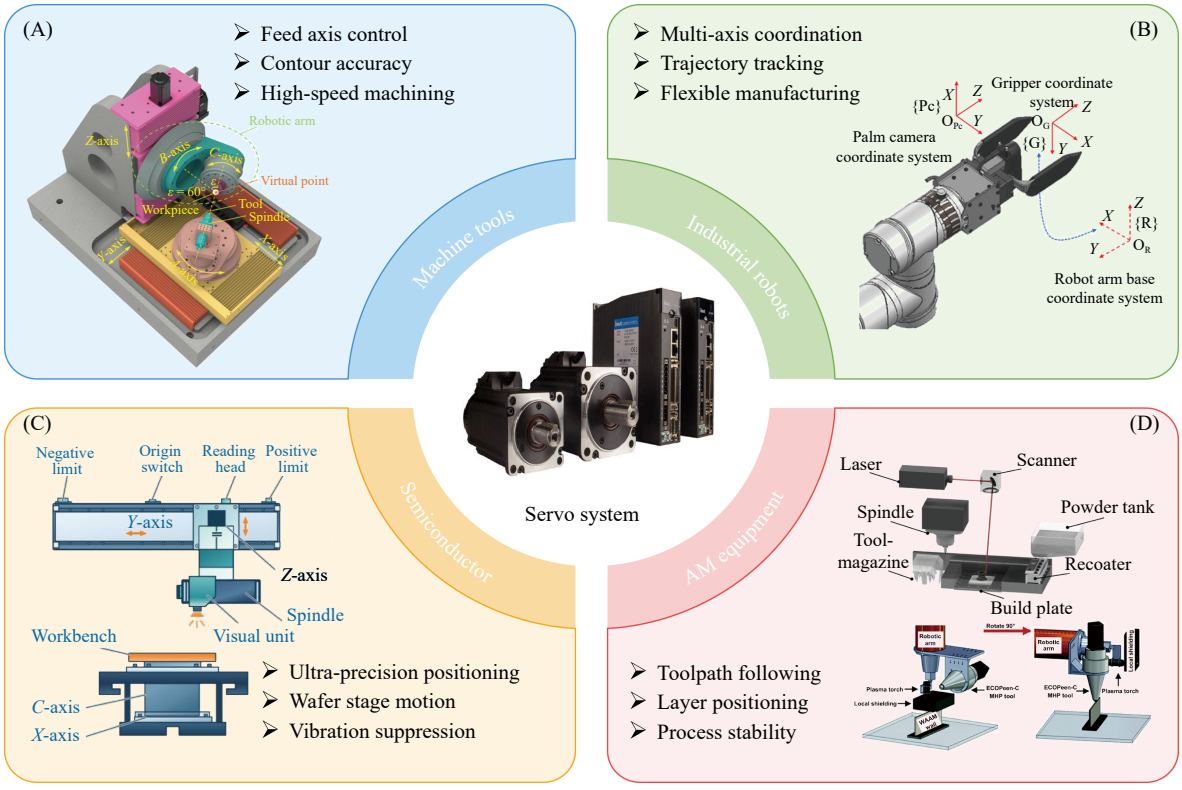


Fig. 1 Overview of servo systems applications in high-performance manufacturing, developed based on previous studies. (A) Reproduced with permission from Ref. [1], © Elsevier 2025. (B) Adapted from Ref. [9], with permission from Elsevier, © 2025. (D) Reproduced from Ref. [55] under the terms of the CC BY 4.0 license.

According to the data in the Web of Science Core Collection, the literature on system identification, parameter tuning and advanced control is very rich, and the number of documents related to manufacturing equipment is shown in the publication statistics summarized in Fig. 2. The continuous growth of related studies indicates that these three aspects remain critical research directions for improving servo performance in high-performance manufacturing equipment. Researchers have extensively investigated servo systems modeling, parameter estimation, optimization, disturbance observation, and error compensation methods to address the challenges arising from nonlinear characteristics, time-varying dynamics, and external disturbances. For instance, recent studies by Wang et al. [56], Tseng et al. [57], and Zheng et al. [58] have provided valuable contributions to complex friction modeling, intelligent multi-objective parameter tuning, and disturbance rejection control, respectively. However, these topics are often reviewed separately, and an integrated perspective linking identification, tuning, and control within the context of high-performance manufacturing remains limited. This motivates the present review.

To improve the rigor and reproducibility of this review, a structured literature search was conducted using the

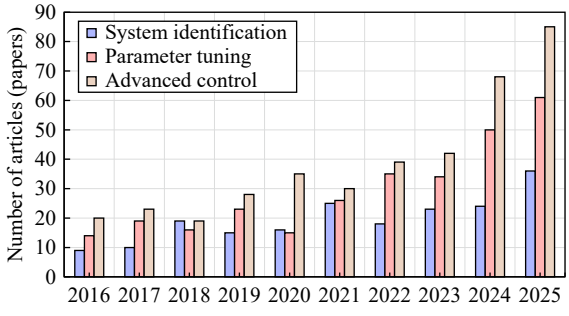


Fig. 2 Overview of the number of publications from 2016 to 2025 (from Web of Science database).

Web of Science Core Collection as the primary database, supplemented by Scopus, IEEE Xplore, ScienceDirect, and Google Scholar. Publications up to 2026 were considered, with no strict lower time limit to retain foundational studies. Search terms were organized around the three main themes of system identification, parameter tuning, and advanced control, using keywords related to servo systems, friction/inertia/load identification, PID tuning, multi-objective optimization, sliding mode control, disturbance observers, ADRC, MPC, and iterative learning control. Studies were included if they

addressed electromechanical servo systems for manufacturing or related precision-motion applications and provided relevant methodological, experimental, or engineering insights. Irrelevant, technically insufficient, highly application-specific, or duplicate studies were excluded. The selected literature was then classified into modeling, identification, tuning, and advanced-control categories for comparative analysis.

Looking toward future high-performance manufacturing, servo systems will face increasingly complex operating conditions and stricter requirements for precision, adaptability, and autonomous operation. Emerging technologies, including artificial intelligence, digital twins, and data-driven optimization, provide new opportunities for enhancing system identification, parameter tuning, and advanced control. However, these technologies should be integrated with physical models, control theory, and engineering constraints rather than replacing conventional servo architectures. These future directions are discussed in detail in Section 6.

This paper presents a comprehensive review of servo-system technologies for high-performance manufacturing, with particular emphasis on system identification, parameter tuning, and advanced control. Section 2 introduces the relationship between servo-system characteristics and manufacturing performance, together with the electromechanical modeling framework, nonlinear characteristics, and major error sources. Section 3 reviews friction, inertia, and load identification methods. Section 4 summarizes classical, adaptive, and optimization-based parameter-tuning approaches. Section 5 discusses robust, disturbance-rejection, predictive, and learning-based advanced control technologies. Section 6 presents future challenges and development trends toward intelligent and integrated servo systems for high-performance manufacturing. Finally, Section 7 concludes this review.

2 Servo Systems Characteristics in Manufacturing Equipment

High-performance manufacturing equipment requires accurate modeling of servo system. As shown in Fig. 3, a complete servo system consists of coupled electrical and mechanical components and is subject to various nonlinearities and time-varying uncertainties that can degrade manufacturing accuracy. Standard linear time-invariant models cannot fully describe practical servo characteristics. This chapter reviews mainstream modeling methods for CNC servo systems, analyzes inherent nonlinear factors and time-varying complex disturbances, laying a theoretical foundation for the parameter identification, gain tuning, feedforward compensation and advanced control strategies elaborated in Sections 3, 4 and 5 respectively.

2.1 Impact of servo systems on manufacturing quality

Servo-level performance and manufacturing-level performance should be distinguished when evaluating

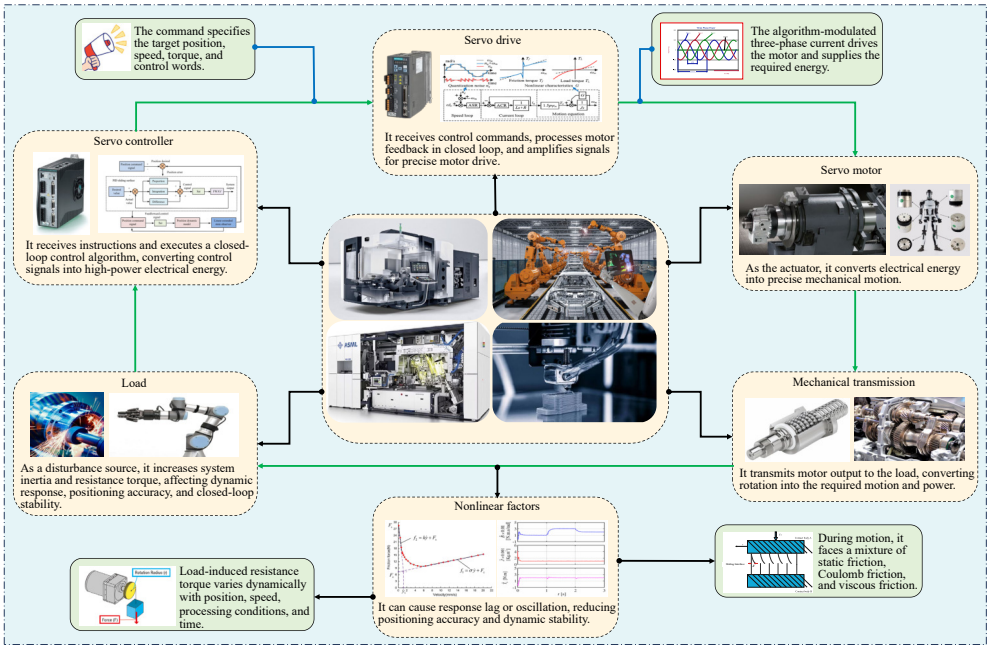


Fig. 3 Composition diagram of servo systems in manufacturing equipment.

high-performance manufacturing equipment. Servo indicators such as positioning error, trajectory tracking accuracy, dynamic response, bandwidth, and disturbance rejection characterize the behavior of the motion-control system, whereas manufacturing quality is also influenced by mechanical transmission, structural dynamics, process disturbances, thermal effects, and task-specific requirements. Therefore, improvements in servo performance do not necessarily translate proportionally into improvements in product quality. Their practical significance depends on how servo-level errors propagate through the mechanical and process chain into manufacturing-level outcomes.

Fig. 4 illustrates how servo-level performance affects manufacturing outcomes across representative high-performance manufacturing platforms. In CNC machine tools, insufficient bandwidth, tracking errors, and reversal deviations may lead to contour errors, dimensional inaccuracies, and surface-quality degradation, particularly during acceleration, deceleration, and corner transitions. In semiconductor manufacturing equipment, positioning error, vibration, and settling behavior can influence stage accuracy, wafer alignment, and process consistency. In industrial robots, joint tracking errors, payload variation, and multi-axis coupling may propagate to end-effector path deviations, reducing assembly, welding, or handling accuracy. In additive manufacturing, path-following and velocity errors can affect layer positioning, deposition uniformity, and geometric consistency. These examples demonstrate that the manufacturing consequences of servo errors are strongly platform- and task-dependent.

Although the reviewed servo technologies share a common electromechanical-control foundation, their practical emphasis varies across manufacturing platforms. In CNC machine tools, friction, structural resonance, contour tracking, and cutting-force disturbances are major concerns. Industrial robots place greater emphasis on multi-axis coupling, payload variation, joint flexibility, and trajectory coordination. Semiconductor manufacturing equipment requires extremely high positioning accuracy, low vibration, and rapid settling, whereas additive manufacturing systems are more sensitive to path-following accuracy, velocity consistency, and deposition stability. Therefore, although common identification, tuning, and control principles can be applied across these platforms, their models, performance objectives, and implementation constraints should be adapted to specific manufacturing tasks. More importantly, servo performance should not be evaluated solely through current-, velocity-, or position-loop indicators. In high-performance manufacturing, the ultimate significance of servo improvement lies in how these servo-level improvements propagate to process- and product-level outcomes. Accordingly, the following sections review system identification, parameter tuning, and advanced control not only from the perspective of servo-performance enhancement, but also in terms of their contributions to manufacturing accuracy, process stability, and production consistency.

2.2 Technical framework and key aspects of servo systems

The development of high-performance servo systems requires a systematic research process, as shown in Fig. 5. This process integrates system modeling, identification, parameter tuning, and advanced control. Among these aspects, system modeling provides the fundamental

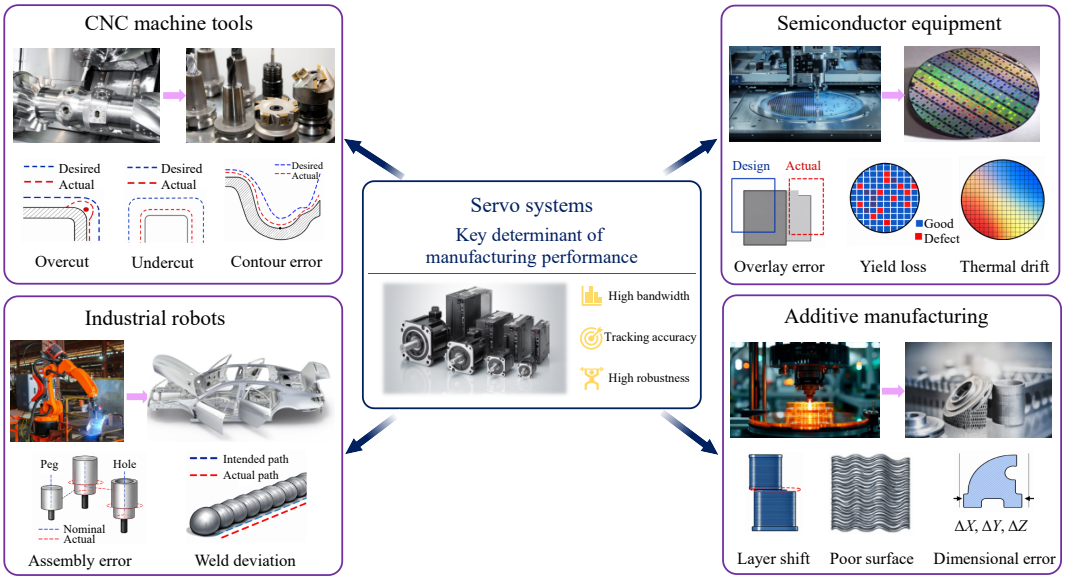


Fig. 4 Impact of servo system performance on manufacturing quality across different types of equipment.

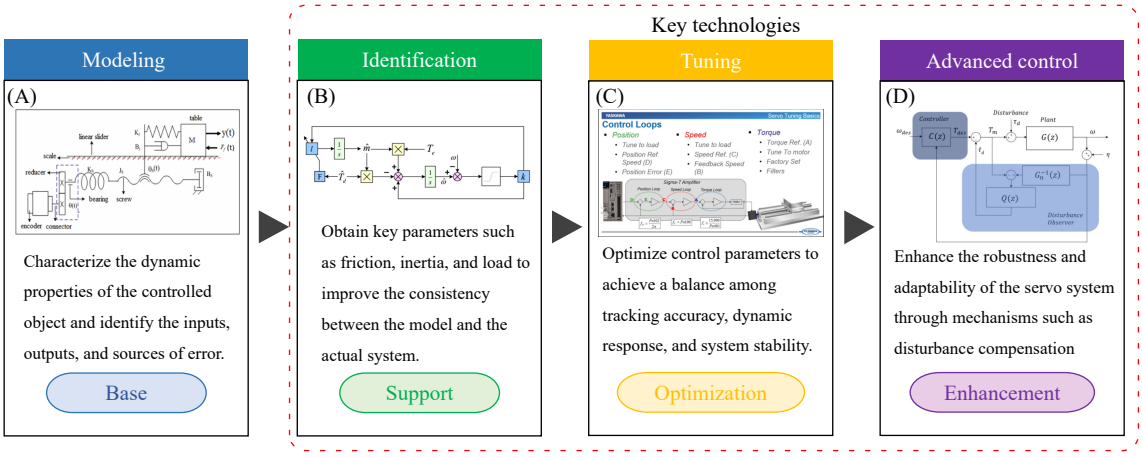


Fig. 5 Research framework and key technologies of high-performance servo systems, adapted from previous studies. (A) Reproduced with permission from Ref. [59], © The Author(s) 2015. (B) Reproduced from Ref. [60] under the terms of the CC BY-NC-ND 4.0 license, © 2022 The Author(s) (D) Reproduced from Ref. [61] under the terms of the CC BY-NC-ND 4.0 license, © 2024 The Authors.

framework for describing servo dynamics and understanding the interaction between electrical, mechanical, and control components. However, due to the inevitable existence of nonlinearities, parameter variations, and external disturbances in practical manufacturing equipment, accurate modeling alone is insufficient to guarantee high-performance motion control. Therefore, system identification, parameter tuning, and advanced control have become the key technical approaches for improving servo performance under real operating conditions.

System identification serves as the foundation for obtaining accurate and updated information about the actual servo systems. Although theoretical models can describe the basic system behavior, practical parameters such as friction characteristics, inertia, and load disturbances often vary with operating conditions and manufacturing processes. Accurate identification methods enable the extraction of these uncertain parameters and dynamic characteristics, providing essential support for controller design, compensation strategies, and performance optimization.

Based on the identified system characteristics, parameter tuning determines whether the servo systems can achieve optimal performance. Since control parameters directly affect response speed, tracking accuracy, stability, and vibration suppression capability, inappropriate parameter selection may lead to degraded performance or even system instability. Traditional manual tuning methods are increasingly insufficient for high-performance manufacturing equipment with complex dynamics and multiple performance requirements. Consequently, adaptive tuning, optimization-based methods, and intelligent parameter tuning strategies have attracted increasing attention.

Advanced control represents the further improvement of servo performance beyond conventional feedback regulation. In practical manufacturing environments, unknown disturbances, nonlinear errors, and time-varying operating conditions cannot be completely eliminated through modeling and parameter tuning alone. Advanced control strategies, including robust control, disturbance rejection control, predictive control, and learning-based intelligent control, provide additional capabilities for compensating uncertainties and enhancing system adaptability. These methods enable servo systems to achieve higher precision, stronger robustness, and improved intelligence.

2.3 Electromechanical coupled modeling of servo systems

Modern high-precision servo systems, particularly PMSM- and induction motor (IM)-based drives, commonly employ *d*–*q* axis vector control to achieve decoupled regulation of electromagnetic torque and magnetic flux [62]. The objective of this strategy is to transform the original three-phase AC motor variables into two orthogonal DC-like components, thereby achieving independent regulation of magnetic flux and electromagnetic torque. Therefore, accurate mathematical modeling of the electromechanical dynamics is essential for analyzing servo characteristics and developing advanced control strategies.

Fig. 6 illustrates the hierarchical modeling framework of high-performance servo systems from the perspective of electromechanical coupling. The electrical dynamics describe the relationship among stator voltages, currents, rotor flux, and electromagnetic torque, while the mechanical dynamics characterize the transmission of motor torque through inertia, damping, friction, and external load. Their integration provides the fundamental model for system identification, parameter tuning, and control design.

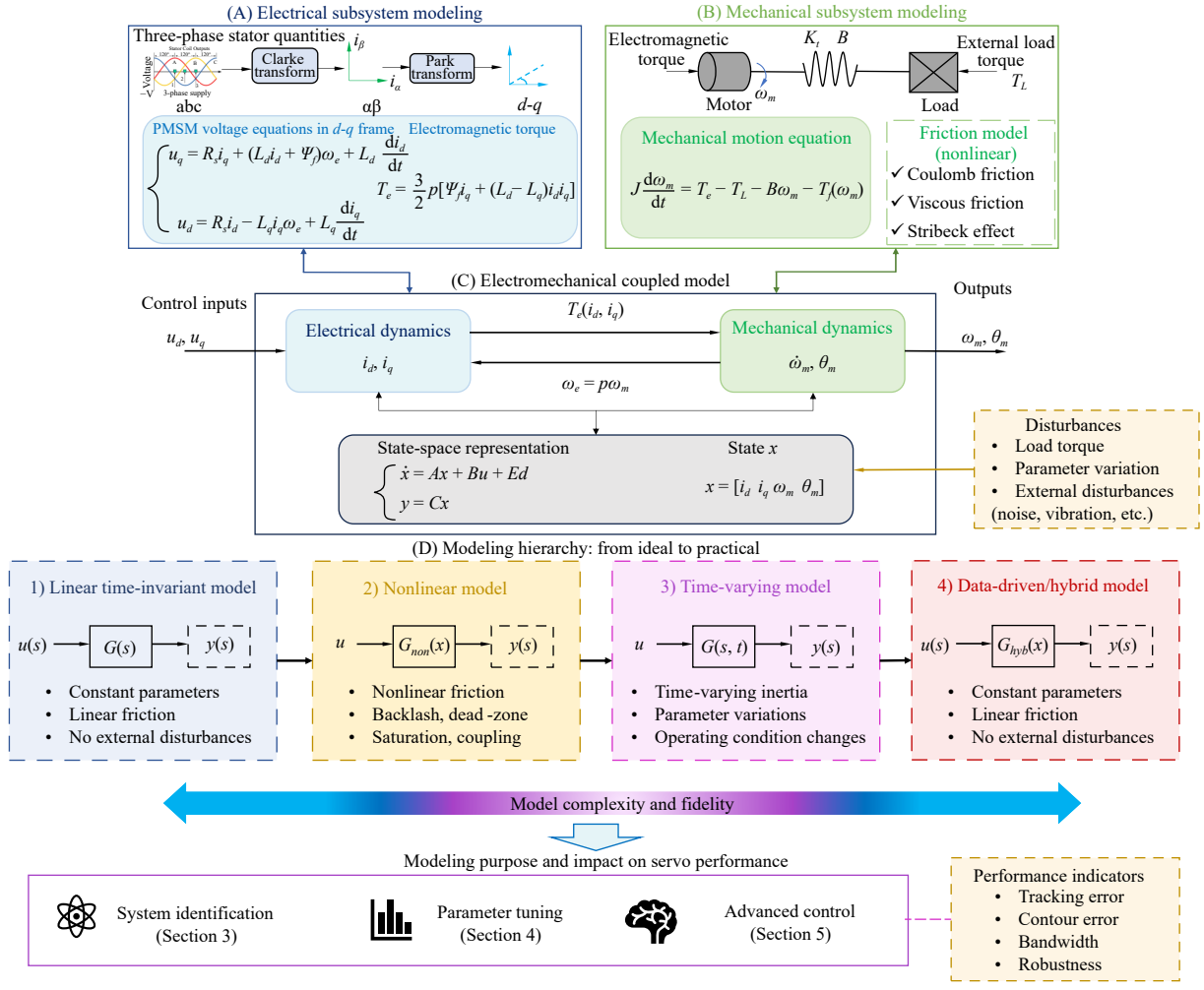


Fig. 6 Modeling method for servo systems of high-performance manufacturing equipment.

At the mechanical transmission side of a single feed axis, the ideal rigid-body dynamic model is widely adopted in preliminary servo analysis by most scholars. The simplified torque balance equation can be simplified as [63]:

$$\frac{\mathrm{d}\omega}{\mathrm{d}t} = \frac{1}{J}(T_e - T_L - B\omega), \tag{1}$$

where T_e is the electromagnetic driving torque, T_L is the external load torque, J is the total moment of inertia, B is the viscous friction coefficient, and ω is the mechanical angular velocity.

However, the simplified lumped-parameter model assumes constant inertia, linear viscous friction, and time-invariant load conditions, which are rarely satisfied in practical manufacturing environments. In CNC machining processes, variations in workpiece mass, cutting force, feed rate, transmission characteristics, and environmental conditions continuously modify the effective system parameters. For example, the equivalent inertia J, damping coefficient B, and external disturbance torque T_L may exhibit significant temporal variations and nonlinear behaviors.

Therefore, controllers designed solely based on nominal electromechanical models may suffer from degraded tracking performance, increased contour errors, reduced robustness, or even instability under dynamic operating conditions. When drivetrain flexibility and multi-inertia dynamics are considered, resonance and antiresonance characteristics may further constrain the achievable servo bandwidth and amplify mechanical vibration under high-gain control. In addition, nonlinearities, parameter variations, unmodeled dynamics, and external disturbances further complicate accurate motion control. These characteristics motivate the detailed discussion of nonlinearities, time-varying parameters, and complex disturbances in Section 2.4, and also provide the modeling basis for the resonance-suppression, robust, disturbance-rejection, and predictive control strategies reviewed in Section 5.

2.4 Nonlinear characteristics and error sources of servo systems

Nonlinearities are inherent in practical servo systems and can significantly limit the positioning accuracy and dynamic performance of high-precision manufacturing equipment. Arising from mechanical contact, transmission mechanisms, actuator limitations, and electromagnetic effects, these nonlinearities introduce uncertainties, hysteresis, and discontinuous dynamics that complicate modeling and compensation. Among them, friction and transmission nonlinearities are particularly critical in precision feed drives requiring sub-micron positioning and high-bandwidth motion control.

2.4.1 Friction-induced nonlinearities

Friction is a major nonlinearity limiting the motion accuracy of high-performance servo systems. In CNC machine tools, it mainly originates from ball screws, guideways, bearings, and other mechanical contacts, and varies with velocity, temperature, lubrication, preload, and external load. Such nonlinear and time-varying behavior is particularly significant at low speeds and velocity reversals, where it can cause stick-slip, velocity ripple, quadrant errors, and tracking deviations, thereby degrading positioning and contouring accuracy.

The Stribeck model is widely used to describe the steady-state relationship between friction and velocity, particularly the reduction in friction occurring during the transition from static to sliding motion. This negative friction–velocity characteristic may introduce effective negative damping and deteriorate low-speed servo stability [64].

The corresponding friction model can be expressed as:

$$T_{\mathrm{fs}} = \mathrm{sgn}(\omega)\left\{(T_{\mathrm{sta}} - T_c)\exp\left[-\left(\frac{\omega}{\omega_{\mathrm{sb}}}\right)^2\right] + T_c\right\} + \sigma_2\omega, \quad (2)$$

where ω denotes the motor speed, ω_{sb} is the Stribeck rate, T_{fs} represents the friction torque, T_c is the Coulomb friction torque, T_{sta} is the maximum static friction torque, and σ_2 is the viscous friction coefficient.

Although the Stribeck model provides a simple and effective representation of steady-state friction, it cannot adequately describe dynamic phenomena such as presliding displacement, hysteresis, and memory effects. Moreover, its parameters may vary considerably with operating conditions, which limits the effectiveness of compensation based on fixed friction parameters.

To represent dynamic friction behavior, models such as LuGre introduce internal states associated with the deformation of microscopic contact interfaces and can capture presliding, hysteresis, and friction memory effects. The LuGre model can be expressed as:

$$\begin{cases} \dfrac{\mathrm{d}z}{\mathrm{d}t} = \omega - \sigma_0 \dfrac{|\omega|}{\mathrm{g}(\omega)} z \\ T_{\mathrm{fl}} = \sigma_0 z + \sigma_1 \dfrac{\mathrm{d}z}{\mathrm{d}t} + \sigma_2 \omega \\ \mathrm{g}(\omega) = (T_{\mathrm{sta}} - T_c)\exp\left[-\left(\dfrac{\omega}{\omega_{\mathrm{sb}}}\right)^2\right] + T_c \end{cases}, \quad (3)$$

where z denotes the average bristle deflection, σ_0 is the bristle stiffness coefficient, σ_1 represents the bristle damping coefficient, $\mathrm{g}(\omega)$ is a nonlinear function describing the Stribeck effect, and T_{fl} indicates the friction torque.

Compared with conventional static friction models, dynamic friction models provide a more accurate description of friction evolution during complex motion conditions and therefore have been widely applied in friction identification and compensation studies. Wang et al. [65] proposed a friction compensation method that combines the Stribeck model with a fuzzy adaptive low-pass filter. Specifically, they established that the LuGre (LG) model is mathematically equivalent to a Stribeck (SB) model cascaded with a low-pass filter, denoted as the SBF model. This equivalent relationship provides a simplified approach for dynamic friction compensation, as illustrated in Fig. 7.

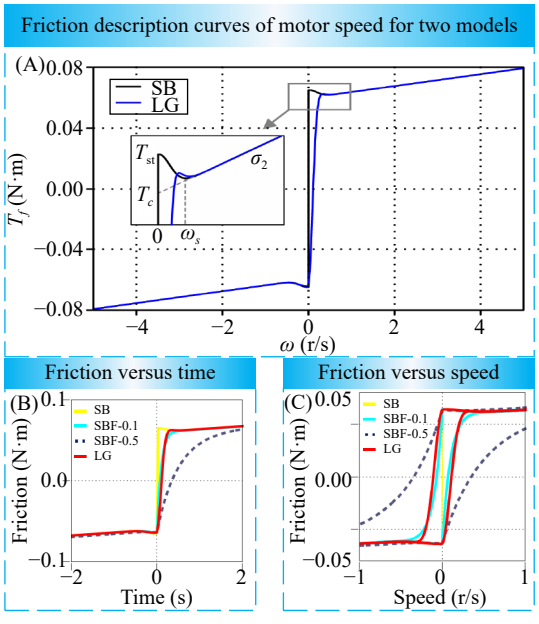


Fig. 7 Different friction models: (A) Relationship between friction torque and motor speed. (B) Friction versus time. (C) Friction versus speed. Reproduced with permission from Ref. [65], © 2023 IEEE.

Therefore, although extensive friction models have been developed, accurately characterizing friction under complex manufacturing conditions remains challenging due to its nonlinear, hysteretic, and time-varying characteristics. These challenges motivate advanced

friction identification techniques and adaptive compensation strategies, which will be further discussed in Sections 3 and 5.

2.4.2 Transmission nonlinearities

In addition to friction, mechanical transmission systems introduce important nonlinearities in practical servo systems. Components such as gears, ball screws, couplings, guideways, and flexible joints may exhibit backlash, dead zones, hysteresis, and elastic compliance due to manufacturing tolerances, assembly errors, contact deformation, and structural flexibility [66]. Fig. 8 summarizes the evolution from mechanical transmission structures to nonlinear modeling and their impacts on servo performance. These transmission nonlinearities disturb the ideal motion relationship between the motor side and the load side, resulting in transmission errors, dynamic uncertainties, degraded tracking accuracy, increased contour errors, and reduced achievable servo bandwidth. Moreover, the nonlinear behaviors are strongly dependent on operating conditions, making it challenging to accurately describe the dynamic characteristics of transmission systems. Therefore, advanced nonlinear modeling approaches are required to characterize transmission behaviors and provide accurate system representations for subsequent parameter identification, servo tuning, and control optimization.

Among these transmission nonlinearities, backlash is one of the most critical factors affecting the dynamic performance of precision servo systems. Backlash originates from the mechanical clearance between mating transmission components, such as gear teeth and screw-nut interfaces. During motion reversal, the clearance region prevents effective torque transmission, resulting in a dead-zone phenomenon between motor displacement and load response. Xiao et al. [67] investigated nonlinear effects associated with mechanical transmission components, including ball screws and linear guides, in CNC machine-tool feed drive systems, and proposed a nonlinear model predictive compensation scheme to improve tracking and contouring accuracy.

A commonly adopted piecewise model for describing backlash nonlinearity can be expressed as [68]:

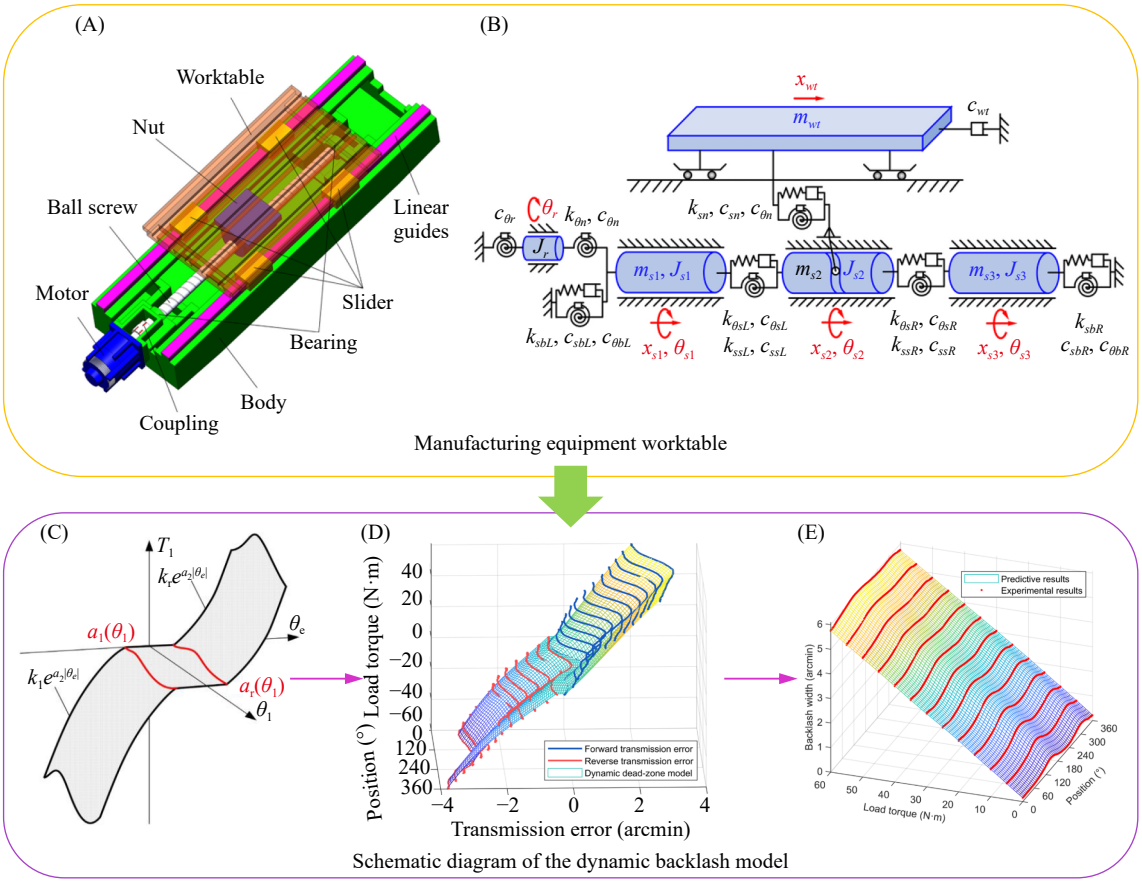


Fig. 8 Modeling framework and dynamic characteristics of transmission nonlinearities in CNC feed drives. (A) Reproduced with permission from Ref. [64], © The Author(s) 2024. (B) Reproduced with permission from Ref. [69], © 2023 Elsevier Inc. (C–E) Reproduced with permission from Ref. [68], © Elsevier 2026.

$$T_L = \begin{cases} K_e(\theta_e - \alpha_h) + B_l\dot{\theta}_e, & \theta_e > \alpha_h \\ 0, & |\theta_e| < \alpha_h \\ K_e(\theta_e + \alpha_h) + B_l\dot{\theta}_e, & \theta_e < -\alpha_h \end{cases}, \quad (4)$$

where T_L represents the transmitted load torque, K_e denotes the equivalent transmission stiffness, B_l represents the damping coefficient, θ_e is the relative displacement between the motor and load sides, and α_h denotes half of the backlash width. This model describes backlash as a piecewise nonlinear mapping between transmission displacement and output torque and has been widely adopted in servo systems modeling and compensation studies.

Transmission nonlinearities arise not only from backlash but also from elastic compliance and structural flexibility, which couple motor-side and load-side dynamics and contribute to displacement fluctuations and motion errors in ball-screw feed systems [69]. At the system level, the servo drive, mechanical transmission, and machining process form a strongly coupled electromechanical system in which disturbances propagate through the transmission chain and jointly affect motion accuracy and machining quality [70]. Backlash further introduces dead-zone behavior during motion reversals, causing temporary loss of torque transmission, phase lag, and impact upon re-engagement; these effects may excite high-frequency mechanical resonances and reduce servo stability margins [71,72]. Therefore, backlash, compliance, and hysteresis should be considered in subsequent identification, tuning, and compensation design.

2.4.3 Actuator and electromagnetic nonlinearities

Actuators represent the energy conversion interface between control commands and mechanical motion in servo systems. In conventional linear servo models, actuators are usually assumed to generate ideal forces or torques proportional to the input signals. However, practical actuators used in manufacturing equipment inevitably exhibit nonlinear characteristics due to electromagnetic interactions, material properties, power conversion limitations, and internal dynamic coupling. As illustrated in Fig. 9, major nonlinear factors include cogging torque, torque ripple, magnetic saturation, and hysteresis. These effects introduce discrepancies between commanded and actual force or torque, which may cause velocity oscillations, resonance excitation, tracking errors, and reduced positioning accuracy and servo

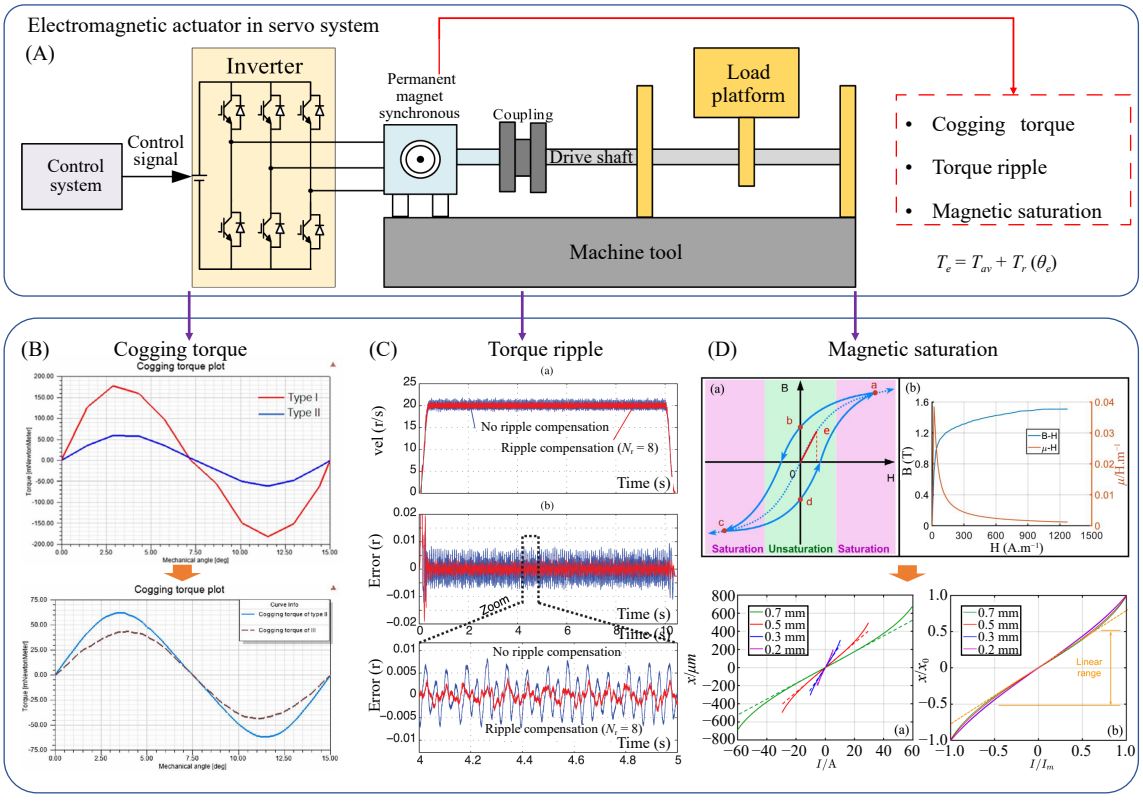


Fig. 9 Nonlinear factors of actuators in servo systems: (A) Reproduced from Ref. [75] under the terms of the CC BY 4.0 license, © 2025 by the authors. (B) Cogging torque. Reproduced with permission from Ref. [73], © 2020 IEEE. (C) Torque ripple. Reproduced with permission from Ref. [74], © 2013 IEEE. (D) Magnetic saturation. Reproduced with permission from Ref. [76], © 2024 Elsevier Inc.

bandwidth. Therefore, accurate modeling and compensation of actuator nonlinearities are important for high-performance servo systems.

Practical servo actuators exhibit nonlinearities arising from electromagnetic interactions, magnetic material properties, and power conversion effects. Their operating-point-dependent characteristics complicate controller design, particularly when high tracking accuracy and robust performance are required over a wide range of operating conditions. In PMSM-based servo systems, periodic torque disturbances are mainly associated with rotor position and originate from stator-slot effects, magnetic saturation, and current harmonics. Cogging torque is a representative source of such disturbances and is strongly influenced by motor structural parameters [73].

These electromagnetic disturbances can further couple with the mechanical transmission system. When their frequencies approach structural resonances or servo-loop bandwidths, vibration and tracking errors may be amplified and ultimately affect machining accuracy. In addition, magnetic saturation, hysteresis, and flux leakage introduce further nonlinear force or torque deviations, particularly in high-precision positioning systems. Therefore, actuator nonlinearities should be considered from an electromechanical-coupling perspective and addressed through appropriate modeling, identification, and compensation strategies.

2.4.4 Time-varying inertia and complex disturbances

Practical manufacturing processes introduce time-varying parameters and complex disturbances beyond the inherent nonlinearities of servo systems. In CNC machining, changes in workpiece mass, cutting conditions, feed rate, tool engagement, and thermal state can cause significant variations in equivalent inertia and load torque. Such parameter mismatch alters closed-loop bandwidth, phase margin, and disturbance rejection capability, making fixed-parameter controllers insufficient under varying operating conditions [77].

External disturbances further degrade servo accuracy. Cutting-force fluctuations propagate through the mechanical transmission chain and directly affect feed-axis motion, while periodic disturbances from cogging torque, flux harmonics, current measurement errors, and inverter nonlinearities can induce speed ripple and vibration [78]. Because these disturbances are often coupled and difficult to model accurately, disturbance estimation and compensation methods, including DOB, ESO, adaptive estimation, and data-driven approaches, have become essential for high-performance servo control. Accurate characterization of time-varying parameters and disturbances therefore provides an important basis for subsequent identification, tuning, and advanced control.

Fig. 10 summarizes the relationship between the servo systems characteristics discussed in this chapter and the subsequent research directions of identification, parameter tuning, and advanced control technologies. The fundamental mathematical models introduced in Section 2.3 provide the basis for parameter estimation and model reconstruction, where electrical-mechanical coupling and nominal servo dynamics serve as the benchmark for system identification. The nonlinear factors analyzed in Section 2.4, including friction-induced nonlinearities, transmission nonlinearities, and actuator-related nonlinearities, represent the major sources of model uncertainty and motivate the development of optimized parameter tuning strategies. Furthermore, the time-varying inertia and complex disturbances introduce dynamic uncertainties under practical manufacturing conditions, requiring advanced disturbance estimation, adaptive compensation, and robust control approaches. This systematic relationship establishes the logical framework for the following sections, where identification techniques, tuning optimization methods, and advanced control technologies are reviewed to address the corresponding challenges in high-performance servo systems.

3 System Identification

Accurate parameter identification is the cornerstone of high-performance servo control. In standard AC servo systems employing vector control, electrical parameters are typically acquired via offline auto-tuning. Conversely, mechanical parameters, specifically the moment of inertia and nonlinear friction coefficients, exhibit severe time-varying characteristics due to varying payloads, mechanical wear, and complex lubrication conditions. Consequently, obtaining an accurate dynamic mechanical model through advanced identification algorithms remains a critical prerequisite for optimal controller design and disturbance rejection.

3.1 Friction identification

Friction is one of the most significant nonlinear factors affecting the accuracy and dynamic performance of servo systems. As illustrated in the electromechanical coupled modeling of servo systems, friction introduces complex nonlinear behaviors, including velocity dependency, hysteresis, and time-varying characteristics, which degrade tracking accuracy and machining performance. Therefore, accurate friction identification is essential for effective compensation and high-performance control. Existing friction identification methods can be generally

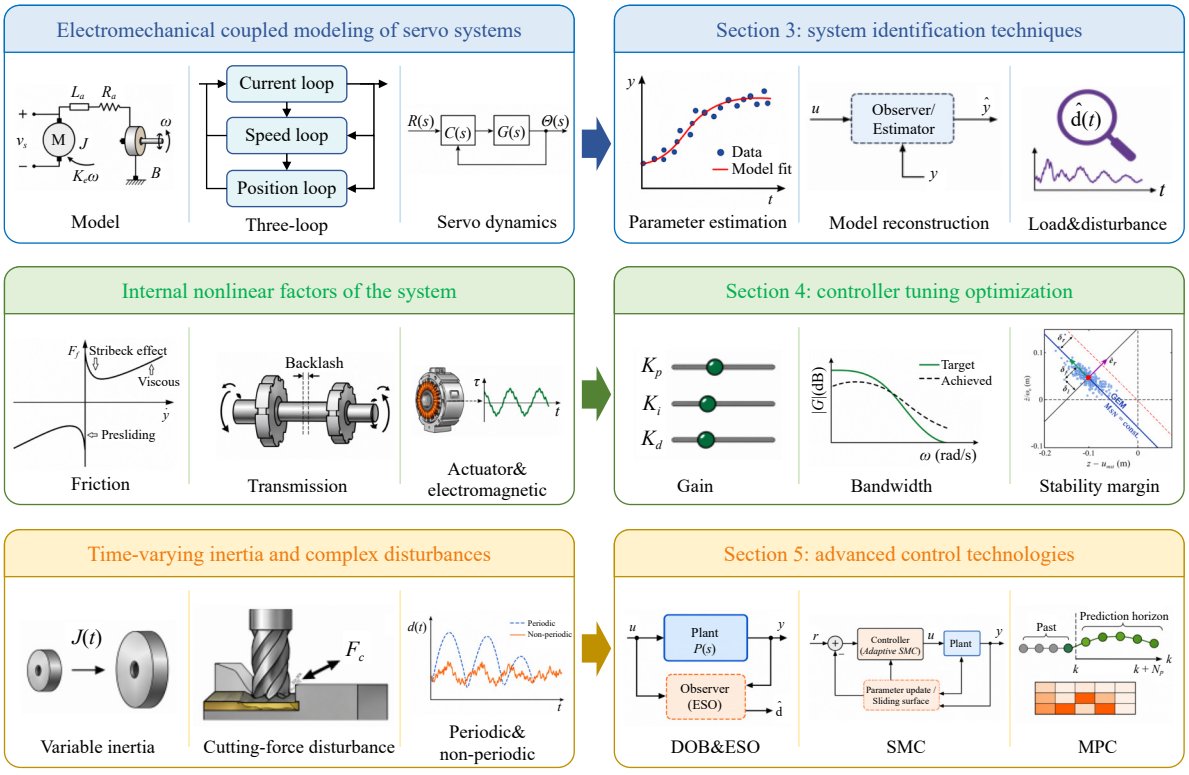


Fig. 10 The correspondence between servo systems characteristics and research work.

categorized into three groups: offline experimental identification, model-based identification, and online adaptive identification. The following sections review these approaches from the perspectives of experimental characterization, friction modeling, and real-time parameter updating.

3.1.1 Offline experimental identification

Offline experimental identification represents one of the earliest and most widely adopted approaches for friction characterization in servo systems. Due to the difficulty of directly measuring friction torque in practical electromechanical systems, researchers usually obtain friction information indirectly through designed motion experiments and measured servo responses. Compared with online identification methods, offline approaches provide a controlled experimental environment, enabling detailed characterization of friction behaviors before controller implementation. Therefore, offline identification has been widely used for initial parameter estimation, friction model construction, and compensation algorithm validation in precision servo systems [79–83]. Nouri [79] systematically investigated friction identification in mechatronic systems and established an experimental framework for extracting friction characteristics under different motion conditions. This study emphasized that friction should be considered as a complex phenomenon involving multiple operating regimes rather than a constant disturbance. The experimental characterization of presliding and sliding behaviors provided an important foundation for subsequent friction identification and compensation studies.

With the increasing requirements for machining accuracy, friction identification has gradually evolved from independent friction measurement toward integrated servo-system identification. In practical manufacturing equipment, especially CNC feed drives, friction is strongly coupled with mechanical characteristics such as transmission flexibility, structural vibration, preload variation, and external disturbances. Therefore, friction parameters obtained from isolated actuator tests may not accurately represent the actual operating conditions of complete servo systems. To address this issue, Chen and Yao [80] investigated a motor-driven servo table considering flexible modes and nonlinear disturbances, demonstrating the importance of simultaneously considering mechanical dynamics and nonlinear effects in servo identification. Such system-level identification approaches provide a more realistic description of manufacturing equipment. Thenozhi et al. [81] presented an offline friction identification framework integrated with compensation strategies, demonstrating that accurate friction estimation can effectively improve servo tracking performance.

The representative offline experimental friction

Table 1 Summary of offline experimental friction identification approaches.

Category	Source	Sensor/signal requirement	Computational burden	Noise sensitivity	Practical characteristics
Experimental friction characterization	Nouri [79], Yan et al. [82]	Designed motion tests; standard motion/torque feedback	Low	Medium	Direct characterization; limited adaptability to varying conditions
System-level servo identification	Chen and Yao [80], Szczepanski et al. [84]	Servo input/output data	Medium	Medium	Includes electromechanical coupling; higher modeling complexity
Optimization-based parameter identification	Thenozhi et al. [81], Lu et al. [85]	Experimental response data	Medium–high	Medium	Improved nonlinear parameter estimation; initialization/model dependent
Dynamic friction identification	Li et al. [86]	Dynamic trajectory data	High	Medium–high	Captures hysteresis/memory; more parameters and computation

identification approaches reported in the literature are summarized in Table 1.

3.1.2 Model-based friction identification

Model-based friction identification [87–95] aims to estimate friction characteristics by constructing mathematical friction models and identifying their unknown parameters from measured system responses. Compared with purely experimental characterization methods, model-based approaches provide a physical interpretation of friction behaviors and better adaptability for compensation design. Therefore, they have been widely investigated in precision servo systems, CNC machine tools, and other high-performance motion platforms. Based on the complexity of friction characterization, existing model-based identification methods can generally be divided into Stribeck model identification and LuGre model identification, as shown in Fig. 11.

Liu and Wu [95] investigated friction parameter identification in machine tool feed systems by combining dynamic modeling with nonlinear least-square estimation. The relationship between critical stick-slip velocity and friction characteristics was analyzed, enabling simultaneous estimation of mechanical parameters and friction-related parameters. This study demonstrated the feasibility of identifying friction characteristics from servo responses without direct friction measurement.

To improve the efficiency and accuracy of static friction parameter estimation, recursive and intelligent optimization algorithms have been introduced. Lee et al. [90] proposed a recursive least-square-based identification method for machine tool feed drives, where friction parameters were sequentially estimated according to different velocity regions. This approach reduced computational complexity while maintaining satisfactory identification accuracy.

The LuGre model introduces an internal state variable related to bristle deformation between contact surfaces, enabling a more comprehensive description of nonlinear friction phenomena. However, the increased model complexity also results in strong parameter coupling and difficulties in parameter identification. To address these challenges, various optimization-based LuGre parameter identification methods have been developed. Liao et al. [92] employed an improved genetic algorithm to identify LuGre model parameters in servo systems. By adaptively adjusting evolutionary parameters, the proposed method improved convergence performance and identification accuracy compared with conventional genetic algorithms. Feng et al. [93] further combined genetic algorithms with particle swarm optimization to establish a hybrid optimization framework for LuGre parameter identification.

Table 2 summarizes friction identification methods based on different models, along with their advantages and limitations.

3.1.3 Online and adaptive friction identification

Although offline experimental identification and model-based parameter estimation can provide accurate friction characteristics under specific operating conditions, the identified parameters are usually fixed after the identification process. However, friction behavior in servo systems is strongly affected by operating conditions, including velocity variation, temperature changes, lubrication conditions, and mechanical wear. Therefore, fixed friction parameters may not accurately describe the actual system dynamics during long-term operation. To overcome this limitation, online and adaptive friction identification methods [96–106] have been developed, aiming to estimate and update friction parameters in real time during system operation. Fig. 12 illustrates the classification of online and adaptive friction identification methods, including recursive parameter estimation, observer-based adaptive identification, advanced adaptive estimation strategies, and intelligent learning-based approaches. These methods progressively enhance the capability of real-time friction tracking by improving parameter convergence, disturbance rejection, and nonlinear approximation performance under time-varying operating conditions.

Early online identification methods mainly relied on recursive parameter estimation and observer-based

approaches. By introducing system states and measurable input-output information, these methods transform unknown friction parameters into adaptive variables and continuously update them during motion. Prasad et al. [96] employed a recursive least square (RLS) method to estimate mechanical parameters of induction machine drive systems using speed loop characteristics, demonstrating the feasibility of online estimation of friction-related parameters without additional experimental procedures. However, conventional recursive estimation methods generally suffer from sensitivity to measurement noise and require persistent

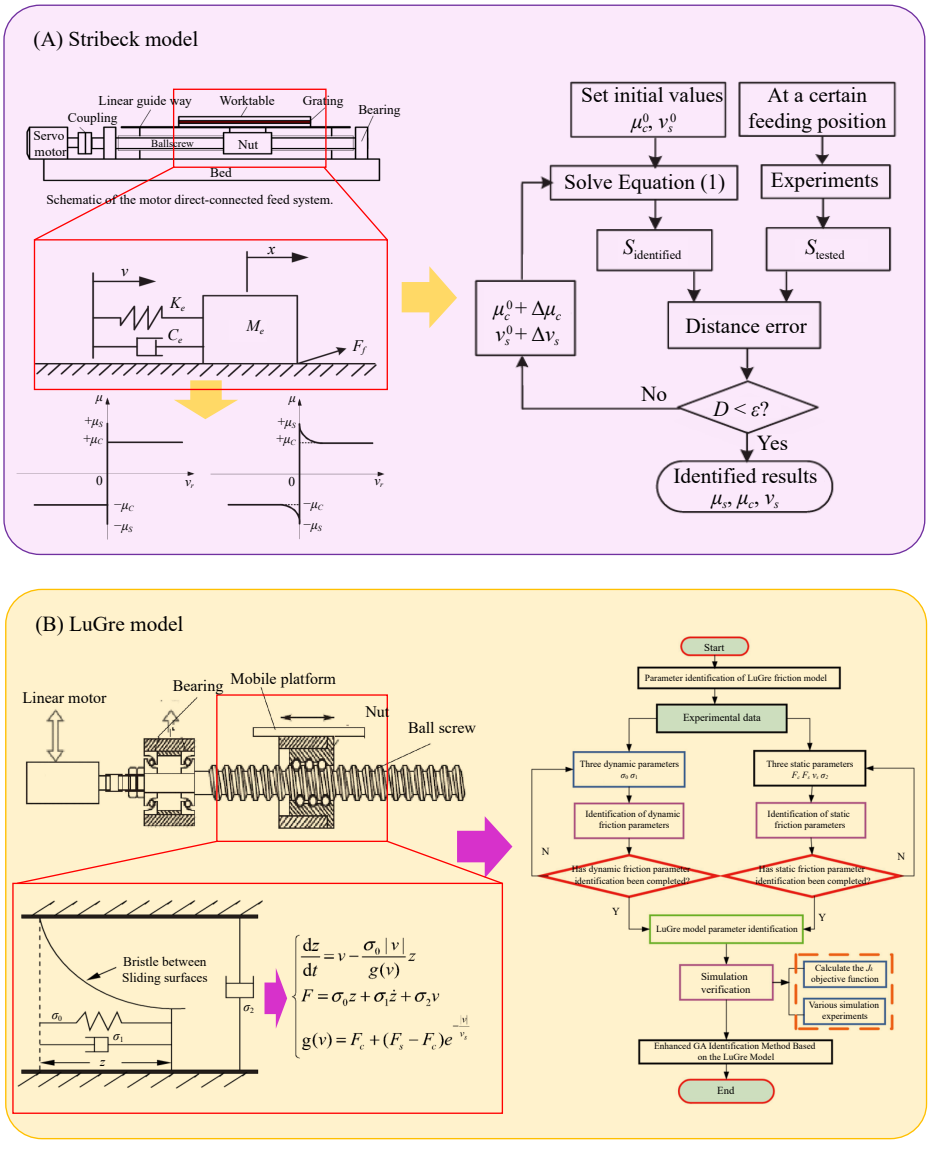


Fig. 11 Two commonly used friction models in servo systems: (A) Stribeck model. Reproduced with permission from Ref. [95], © 2015 Elsevier Ltd. (B) LuGre model. Reproduced from Ref. [94] under the terms of the CC BY 4.0 license, © 2025 Zhang et al.

Table 2 Summary of representative model-based friction identification approaches.

Category	Source	Data requirement	Implementation	Computational burden	Practical characteristics
Stribeck models	Liu and Wu [95], Lee et al. [90]	Velocity–torque response	Mainly offline	Low	Simple; suitable for steady-state friction; cannot represent hysteresis/memory
Improved Stribeck models	Liang and Zhou [91]	Extended operating-range data	Mainly offline	Medium	Better low-speed representation; parameter-selection dependent
LuGre models	Liao et al. [92], Feng et al. [93], Zhang et al. [94]	Transient + steady-state data	Mainly offline	High	Captures presliding, hysteresis and memory; strong parameter coupling

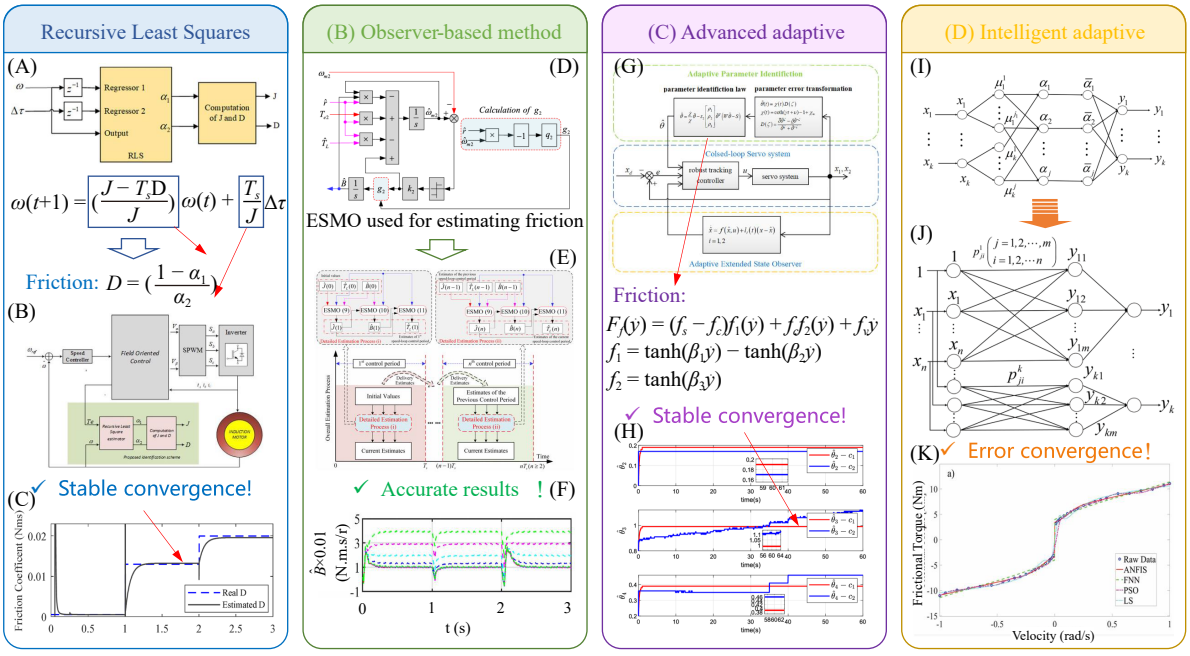


Fig. 12 Different online identification methods for friction: (A–C) Recursive least squares. Reproduced with permission from Ref. [96], © 2022 IEEE. (D–F) Observer-based. Reproduced with permission from Ref. [100], © 2021 IEEE. (G and H) Advanced adaptive. Reproduced with permission from Ref. [101], © 2025 Elsevier Ltd. (I–K) Intelligent adaptive. Reproduced from Ref. [97] under the terms of the CC BY 4.0 license, © 2026 The Authors.

excitation conditions to guarantee parameter convergence.

To improve robustness against nonlinear friction and external disturbances, observer-based adaptive identification methods have been widely investigated. Yang et al. [100] proposed an online parallel estimation method for PMSM drives based on interconnected extended sliding-mode observers, where mechanical parameters including inertia, friction coefficient, and load torque were simultaneously estimated through multiple observer structures. Tang et al. [99] investigated friction identification and compensation for SPMSM systems using a robust adaptive observer. By incorporating the LuGre friction model into the observer framework, the proposed method achieved online estimation and compensation of nonlinear friction without relying on offline identification experiments. Yang et al. [102] further proposed a parallel-observer-based network with model compensation for PMSM drives, enabling simultaneous identification of nonlinear friction and load torque. Compared with traditional single-observer structures, the proposed network improves estimation accuracy under varying operating conditions.

In addition to observer-based methods, learning-based approaches have also attracted increasing attention due to their ability to approximate complex nonlinear friction characteristics. Wan et al. [97] proposed a fuzzy neural network-based friction compensation method for robotic systems. By combining the Stribeck friction model with an adaptive neuro-fuzzy inference system (ANFIS), nonlinear friction characteristics were identified from measured velocity-torque data, and the identified model was further integrated into an external force estimation framework.

The representative online and adaptive friction identification approaches are summarized in Table 3.

Table 3 Summary of friction online identification methods.

Category	Source	Sensor/data requirement	Computational burden	Noise sensitivity	Practical characteristics
Recursive parameter estimation	Prasad et al. [96]	Standard servo input/output; sufficient excitation	Low	High	Simple and real-time; convergence depends on excitation
Observer-based identification	Yang et al. [100], Tang et al. [99], Yang et al. [102]	Standard servo feedback	Medium	Medium–high	Strong disturbance estimation; observer/gain dependent
Advanced adaptive estimation	Wang et al. [101], Li and Tao [98]	Standard servo feedback	Medium–high	Medium	Faster/fixed-time convergence; increased algorithm complexity
Intelligent adaptive identification	Wan et al. [97]	Training/operational data	High	Data-dependent	Strong nonlinear approximation; data and computation intensive

3.2 Inertia identification

The moment of inertia is a key mechanical parameter governing servo-system dynamics and control performance. Variations in payload, mechanical configuration, and transmission characteristics can significantly affect tracking accuracy and controller tuning, making reliable inertia identification essential for high-performance and adaptive servo control. The following sections review representative methods based on experimental estimation, state observation, and adaptive updating.

3.2.1 Direct measurement and model-based inertia identification

Early inertia identification methods mainly relied on direct measurements and model-based estimation approaches, where the moment of inertia was obtained by analyzing the relationship between applied torque and system motion response. These methods [107–116] typically utilize transient acceleration characteristics or specially designed excitation signals to separate inertia-related dynamics from other mechanical effects, providing fundamental parameter information for servo systems modeling and controller design. As illustrated in Fig. 13, direct measurement and model-based identification methods have gradually evolved through improved experimental strategies, dynamic modeling techniques, and parameter estimation algorithms, achieving higher identification accuracy, robustness, and applicability for practical high-performance servo systems.

The acceleration/deceleration-based identification method is one of the most intuitive approaches. By applying constant acceleration or deceleration commands under no-load conditions, the moment of inertia can be directly calculated from the transient velocity response. Babau et al. [108] investigated the inertia identification of large asynchronous induction motors by conducting constant acceleration startup and natural deceleration tests. The instantaneous driving power was measured, and the average moment of inertia was obtained over the entire testing cycle.

To further improve identification accuracy, regression-based identification methods have been introduced by establishing dynamic models between system inputs and measured responses. Erkorkmaz and Altintas [110] developed a dynamic parameter identification method for CNC feed drives based on an unbiased least squares scheme. By incorporating the control input and measured motor velocity into the identification model, the inertia and viscous friction parameters were accurately estimated, providing essential parameters for high-performance feed drive control.

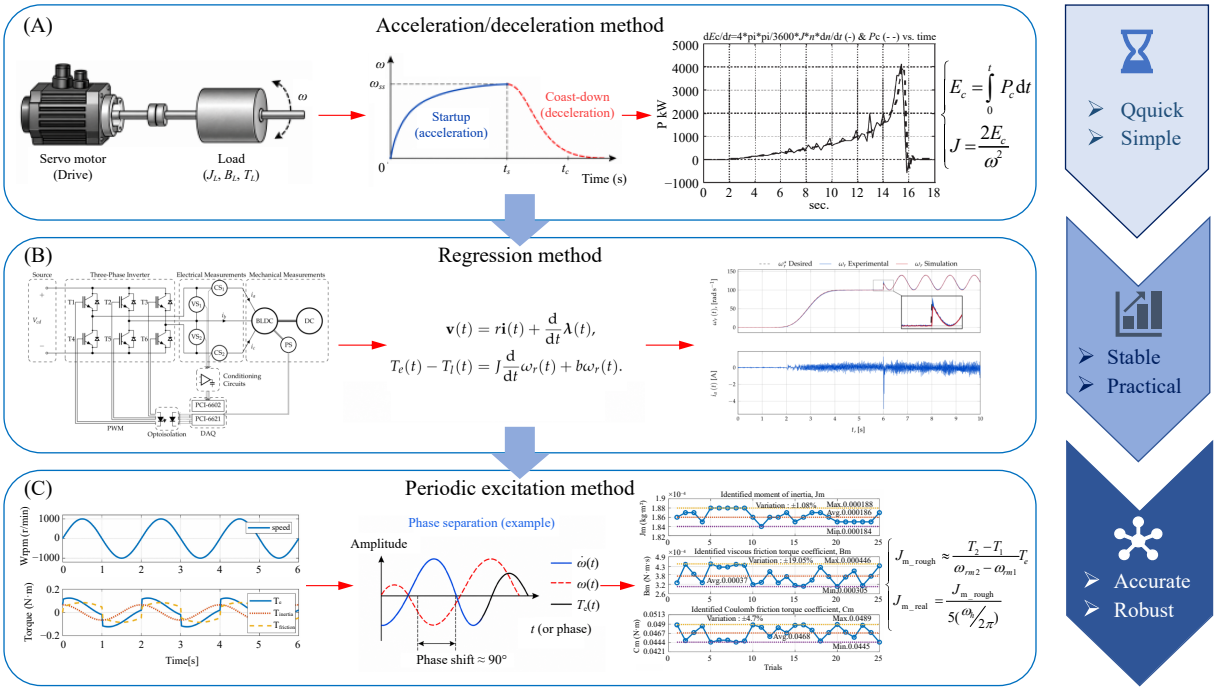


Fig. 13 Several methods for inertia identification of servo systems: (A) Acceleration/deceleration method. Reproduced with permission from Ref. [108], © 2007 IEEE. (B) Regression method. Reproduced from Ref. [111] under the terms of the CC BY 4.0 license, © 2021 by the authors. (C) Periodic excitation method. Reproduced with permission from Ref. [117], © 2018 IEEE.

Besides regression-based methods, periodic excitation approaches have also attracted considerable attention. These approaches introduce periodic velocity commands, such as sinusoidal or cosine signals, into the servo systems under known load conditions. By exploiting the phase differences among inertia torque, friction torque, and load torque, the inertia component can be effectively separated and analytically identified [113–115,117]. Kim [117] proposed a periodic command-based identification method under no-load conditions. By integrating the driving torque over half of a sinusoidal velocity cycle, the inertia torque was separated from the friction torque based on phase orthogonality, and analytical expressions for the moment of inertia and friction coefficient were derived.

Table 4 summarizes representative inertia identification methods for servo systems according to their main identification principles, including acceleration-based methods, observer-based methods, and adaptive estimation approaches.

3.2.2 Observer and adaptive inertia identification

With the increasing demand for high-performance servo systems under varying operating conditions, offline inertia identification methods are insufficient for tracking dynamic parameter variations during practical operation. Therefore, observer-based and adaptive identification methods [118–128] have been developed to estimate the moment of inertia online by integrating state observation and parameter adaptation mechanisms. Compared with direct measurement approaches, these methods can simultaneously estimate mechanical parameters and system states, thereby providing improved adaptability to load variations, external disturbances, and operating-condition changes. As illustrated in Fig. 14, the development of observer-based and adaptive methods reflects a clear transition from offline parameter estimation toward real-time and adaptive inertia identification, enhancing the capability of servo systems to maintain accurate parameter information under dynamically varying conditions.

Kalman filter-based methods are among the most widely investigated observer approaches for online inertia identification. By constructing extended state-space models, these methods incorporate unknown parameters, such as load torque and inertia-related variables, into the state vector and estimate them through recursive filtering. Zhang et al. [118] proposed an inertia identification method based on an extended Kalman filter (EKF), where the reciprocal of the moment of inertia and load torque were selected as extended state variables. By introducing an adaptive factor to dynamically adjust the covariance matrix of state prediction errors, the proposed method achieved improved identification accuracy and adaptive capability.

Besides Kalman filtering methods, recursive least squares (RLS) algorithms have also been widely applied for online inertia estimation due to their simple structure and fast convergence characteristics. Under known load torque or no-load conditions, the inertia parameter can be recursively updated according to the motor dynamic equation. Ke et al. [120] proposed a variable forgetting factor recursive least squares method for inertia identification. By employing a Luenberger observer to estimate motor speed and angular position and assuming that the identification error follows a normal distribution, the forgetting factor was adaptively adjusted between 0 and 1, improving both identification accuracy and computational efficiency.

Furthermore, model reference adaptive methods have attracted considerable attention due to their strong theoretical stability and adaptability. Wang and Wan [122] proposed a model reference adaptive identification algorithm for simultaneous estimation of load torque and moment of inertia in non-salient pole permanent magnet synchronous motors. By establishing the state error equation and applying a proportional-integral regulation mechanism, the convergence of the proposed algorithm was proven based on Popov's hyperstability theorem.

Table 5 summarizes representative observer-based and adaptive inertia identification methods for online servo applications.

3.3 Load identification

Load torque is a key time-varying disturbance that directly affects servo dynamics and tracking accuracy, yet

Table 4 Summary of typical methods for inertia identification of servo systems.

Method	Source	Excitation/signal requirement	Computational burden	Noise sensitivity	Practical characteristics
Acceleration/deceleration-based	Babau et al. [108], Jing et al. [109]	Designed acceleration/deceleration trajectory	Low	High	Simple and interpretable; acceleration estimation vulnerable to noise
Regression-based	Erkorkmaz and Altintas [110], Jimenez-Gonzalez et al. [111]	Motor input/output data	Low–medium	Medium	Practical and quantitative; model dependent
Periodic excitation-based	Li and Liu [113], Garrido and Concha [114], Chen et al. [115], Kim [117]	Sinusoidal/periodic excitation	Low–medium	Medium	Reduces friction influence; interrupts normal operation

it is difficult to measure directly in practical operation. Accurate load identification is therefore important for disturbance compensation and high-performance motion control. Existing methods are mainly classified into observer-based and adaptive approaches. In this review, load identification refers broadly to the estimation of load-related quantities, load-torque estimation specifically denotes real-time estimation of mechanical load torque, and disturbance estimation refers to the estimation of lumped disturbances that include load torque together with other uncertainties or external disturbances.

3.3.1 Observer-based load identification

Load torque is one of the most critical disturbances affecting the dynamic performance of servo systems. Unlike intrinsic mechanical parameters, such as inertia and friction coefficients, external load torque is generally time-varying and difficult to measure directly during practical operation. In CNC machine tools, variations in cutting conditions, workpiece properties, and machining trajectories introduce continuously changing load disturbances, which may deteriorate tracking accuracy and contouring performance. Therefore, accurate online load identification is essential for disturbance compensation and high-performance servo control.

Compared with torque sensor-based measurement approaches, observer-based methods [129–144] avoid additional hardware installation and provide better engineering applicability. Existing observer-based load identification approaches mainly include sliding-mode

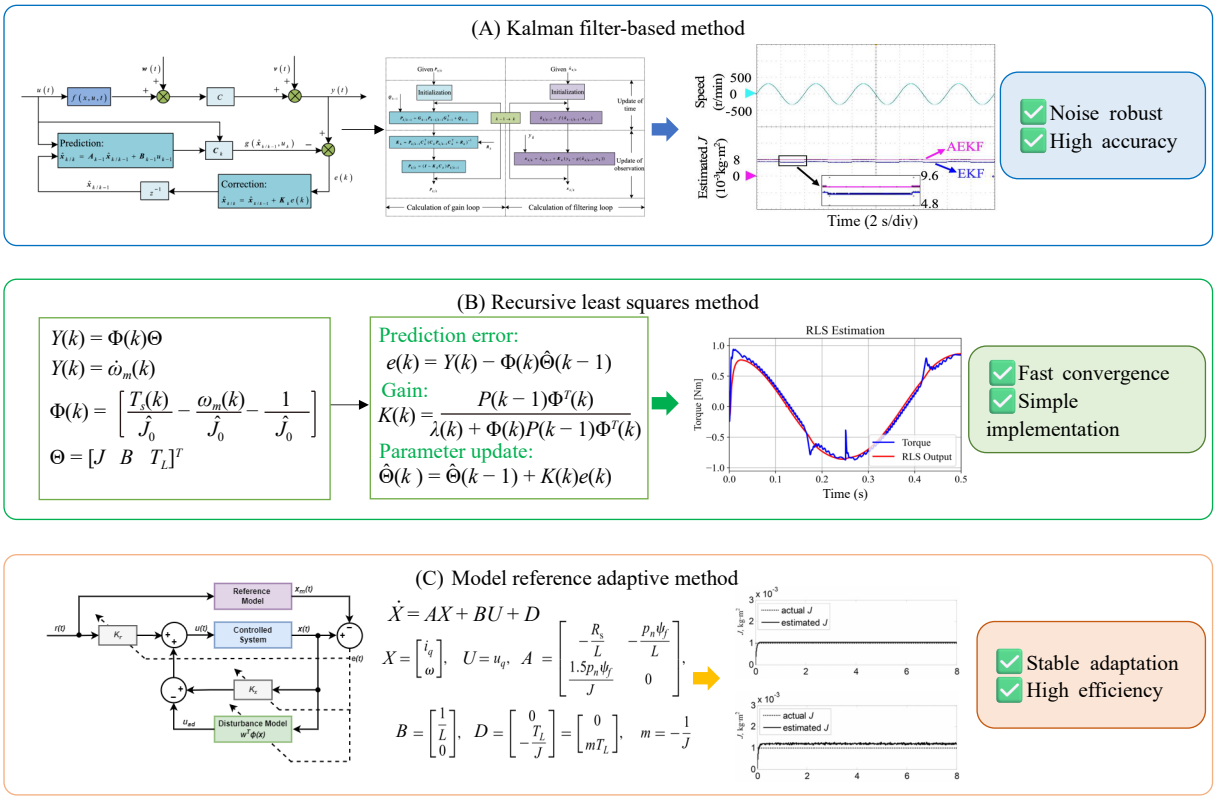


Fig. 14 Comparison of different methods for inertia identification: (A) Kalman filter-based method. Reproduced with permission from Ref. [118], © 2025 IEEE. (B) Recursive least square method. Reproduced with permission from Ref. [116], © 2025 IEEE. (C) Model reference adaptive method. Reproduced with permission from Ref. [122], © The Institution of Engineering and Technology 2013.

Table 5 Summary of inertia identification methods based on observers.

Method	Source	Implementation	Noise sensitivity	Computational burden	Practical characteristics
Kalman filter-based	Zhang et al. [118], Yang et al. [119]	Online	Low–medium	High	Strong stochastic-noise handling; recursive covariance computation
Recursive least squares	Ke et al. [120], Wang et al. [121]	Online	High	Low	Fast update and simple implementation; affected by noise/model mismatch
Model reference adaptive	Wang and Wan [122]	Online	Medium	Medium	Continuous adaptation with stability basis; model/adaptive-law dependent

observers, extended state observers, disturbance observers, and their improved adaptive structures. Fig. 15 summarizes four representative observer-based load identification methods, illustrating the application of different observer structures and parameter estimation mechanisms for online load torque estimation. These approaches provide a basis for comparing their characteristics, advantages, and applicability under various servo operating conditions. Their development has gradually evolved from single disturbance estimation toward synchronous identification of multiple mechanical parameters, including inertia, friction, and load torque.

Early load torque estimation methods mainly employed conventional disturbance observers and state observers to reconstruct unknown disturbances based on nominal system models. Lu et al. [131] proposed an improved sliding-mode observer for load adaptive identification in PMSM position servo systems. By introducing adaptive feedback gains and optimizing observer parameters, the proposed method improved the convergence speed and estimation accuracy under varying load conditions. Compared with conventional fixed-gain SMOs, the adaptive structure provides better adaptability when the external disturbance changes dynamically. Tahami et al. [132] further combined adaptive fuzzy mechanisms with sliding-mode observation and proposed an adaptive fuzzy sliding-mode observer for PMSM drives. In this method, the load torque was regarded as an extended disturbance state, and fuzzy rules were employed to adjust observer gains dynamically. The proposed approach reduced chattering while maintaining accurate disturbance estimation.

Although single load torque observers can effectively estimate external disturbances, practical servo systems often exhibit coupled variations among multiple mechanical parameters. In particular, inertia variation directly affects load torque estimation accuracy, especially during acceleration and deceleration processes. Therefore, recent studies have shifted from independent load disturbance estimation toward simultaneous identification of inertia and load torque. Wang et al. [133] further considered PMSM-driven spindle-tool systems and developed a double extended sliding-mode observer (DESMO) for synchronous estimation of total inertia and load torque. By introducing two extended observers and designing decoupling conditions, the proposed method reduced the interaction between inertia and load estimation processes. The effectiveness of the method was verified under varying friction conditions and measurement noise, demonstrating its potential for

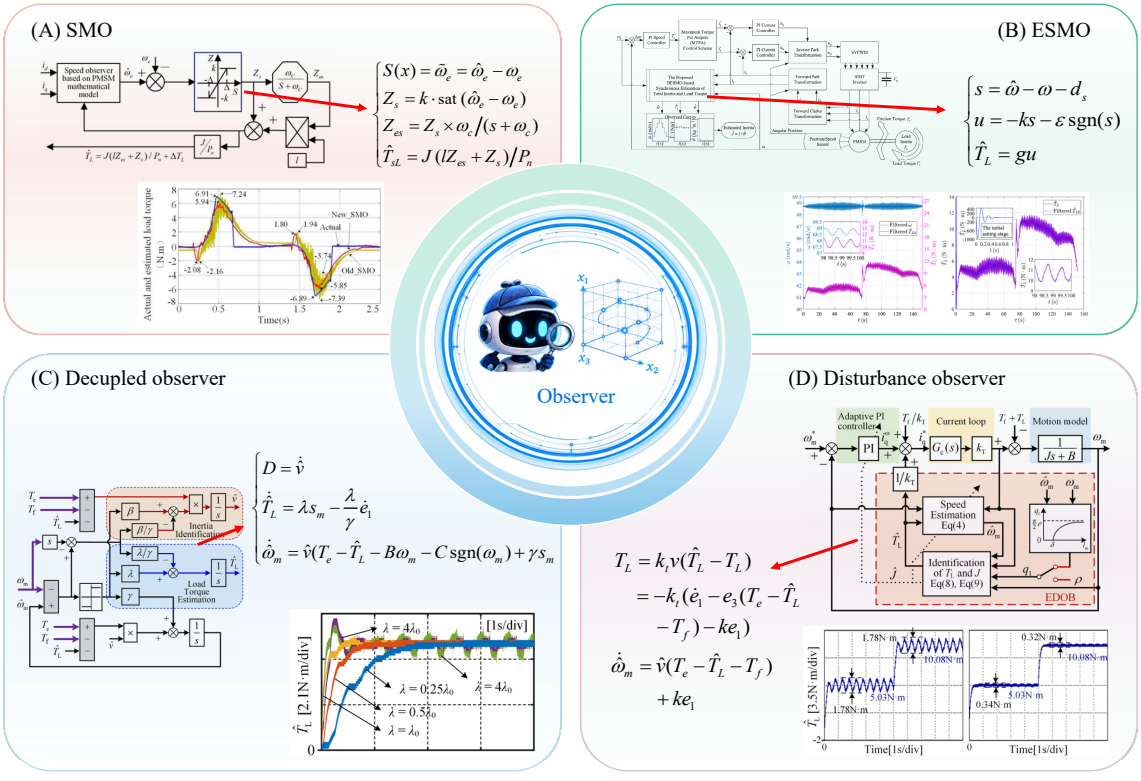


Fig. 15 Several observer based load identification methods: (A) SMO. Reproduced with permission from Ref. [131], © 2020 IEEE. (B) ESMO. Reproduced with permission from Ref. [133], © 2022 IEEE. (C) Decupled observer. Reproduced with permission from Ref. [135], © 2024 IEEE. (D) Disturbance observer. Reproduced with permission from Ref. [137], © 2024 IEEE.

manufacturing equipment applications.

To further improve parameter estimation accuracy and suppress chattering, higher-order sliding-mode and advanced observation structures have been investigated. Wang et al. [134] proposed a dual super-twisting parallel observation network with cogging torque compensation for accurate servo parameter identification. By employing multiple super-twisting observers in parallel, the proposed method achieved high-precision estimation of mechanical parameters while compensating cogging torque disturbances. Beyond conventional extended sliding-mode observers, variable-structure and decoupled observation methods have been developed to address the coupling problem between inertia and load torque estimation.

In addition to observer structure improvements, some studies have focused on integrating load identification with disturbance compensation control. Liu et al. [136] combined parameter identification with active disturbance rejection control (ADRC), where model reference adaptive methods and Luenberger observers were employed to estimate inertia and load torque. The estimated parameters were subsequently utilized to adjust controller parameters and improve disturbance rejection capability. Tang et al. [137] proposed an extended disturbance observer with a triggering mechanism for simultaneous online estimation of load torque and inertia. By analyzing the coupling relationship between inertia and load estimation errors, the proposed triggering strategy improved identification accuracy while reducing unnecessary parameter updates.

Table 6 summarizes representative observer-based load identification methods, which have evolved from single-disturbance estimation toward multi-parameter estimation and compensation.

3.3.2 Adaptive load identification

Unlike observer-based methods that focus on disturbance reconstruction, adaptive identification methods [145–154] update unknown parameters through adaptive laws. By establishing an adaptive mechanism between system output errors and parameter estimation errors, these methods can continuously adjust the estimated load torque or related mechanical parameters during operation. Compared with conventional identification approaches, adaptive methods are more suitable for servo systems with time-varying loads and uncertain operating conditions.

Early adaptive load identification methods were mainly developed based on the model reference adaptive system (MRAS). Wang et al. [145] proposed an online load torque identification strategy for salient-pole PMSM drives based on a variable-structure MRAS. In this method, the PMSM itself was selected as the reference model, while the adjustable model contained the estimated load torque as an unknown parameter. The adaptive law was derived from the output error between two models, and a sliding-mode surface was introduced to improve robustness against load variations. Simulation results demonstrated that the proposed method could accurately track sudden load changes and improve speed regulation performance.

With the increasing requirements for dynamic performance, adaptive identification methods have gradually incorporated nonlinear adaptation mechanisms. Jiang et al. [148] proposed an improved MRAS observer combined with a fast super-twisting sliding mode adaptive mechanism. The conventional PI adaptive law in MRAS was replaced by a nonlinear adaptive strategy to improve convergence speed and robustness under parameter variations and load disturbances. Meanwhile, an extended sliding-mode load torque observer was designed to provide real-time load torque feedback for model predictive control. The results verified that the proposed method achieved improved disturbance rejection capability compared with traditional MRAS structures.

In addition to adaptive laws based on model errors, recent studies have introduced adaptive filtering and nonlinear adjustment techniques to enhance load identification performance. Jiang et al. [146] integrated an extended state observer with MRAS to estimate lumped disturbances caused by load variations and parameter uncertainties. A super-twisting sliding-mode adaptive mechanism was employed instead of the traditional PI adaptive law, improving robustness under

Table 6 Summary of load identification methods based on observers.

Method	Source	Implementation	Computational burden	Noise sensitivity	Practical characteristics
SMO	Lu et al. [131], Tahami et al. [132]	Online	Low–medium	Medium–high	Robust load estimation; chattering
ESMO	Wang et al. [133]	Online	Medium–high	High at large observer gains	Multi-parameter estimation; parameter coupling
Decupled observer	Wang et al. [134], Tang et al. [135]	Online	High	Medium	Reduced inertia–load coupling; complex observer design
Disturbance observer	Liu et al. [136], Tang et al. [137]	Online	Low–medium	Medium	Simple estimation/compensation; nominal-model dependent

varying operating conditions. Sun et al. [149] proposed a nonsingular terminal sliding-mode load torque identification method combined with a frequency adaptive filter. By adaptively extracting disturbance components and compensating parameter variations, the proposed method achieved higher identification accuracy under dynamic load conditions.

Table 7 summarizes representative adaptive load identification methods for servo systems under varying operating conditions.

4 Parameter Tuning

Controller tuning is essential for achieving high servo performance, as dynamic response, tracking accuracy, and disturbance rejection strongly depend on appropriate parameter selection. Conventional manual tuning is often insufficient under varying operating conditions and multiple performance requirements. Accordingly, tuning methods have evolved from classical response- and model-based approaches to adaptive, online, and optimization-based strategies that determine controller parameters according to system dynamics, performance objectives, and operational constraints.

4.1 Classical tuning methods

Classical tuning methods remain widely used in servo systems because of their simplicity and practical applicability. They mainly include response-based methods, which determine controller parameters from transient or frequency-response characteristics, and model-based analytical methods, which derive parameters from system dynamics and performance requirements. Although easy to implement and physically interpretable, these methods depend strongly on operator experience and model accuracy, limiting their adaptability to varying operating conditions and multiple performance objectives.

4.1.1 Response-based and performance-chart-based tuning

Response-based tuning methods determine controller parameters by analyzing the characteristic responses of servo systems. The classic Ziegler–Nichols (Z–N) method [155–157] and relay feedback approaches [158–161] are representative examples, where critical system characteristics are obtained from time-domain responses or frequency-domain oscillation behaviors. Subsequently, PID parameters are calculated according to predefined tuning rules or empirical formulas, providing a simple and practical solution for industrial controller configuration. Fig. 16 compares these two representative classical tuning strategies and highlights their basic tuning mechanisms and implementation characteristics.

Among these methods, relay feedback autotuning has attracted extensive attention due to its capability of obtaining critical system characteristics without requiring an accurate mathematical model. Lee et al. [160] proposed a relay feedback autotuning method based on the method of weighted moments. Unlike conventional relay feedback approaches that mainly utilize steady-state oscillation amplitude and frequency, the proposed method extracts additional dynamic information from relay feedback transients by applying weighted integral calculations. This approach reduces the influence of high-frequency parasitic dynamics and improves the reliability of the identified low-order process model, enabling more consistent PI controller tuning performance.

To improve the visualization and flexibility of parameter selection, design chart methods [163–166] have been developed based on the relationship between controller parameters and system performance indicators. By traversing the controller parameter space and calculating corresponding performance indices, contour maps are constructed to describe the distribution of system characteristics. These charts enable engineers to select appropriate controller parameters according to specific performance requirements. Verma and Padhy [163] proposed a robust fine-tuning method for PID controllers based on an indirect design approach. Rather than independently adjusting the proportional, integral, and derivative gains, the proposed method introduced a single frequency-shift parameter to modify the previously optimized controller. The relationship between this parameter and robustness indicators, including gain margin, phase margin, and maximum sensitivity, was established, allowing efficient adjustment of controller

Table 7 Summary of adaptive load identification methods.

Method	Source	Implementation	Computational burden	Noise sensitivity	Practical characteristics
MRAS-based	Wang et al. [145], Jiang et al. [148], Jiang et al. [146]	Online	Medium	Medium	Continuous update; underlying-model dependent
Adaptive observer	Wen et al. [147]	Online	Medium	Gain-dependent	Fast transient estimation; bandwidth/gain design critical
Adaptive nonlinear estimation	Sun et al. [149]	Online	Medium	Medium	Improved robustness to varying loads; higher implementation complexity

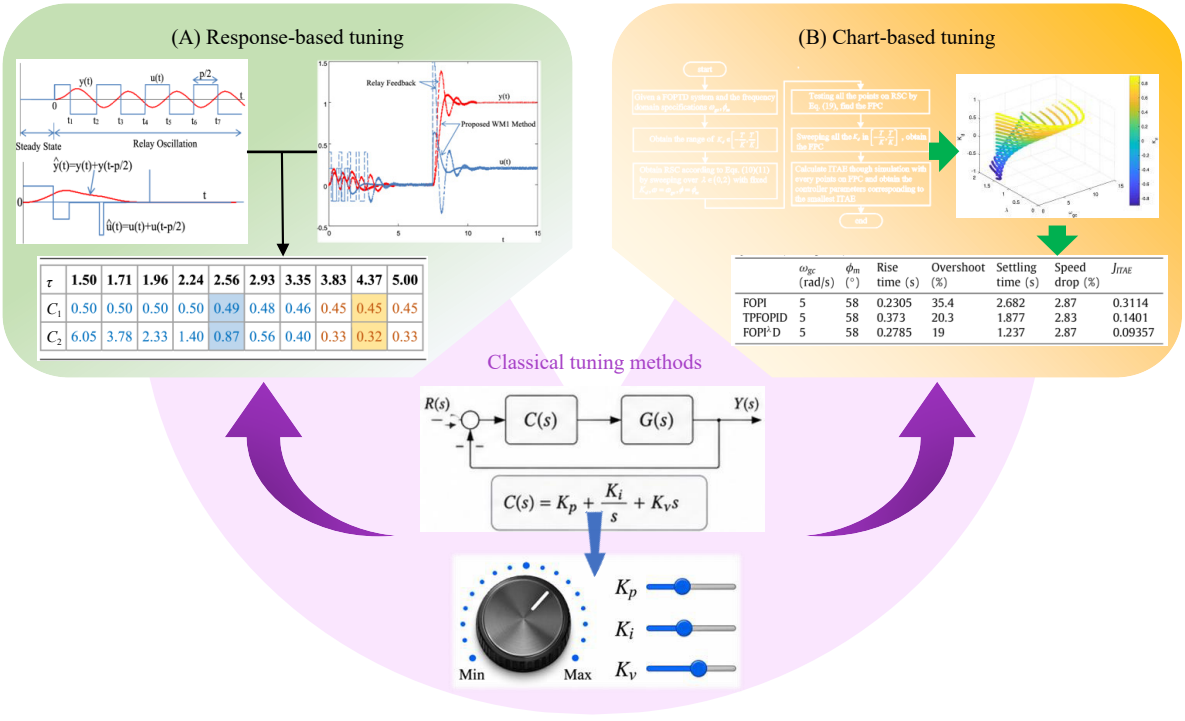
robustness while maintaining satisfactory performance.

Table 8 provides a comparative summary of representative response-based and performance-chart-based tuning methods, including their tuning mechanisms, representative techniques, advantages, and limitations.

4.1.2 Model-based analytical tuning

Model-based analytical tuning methods [167–172] determine servo controller parameters by establishing mathematical models of the controlled electromechanical system and analytically deriving the relationship between controller gains and predefined performance specifications. Unlike response-based approaches, these methods avoid repeated trial-and-error procedures and provide quantitative tuning criteria based on system dynamics. For servo systems in manufacturing equipment, the controlled plant is commonly represented by cascaded current, velocity, and position loops, where electrical parameters, mechanical inertia, damping, and load characteristics are incorporated into the controller design process. Fig. 17 illustrates the principle of model-based analytical tuning methods. By establishing an electromechanical servo model and incorporating identified system parameters, such as motor characteristics and moment of inertia, controller parameters can be analytically determined according to predefined performance requirements.

A representative model-based tuning framework was presented by Yang and Lin [167], who developed an automatic tuning scheme for permanent-magnet AC servo drives. By identifying motor electrical parameters, including resistance and inductances, the current-loop PI gains were analytically calculated according to the desired bandwidth. Furthermore, considering the mechanical dynamics of the velocity loop, the



τ	1.50	1.71	1.96	2.24	2.56	2.93	3.35	3.83	4.37	5.00
C_1	0.50	0.50	0.50	0.50	0.49	0.48	0.46	0.45	0.45	0.45
C_2	6.05	3.78	2.33	1.40	0.87	0.56	0.40	0.33	0.32	0.33

	ω_{gc} (rad/s)	ϕ_m (°)	Rise time (s)	Overshoot (%)	Settling time (s)	Speed drop (%)	J_{ITAE}
FOPI	5	58	0.2305	35.4	2.682	2.87	0.3114
TPFOPID	5	58	0.373	20.3	1.877	2.83	0.1401
FOPI$^\lambda$D	5	58	0.2785	19	1.237	2.87	0.09357

Fig. 16 Two classic servo parameter tuning methods: (A) Response-based tuning. Reproduced with permission from Ref. [160], © 2020 Elsevier Ltd. Reproduced with permission from Ref. [161], © 2020 The Franklin Institute. Published by Elsevier Ltd. (B) Chart-based tuning. Reproduced with permission from Ref. [162], © 2020 ISA. Published by Elsevier Ltd.

Table 8 Summary of traditional servo parameter tuning methods.

Method	Source	Model/data requirement	Computational burden	Adaptability	Practical characteristics
Response-based tuning	Z–N method [155], Åström and Hägglund [158], Bazanella et al. [159], Lee et al. [160], Rehan et al. [161]	Low/response test	Low	Low	Simple and model-light; limited multi-objective optimization
Performance-chart-based tuning	Verma and Padhy [163], Chen et al. [164], Bošković et al. [165], Wang [166]	Model/performance map	Medium–high	Low–medium	Quantitative multi-constraint tuning; chart generation is costly

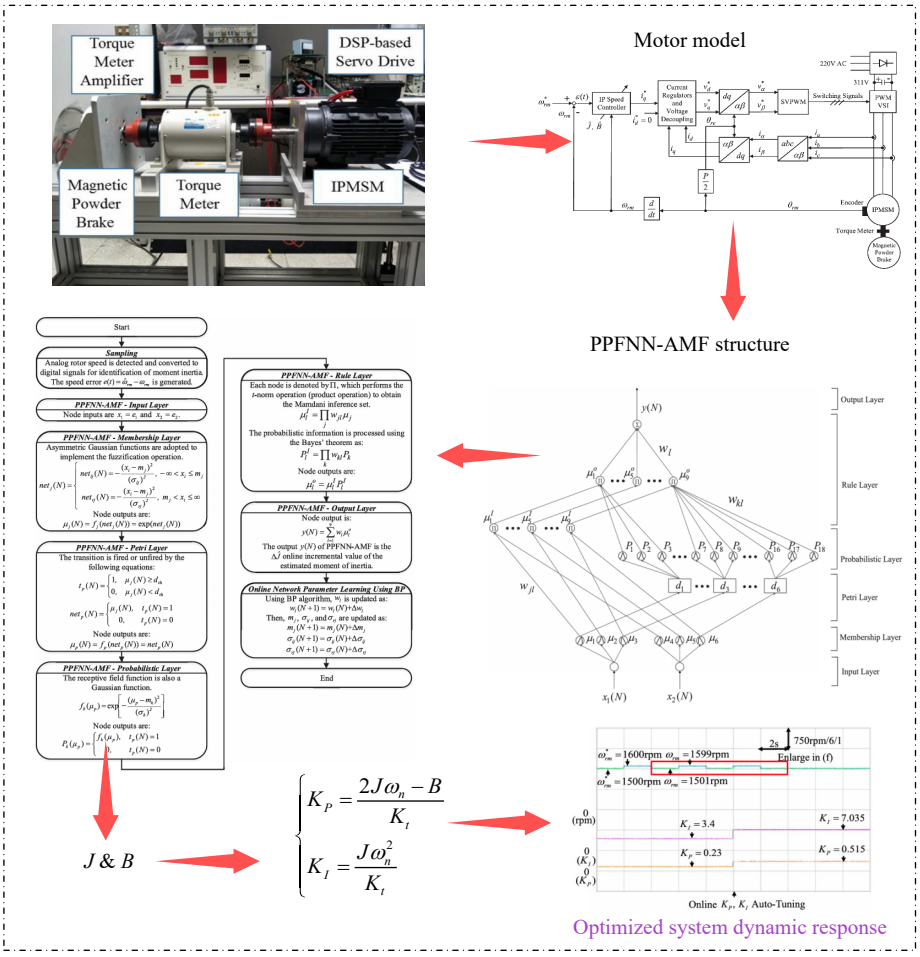


Fig. 17 A model reference analysis method for servo parameter tuning. Reproduced with permission from Ref. [169], © 2020 IEEE.

proportional and integral gains were derived from the identified inertia and viscous damping coefficients. This method established a direct mapping between physical parameters and controller gains, enabling consistent dynamic performance without manual commissioning.

Besides frequency-domain design, pole-placement approaches provide another important analytical tuning strategy by directly assigning desired closed-loop dynamic characteristics. Das et al. [170] proposed a robust PID tuning method based on dominant pole placement. By matching the characteristic polynomial of the closed-loop system with predefined dominant poles, the controller parameters were analytically obtained according to desired damping ratio and natural frequency requirements.

With increasing requirements for servo performance, model-based analytical tuning has also been extended from conventional integer-order controllers to fractional-order control structures. Tepljakov et al. [168] incorporated fractional-order dynamics into existing PI/PID control loops and investigated the influence of additional fractional parameters on closed-loop performance. By introducing fractional integration and differentiation orders, the controller design gains additional degrees of freedom, enabling improved adjustment of phase margin, crossover frequency, and robustness characteristics. Nevertheless, the increased number of tuning variables also increases the complexity of parameter selection and implementation.

Although model-based analytical methods provide clear physical interpretations and quantitative design criteria, their performance strongly depends on model accuracy. In practical CNC servo systems, nonlinear friction, transmission flexibility, varying inertia, and external disturbances are difficult to accurately describe using simplified models. To overcome the limitations caused by fixed model parameters, recent studies have gradually incorporated online parameter estimation into model-based tuning frameworks. Dang et al. [171] proposed an online parameter estimation method for IPMSM drives, where estimated motor parameters were utilized to update adaptive PI controller gains under

varying operating conditions.

Table 9 summarizes representative model-based analytical tuning methods, highlighting their design strategies, representative approaches, advantages, and limitations.

4.2 Adaptive and online parameter tuning

Classical analytical tuning may lose effectiveness under varying operating conditions because changes in payload, friction, and external disturbances alter servo dynamics. Adaptive and online tuning methods address this issue by updating controller parameters according to real-time system states or identified parameters. Typical approaches include online parameter scheduling and intelligent adaptive tuning, which improve servo adaptability under time-varying conditions.

4.2.1 Online parameter scheduling

With the increasing requirements for high-performance servo systems, conventional offline tuning methods with fixed controller parameters are insufficient to maintain consistent dynamic performance under varying operating conditions. In practical manufacturing equipment, servo systems are inevitably affected by changes in payload, operating speed, mechanical characteristics, and external disturbances. These variations alter the dynamic characteristics of the controlled plant, resulting in degraded tracking accuracy and reduced robustness when constant-gain controllers are applied. Therefore, online parameter scheduling methods [173–177] have been developed to adjust controller parameters according to real-time operating conditions, enabling servo systems to maintain desirable performance over a wide operating range.

Gain scheduling is a widely used online tuning strategy that adjusts controller gains according to measurable operating variables. Mademlis and Kioskeridis [173] applied this approach to switched reluctance motor drives, improving dynamic and positioning performance across different operating regions. Although computationally efficient, gain scheduling depends strongly on the choice of scheduling variables and predefined gain maps, limiting its adaptability to strong nonlinearities and unexpected variations. To overcome this limitation, Lee et al. [174] proposed a variable PID tuning method based on backstepping control, time-delay estimation, and nonlinear damping, enabling PID gains to be adjusted online according to tracking errors and system dynamics. This approach improves robustness to disturbances and varying dynamics without requiring complete prior system knowledge.

Another important direction is parameter identification-driven online tuning, where estimated system parameters are directly utilized to update controller gains. Jiang et al. [175] combined transfer-learning-based parameter identification with adaptive control for PMSM trajectory tracking, enabling controller parameters to follow variations in motor characteristics. This approach strengthens the link between online identification and tuning, although its effectiveness depends on the accuracy and convergence speed of parameter estimation.

Table 10 summarizes representative online parameter scheduling methods, including their adjustment strategies, representative approaches, advantages, and limitations.

4.2.2 Intelligent adaptive tuning

Intelligent adaptive tuning methods [178–189] enhance the self-adjustment capability of servo controllers by introducing intelligent learning and reasoning mechanisms into parameter regulation. Unlike

Table 9 Summary of several model-based parameter tuning methods.

Method	Source	Model requirement	Computational burden	Adaptability	Practical characteristics
Parameter/Frequency-based	Yang and Lin [167], Poola et al. [172]	High	Low	Low	Direct physical interpretation; sensitive to parameter variation
Pole/Fractional-order	Das et al. [170], Tepljakov et al. [168],	Medium–high	Medium	Low–medium	Flexible design; more tuning variables
Online model-driven	Dang et al. [171], Lin et al. [169]	Identified model/parameters	Medium–high	High	Adaptive gain update; depends on identification quality

Table 10 Summary of several online servo parameter tuning methods.

Method	Source	Required information	Computational burden	Adaptability	Practical characteristics
Gain scheduling	Mademlis and Kioskeridis [173]	Operating condition + predefined gain map	Low	Medium	Fast real-time update; limited outside predefined regions
Variable PID tuning	Lee et al. [174]	Tracking/state feedback	Low–medium	Medium–high	Handles changing dynamics; tuning-law design required
Identification-driven tuning	Jiang et al. [175]	Online identified parameters	Medium	High	Direct identification–tuning link; depends on estimation accuracy/convergence

conventional online parameter scheduling approaches that rely on predefined relationships between operating conditions and controller gains, intelligent adaptive methods establish nonlinear mappings between system states and control parameters through fuzzy inference, neural networks, or hybrid intelligent structures. Therefore, these methods have been widely investigated for servo systems with nonlinear dynamics, uncertain parameters, and time-varying disturbances. As illustrated in Fig. 18, representative intelligent adaptive tuning strategies can be categorized into fuzzy-based, neural-network-based, and hybrid intelligent methods. Fuzzy tuning achieves model-free parameter tuning by incorporating expert knowledge, neural-network-based tuning improves adaptation capability through nonlinear learning, and hybrid intelligent tuning integrates multiple algorithms to achieve enhanced robustness and adaptability under complex operating conditions.

Fuzzy-based adaptive tuning is one of the most commonly adopted intelligent approaches for improving servo controller adaptability. By constructing fuzzy rules according to tracking errors and their variations, controller parameters can be adjusted online without requiring an accurate mathematical model. Liu et al. [179] proposed a fuzzy adaptive PID control strategy for a belt-driven servo system, where the speed error and error variation were selected as fuzzy inputs to update PID gains. The proposed method improved transient response performance and reduced overshoot compared with conventional PID control.

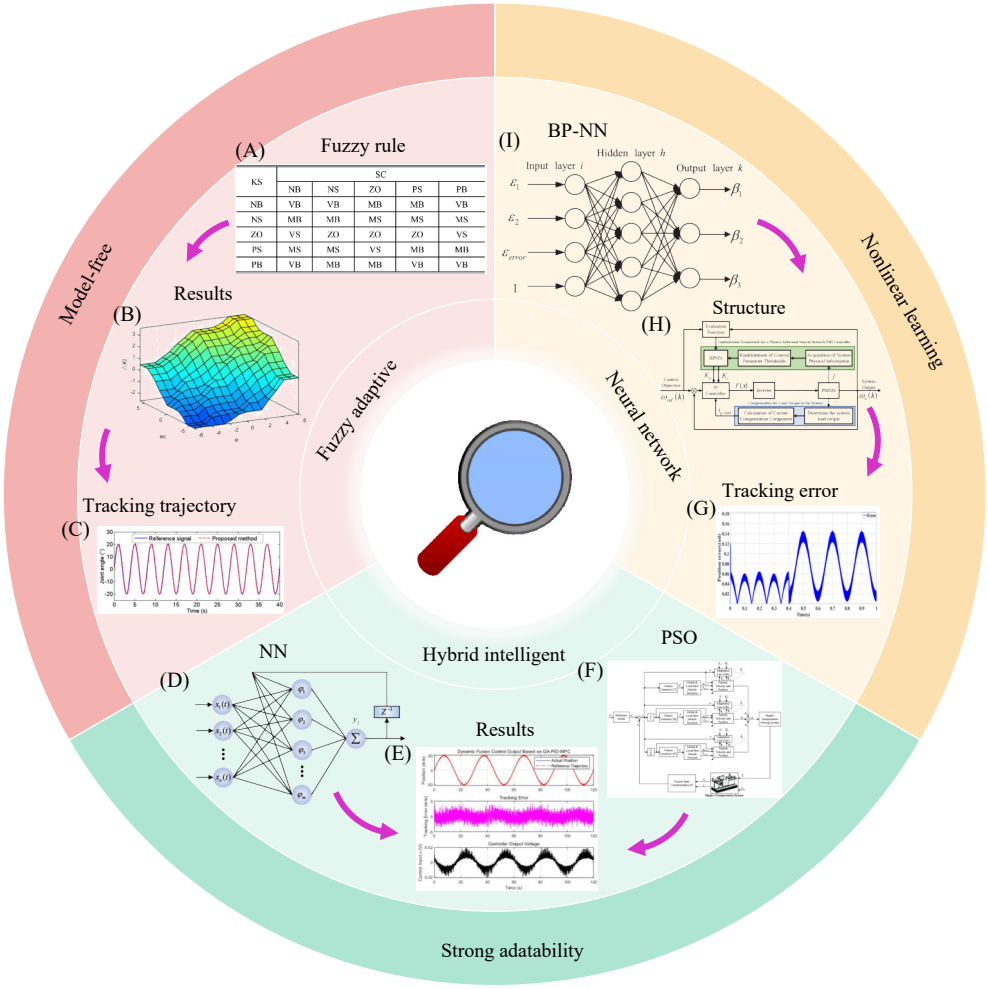


Fig. 18 Several intelligent adaptive parameter tuning methods. （A and C) Reproduced with permission from Ref. [184], © 2023 IEEE. (B) Reproduced with permission from Ref. [179]. © The Author(s) 2021. (D) Reproduced with permission from Ref. [181], © 2025 IEEE. (E) Reproduced from Ref. [182], © 2025 by the authors. Published by MDPI under the CC BY 4.0 license. (F) Reproduced with permission from Ref. [178], © 2011 IEEE. (G and H) Reproduced from Ref. [186] under the terms of the CC BY 4.0 license, © 2025 by the authors. Published by MDPI, Basel, Switzerland. (I) Reproduced with permission from Ref. [185], © 2021 ISA. Published by Elsevier Ltd.

Table 11 Summary of several intelligent adaptive parameter tuning methods.

Method	Source	Data requirement	Computational burden	Adaptability	Practical characteristics
Fuzzy adaptive tuning	Liu et al. [179], Tang et al. [184], Sui and Zhao [185]	Expert rules	Low–medium	Medium	Interpretable and model-light; rule dependent
Neural-network tuning	de Moura et al. [180], Song and Huang [186], Xu et al. [181], Wang et al. [183]	Training/operational data	High	High	Strong nonlinear learning; data/computation dependent
Hybrid intelligent tuning	Zhou et al. [182], Wai et al. [178]	Multiple models/algorithms	High	High	Strong adaptability; complex implementation and stability analysis

To further enhance the learning capability of intelligent tuning methods, neural-network-based approaches have been developed for automatic controller parameter tuning. Neural networks can approximate complex nonlinear relationships between system states and optimal controller parameters, providing stronger adaptability for uncertain servo systems. de Moura et al. [180] proposed a neuro-fuzzy model for online optimal PID tuning in industrial applications, combining neural learning and fuzzy reasoning to achieve adaptive controller adjustment.

Hybrid intelligent tuning methods combine multiple intelligent mechanisms to achieve improved adaptability and robustness. Zhou et al. [182] proposed an integrated intelligent control framework combining adaptive PID tuning and model predictive control for nonlinear hydraulic servo systems under model uncertainty. The adaptive PID module updated controller parameters online, while MPC provided predictive compensation for nonlinear system dynamics.

Table 11 summarizes representative intelligent adaptive tuning methods for servo parameter optimization, including fuzzy-based, neural-network-based, and hybrid intelligent strategies, from the perspectives of optimization mechanisms, advantages, and practical limitations.

4.3 Optimization-based parameter tuning

Optimization-based tuning addresses the difficulty of satisfying multiple conflicting servo performance requirements through systematic parameter search. By formulating controller tuning as an optimization problem, these methods determine parameters according to defined performance objectives. Existing approaches are generally divided into single-objective and multi-objective optimization, focusing respectively on individual performance enhancement and coordinated trade-offs among response speed, tracking accuracy, and robustness.

4.3.1 Single-objective optimization

Single-objective optimization methods [190–199] formulate parameter tuning as an optimization problem by defining a single performance criterion and searching for the optimal controller parameters. Compared with classical tuning methods based on empirical rules and analytical calculations, optimization-based approaches provide a quantitative evaluation mechanism and reduce the dependence on manual parameter tuning. Typical objective functions include time-domain performance indices, such as integral absolute error (IAE), integral square error (ISE), and integral time absolute error (ITAE), as well as frequency-domain specifications including bandwidth, gain margin, and phase margin. These methods have been widely applied to PID and fractional-order controllers for improving the dynamic performance of servo systems. As illustrated in Fig. 19, the single-objective optimization-based tuning framework mainly consists of controller parameter initialization, performance index evaluation, optimization algorithm searching, and parameter updating processes. Through iterative optimization, the controller parameters are gradually adjusted toward the solution that achieves the best performance with respect to the selected objective criterion.

Performance-index-oriented optimization is one of the most commonly used strategies for single-objective parameter tuning. By minimizing a predefined objective function, controller parameters can be automatically determined according to specific performance requirements. Choubey et al. [196] proposed a Harris Hawk Optimization (HHO)-based tuning method for a frequency-shifted internal model control PID (FSIMC-PID) controller. The controller parameters were optimized by considering the integral time square error (ITSE) as the objective function, and the performance was evaluated using multiple error indices, including IAE, ISE, ITAE, and ITSE. The proposed method achieved improved transient response and disturbance rejection performance compared with conventional PID tuning methods. For servo systems requiring precise dynamic specifications, time-domain performance constraints have also been incorporated into the optimization process. Lee and Peng [191] proposed a genetic algorithm (GA)-based PID tuning method for servo motor position control. By constructing fitness functions and constraints according to desired time-domain specifications, including overshoot, peak time, and settling time, the proposed method directly searched

PID gains satisfying predefined performance requirements. Compared with traditional trial-and-error tuning approaches, the GA-based method reduced manual adjustment and improved the accuracy of controller design.

In addition to time-domain criteria, frequency-domain specifications have been employed as optimization objectives to improve the robustness and dynamic characteristics of servo controllers. Song et al. [195] investigated a fractional-order PI controller design for a permanent magnet linear synchronous motor (PMLSM) system, where frequency-domain specifications such as crossover frequency and phase margin were optimized to achieve desired dynamic performance. Furthermore, Zheng et al. [193] proposed an enhanced stochastic multi-parameters divergence-based optimization algorithm for tuning fractional-order PI controllers in permanent magnet synchronous motor (PMSM) servo systems. By optimizing controller parameters under frequency-domain constraints, the proposed method improved tracking performance and robustness against system uncertainties.

To enhance the global search capability and avoid premature convergence, various metaheuristic optimization algorithms have been introduced for single-objective parameter tuning. Qi et al. [190] proposed a particle swarm optimization (PSO)-based tuning strategy for digital PID controllers in a CAN-based DC motor system with stochastic delays. The proposed method incorporated system constraints into the optimization process and achieved improved control performance under communication uncertainties.

Table 12 summarizes representative single-objective optimization methods for servo parameter tuning from the perspectives of optimization strategies, representative approaches, performance advantages, and practical limitations.

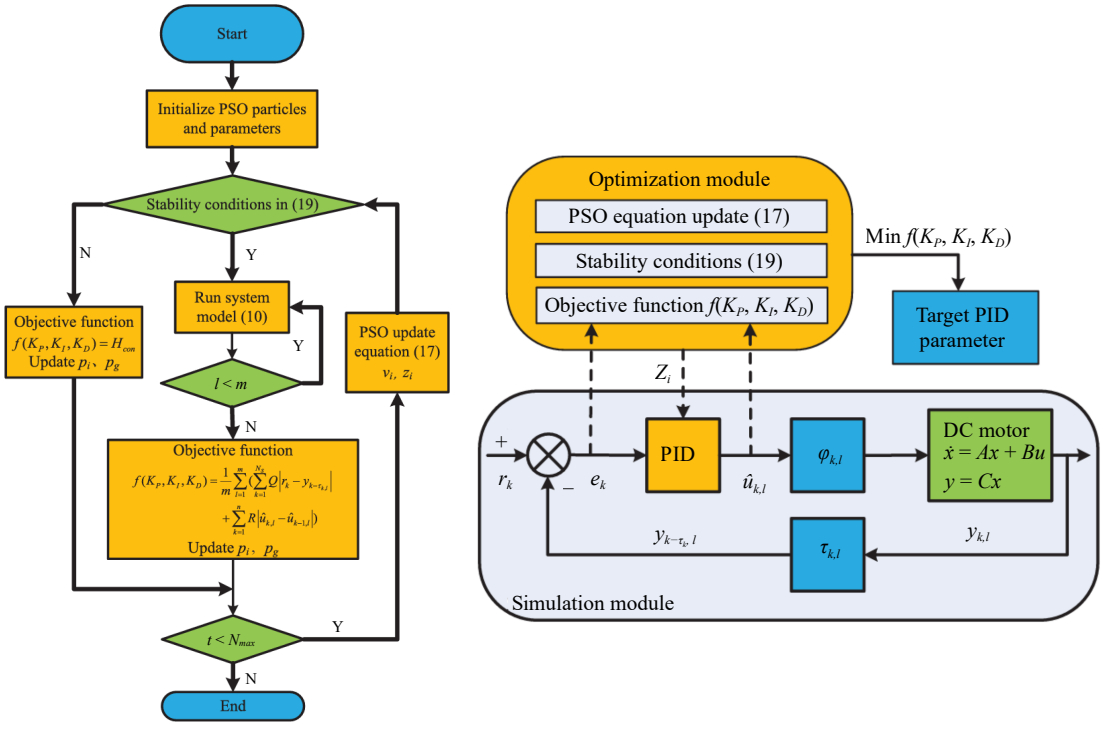


Fig. 19 A PID intelligent optimization and tuning architecture for DC motors with random CAN delayReproduced with permission from Ref. [190], © 2020 IEEE.

Table 12 Summary of several single objective optimization methods.

Strategy	Source	Implementation	Objective/model requirement	Computational burden	Practical characteristics
Performance-oriented	Choubey et al. [196], Li [192], Lee and Peng [191]	Offline	Defined IAE/ISE/ITAE etc.	Medium	Quantitative tuning; strongly objective-dependent
Model-based	Song et al. [195], Zheng et al. [193]	Offline	Accurate plant model	Medium	Direct robustness/bandwidth optimization; model dependent
Algorithm-based	Qi et al. [190], Maheedhar and Deepa [197], Moharam et al. [194]	Offline	Fitness function; no analytic gradient required	High	Strong global search capability; convergence/computation issues

4.3.2 Multi-objective optimization

Compared with single-objective optimization methods that optimize only one predefined performance index, multi-objective optimization methods [200–210] aim to achieve a coordinated improvement of multiple conflicting performance requirements. In practical servo systems, improving one performance indicator, such as tracking accuracy or response speed, may lead to degradation in other aspects, including robustness, disturbance rejection capability, and control smoothness. Therefore, parameter tuning can be formulated as a multi-objective optimization problem, where Pareto optimal solutions are obtained to describe different trade-offs among multiple objectives. According to the optimization mechanisms and application characteristics, existing studies can be generally classified into Pareto-based evolutionary optimization, intelligent multi-objective optimization, and servo-oriented dynamic multi-objective tuning. As illustrated in Fig. 20, the multi-objective servo parameter tuning framework based on NSGA-II involves controller parameter encoding, multi-objective performance evaluation, non-dominated sorting, genetic evolution, and Pareto solution selection. Through iterative evolution, the algorithm searches for a set of optimal solutions rather than a single optimum, enabling

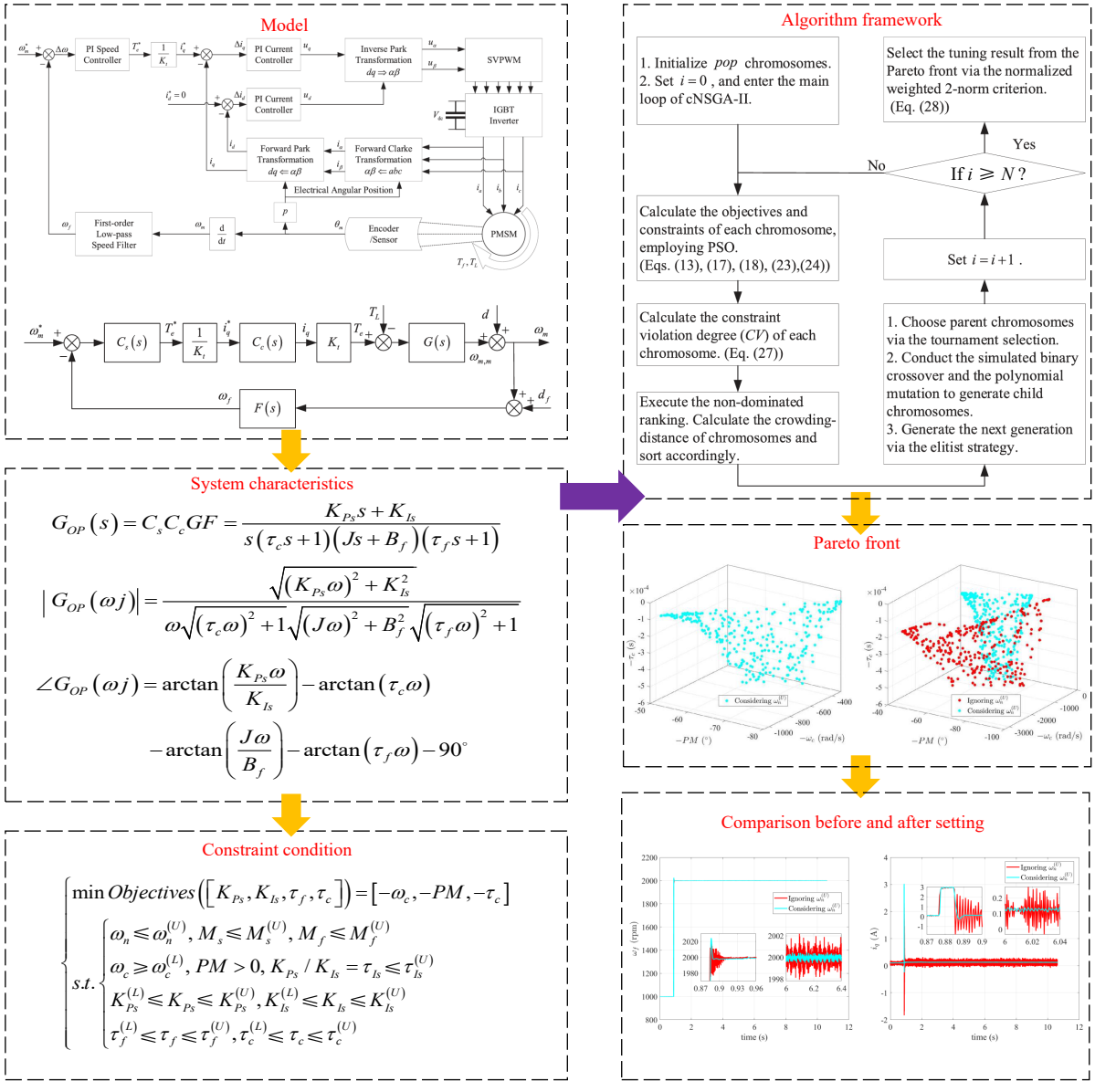


Fig. 20 A multi-objective optimization method for servo parameters based on NSGA-II. Reproduced from Ref. [210] under the terms of the CC BY 4.0 license, © 2025 by the authors.

flexible selection of controller parameters according to different servo performance requirements and operating conditions.

Evolutionary multi-objective optimization algorithms have been widely applied to controller parameter tuning due to their capability of obtaining multiple Pareto-optimal solutions without requiring explicit weighting coefficients. Among these methods, the non-dominated sorting genetic algorithm II (NSGA-II) has become one of the most representative approaches. Hultmann Ayala and dos Santos Coelho [204] proposed an NSGA-II-based PID tuning method for a robotic manipulator, where position and velocity tracking performances were simultaneously optimized. The obtained Pareto front provided multiple controller candidates with different performance compromises. Chen et al. [202] developed a chaotic NSGA-II algorithm for fractional-order PID controller design, in which integral square error (ISE) and integral time square error (ITSE) were simultaneously minimized to improve both transient performance and robustness. Similarly, Pan and Das [203] employed chaotic multi-objective optimization for fractional-order load-frequency control, demonstrating the effectiveness of Pareto-based optimization in balancing multiple dynamic objectives.

Beyond conventional evolutionary algorithms, intelligent multi-objective optimization methods have been developed to improve search efficiency and adaptability. Reynoso-Meza et al. [208] proposed an evolutionary multi-objective optimization framework with preference information for multivariable PI controller tuning. By incorporating designer preferences into the optimization process, the proposed method improved the selection efficiency of final controller parameters from the Pareto solution set. For complex electromechanical systems with multiple design parameters and performance constraints, Wei and Söffker [201] proposed a multi-objective genetic algorithm (MOGA)-based optimization strategy for PID controller design of active magnetic bearing (AMB) rotor systems. Different from conventional PID tuning methods, their approach integrated time-domain and frequency-domain criteria into the fitness evaluation process. Furthermore, hierarchical fitness evaluation and sensitivity-based parameter reduction strategies were introduced to reduce optimization complexity and improve convergence efficiency. Experimental results on AMB rotor systems verified the effectiveness of the optimized controller under high-speed operating conditions.

Recently, multi-objective optimization has further developed toward dynamic and adaptive optimization for time-varying systems. Tang et al. [210] proposed a multi-objective optimal tuning framework for the entire PMSM-driven servo systems considering high-frequency disturbance suppression. Unlike conventional methods focusing only on speed-loop parameters, the proposed framework simultaneously optimized speed-loop PI parameters, filtering parameters, and current-loop equivalent time constants by using constrained NSGA-II. The results demonstrated improved overall servo performance and disturbance suppression capability.

Table 13 summarizes representative multi-objective optimization methods for servo parameter tuning from the perspectives of optimization strategies, representative approaches, performance advantages, and practical limitations.

5 Advanced Control

Building on accurate parameter identification and controller tuning, advanced control strategies are required to address nonlinearities and disturbances beyond the capability of conventional PID control. In applications such as multi-axis CNC machining, friction, inertia variation, and cutting-force disturbances can cause significant contouring errors. Advanced control methods therefore aim to enhance trajectory tracking, disturbance rejection, and robustness under complex operating conditions.

5.1 Robust and nonlinear control

Conventional linear controllers are often insufficient for servo systems with nonlinearities, parameter uncertainties, and time-varying conditions. Friction, transmission elasticity, and load variations can degrade tracking accuracy and stability. Robust and nonlinear

Table 13 Summary of several multi objective optimization methods.

Strategy	Source	Implementation	Computational burden	Adaptability	Practical characteristics
Pareto-based evolutionary	Hultmann Ayala and dos Santos Coelho [204], Wei and Söffker [201], Reynoso-Meza et al. [208]	Offline	High	Medium	Provides multiple trade-off solutions; high computational cost
Intelligent multi-objective	Sun et al. [205], Kumar and Kumar [207]	Offline	High	Medium–high	Flexible nonlinear search; convergence/selection issues
Adaptive decision-making	Li et al. [206], Tang et al. [210]	Offline/potentially online	High	High	Responds to operating changes; complex decision mechanism

control methods address these effects by improving tolerance to uncertainties and enhancing stability, disturbance rejection, and tracking performance. Representative approaches include sliding mode control and adaptive robust control.

5.1.1 Sliding mode control

Sliding mode control (SMC) [211–221] is one of the most widely investigated nonlinear robust control methods for high-performance servo systems. By designing an appropriate sliding surface and switching control law, SMC forces the system states to converge toward the predefined manifold and maintains robustness against parameter uncertainties and external disturbances. Compared with conventional PID controllers, SMC provides stronger disturbance rejection capability and adaptability to nonlinear dynamics, making it attractive for precision motion control applications such as CNC machine tools, industrial robots, and high-performance servo drives. However, the discontinuous switching term in conventional SMC may introduce chattering, which can excite mechanical resonance and deteriorate positioning accuracy. Therefore, recent research has mainly focused on improving disturbance estimation capability, reducing chattering, and enhancing convergence performance. As illustrated in Fig. 21, the algorithm structure and performance comparison of SMC demonstrate its advantages in convergence speed and disturbance rejection compared with conventional PI control methods under uncertain operating conditions.

For manufacturing equipment servo systems, early studies mainly focused on applying conventional SMC to improve robustness against mechanical uncertainties and external disturbances. Neubauer et al. [211] proposed a cascaded sliding mode position controller combined with a PI speed controller (SMC-PI) for elastic feed drives of machine tools. By replacing the conventional

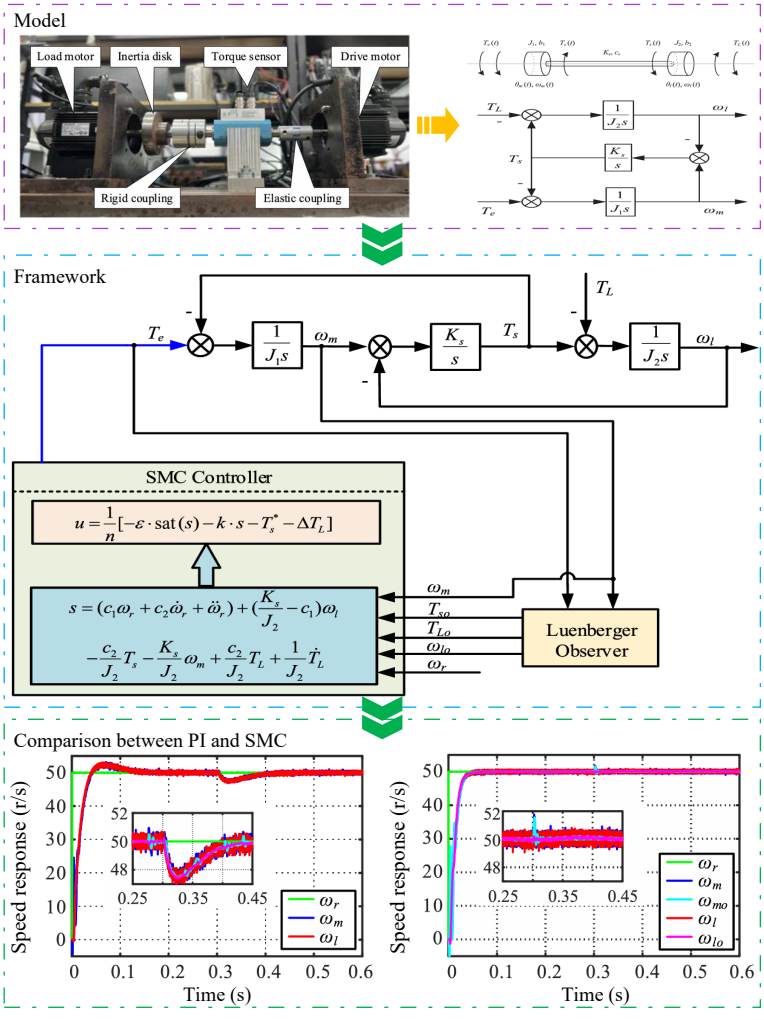


Fig. 21 A speed control method for elastic servo system based on SMC. Reproduced with permission from Ref. [212], © 2024 IEEE.

proportional position controller with a continuous sliding mode controller, the proposed method improved trajectory tracking accuracy while maintaining compatibility with industrial servo structures.

To overcome the dependence of conventional SMC on high switching gains and alleviate chattering problems, observer-assisted sliding mode control has become an important research direction. Zheng et al. [215] proposed a fractional-order sliding mode control method for PMSM speed servo systems through an improved disturbance observer. The fractional-order sliding surface provided additional design flexibility, while the disturbance observer compensated unknown disturbances and parameter uncertainties. The combination of disturbance estimation and sliding mode control improved the dynamic response and robustness of the servo system.

Beyond disturbance compensation, advanced sliding mode strategies based on adaptive mechanisms and finite-time convergence theories have been extensively investigated. Liang and Liu [217] proposed an adaptive predefined-time compound sliding mode control method based on fractional-order theory for PMSM systems. By introducing a predefined-time reaching law and adaptive disturbance compensation mechanism, the proposed controller achieved faster convergence while maintaining robustness against uncertain disturbances. Tang et al. [218] developed an adaptive disturbance rejection terminal sliding mode controller for motor-driven servo systems. An extended sliding mode observer was designed to estimate time-varying disturbances, and an adaptive disturbance rejection attractor was introduced to compensate for observation errors. Experimental results demonstrated improved speed regulation performance under complex disturbance conditions.

Recently, hybrid sliding mode control architectures combining SMC with intelligent algorithms and advanced control strategies have attracted increasing attention. Xu et al. [221] proposed a compound neural-network-based nonsingular fixed-time sliding mode controller for distributed permanent magnet arc motor servo systems. The proposed method employed a neural network to approximate periodic nonlinear disturbances and combined it with a high-order sliding mode disturbance observer to improve disturbance estimation accuracy. The results demonstrated enhanced tracking performance and robustness.

Table 14 summarizes representative sliding mode control methods from the perspectives of control strategies, representative approaches, advantages, and limitations.

5.1.2 Adaptive robust control

Although robust control methods can guarantee system stability under bounded uncertainties and disturbances, their controller parameters are usually designed based on worst-case scenarios, which may lead to conservative control performance when the actual operating conditions deviate from the assumed uncertainty boundary. To overcome this limitation, adaptive robust control methods have been developed by integrating adaptive parameter estimation mechanisms with robust compensation strategies. These approaches enable the controller to actively adjust control parameters according to real-time system information, thereby improving tracking accuracy and disturbance rejection capability in servo systems with uncertain dynamics. As illustrated in Fig. 22, adaptive robust control provides a practical framework for simultaneously addressing model uncertainties and operating-condition variations, demonstrating strong potential for engineering implementation in high-performance servo systems.

Li et al. [223] proposed an adaptive robust position controller for an uncertain PMSM servo system by combining backstepping control with an extended state observer (ESO). The adaptive algorithm was designed to estimate variations of the position-loop structural parameters, while the ESO was employed to estimate the upper bound of lumped disturbances. This strategy reduced the dependence on prior disturbance knowledge and improved robustness against parameter uncertainties and external disturbances. However, the repeated differentiation of virtual control variables in the backstepping framework increases computational complexity, which may restrict its application in high-speed industrial servo systems.

Beyond uncertainty compensation, adaptive robust control has gradually evolved toward performance-

Table 14 Summary of several sliding mode control methods.

Strategy	Source	Computational burden	Model dependence	Noise/implementation issue	Practical characteristics
Conventional sliding mode control	Neubauer et al. [211], Wang et al. [212]	Low	Low	Chattering; switching noise	Simple and robust; may excite mechanical resonance
Observer-assisted sliding mode control	Zhao and Liu [213], Zheng et al. [215], Li et al. [216]	Medium	Medium	Observer gain/noise trade-off	Improved disturbance rejection; additional observer tuning
Adaptive and hybrid sliding mode control	Liang and Liu [217], Tang et al. [218], Zhang et al. [219], Wang [220], Xu et al. [221]	High	Low–medium	Algorithm/parameter complexity	Improved adaptability and chattering suppression; higher computation

oriented and intelligent strategies. Yin et al. [224] proposed an adaptive optimal control strategy for PMSM speed regulation systems, which combined adaptive compensation with optimal control to improve disturbance attenuation and dynamic performance. Song et al. [225] extended this concept to multimotor driving servo systems by considering spatiotemporal performance constraints and energy optimization. Meanwhile, internal model-based adaptive control has been investigated for systems with periodic and time-varying disturbances.

Another important development trend is the integration of adaptive control with internal model theory and intelligent algorithms to handle unknown and time-varying disturbances. Song et al. [226] introduced an internal model adaptive controller for PMSM speed servo systems, achieving improved disturbance rejection under parameter uncertainties.

Table 15 summarizes representative adaptive robust control methods for servo systems from the perspectives of control strategies, adaptation mechanisms, representative approaches, advantages, and practical limitations.

5.2 Disturbance rejection and compensation control

External disturbances and internal uncertainties, such as load variations, friction, transmission errors, and unmodeled dynamics, can significantly degrade servo tracking performance. Disturbance-rejection methods address these effects through explicit disturbance estimation and compensation. Two representative approaches are disturbance observer (DOB)-based control, which estimates disturbances from system models for compensation, and active disturbance rejection control (ADRC), which treats unknown dynamics and external disturbances as a generalized disturbance and rejects them through extended state observation.

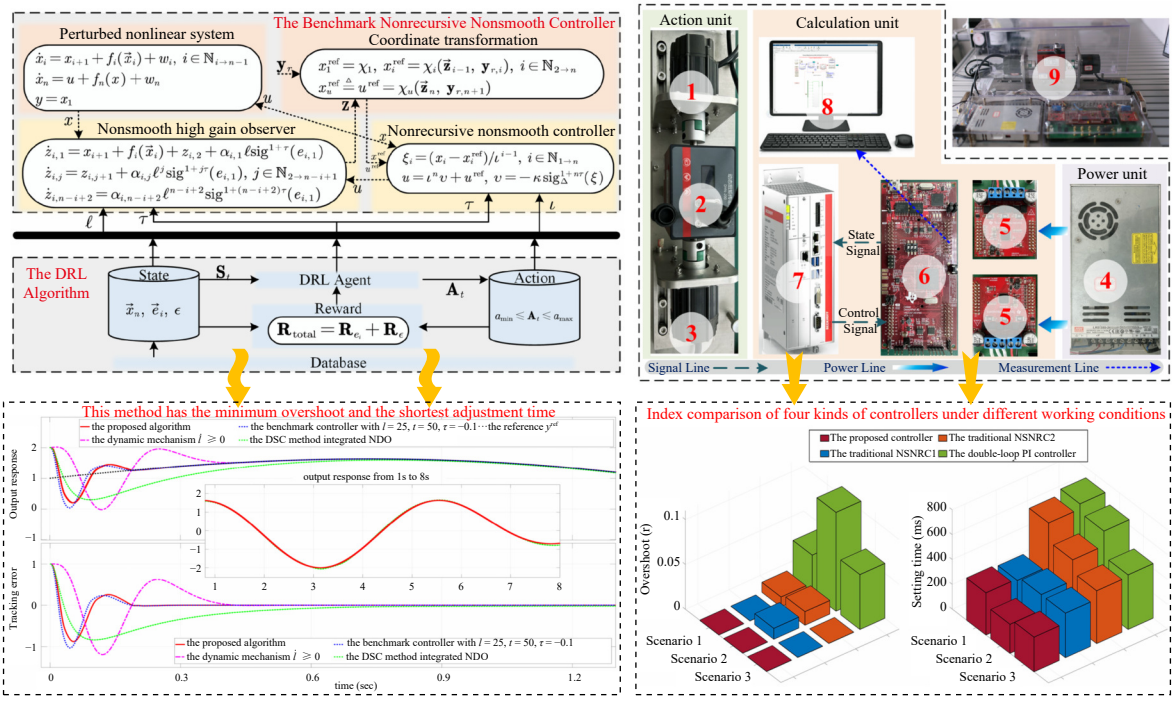


Fig. 22 An adaptive robust control method based on deep reinforcement learning. Reproduced with permission from Ref. [222], © 2025 IEEE.

Table 15 Summary of several adaptive robust control methods.

Strategy	Source	Computational burden	Model dependence	Stability/design issue	Practical characteristics
Adaptive compensation	Li et al. [223], Wu et al. [227]	Medium	Medium	Adaptive-law/parameter tuning	Handles parameter uncertainty; backstepping may increase computation
Optimal adaptive control	Yin et al. [224], Song et al. [225]	Medium–high	Medium–high	More complex design	Explicit performance optimization; engineering implementation more difficult
Intelligent adaptive control	Song et al. [226], Dong et al. [222]	High	Data/model dependent	Training and stability assurance	Strong adaptability; computational and deployment burden

5.2.1 Disturbance observer based control

Disturbance observer (DOB)-based control is one of the most representative disturbance rejection methods in high-performance motion control systems. The basic idea of DOB is to estimate the equivalent disturbances caused by external loads, parameter variations, friction, and unmodeled dynamics, and then compensate them through a feedforward channel. Compared with directly modifying the feedback controller, DOB-based methods provide an explicit disturbance compensation mechanism and have been widely applied in precision servo systems. As illustrated in Fig. 23, disturbance observer-based control can achieve effective disturbance estimation and compensation, particularly under sudden load variations, enabling servo systems to maintain stable performance under uncertain operating conditions.

Talapiden et al. [61] investigated digital DOB design for PMSM drives and analyzed the influence of different discretization methods on disturbance estimation performance. By comparing several discrete-time conversion approaches, the study demonstrated that appropriate discretization strategies can improve the stability and accuracy of digital DOB-based servo systems. However, conventional DOB methods generally rely on nominal models, and the trade-off between disturbance rejection bandwidth and noise amplification remains a critical issue.

To improve disturbance estimation capability under complex operating conditions, various enhanced DOB structures have been developed. Wang et al. [229] proposed a scheduled DOB-based robust motion control strategy, where multiple DOBs with different frequency characteristics were designed and switched according to system states. This method achieved both smooth transient responses and strong disturbance rejection performance. Recently, DOB-based control has been increasingly integrated with high-performance servo strategies to improve tracking accuracy under challenging operating conditions. Xia et al. [230] developed a high-frequency position tracking framework for PMSM servo systems by combining disturbance observation with dynamic load identification. The proposed method treated load variations as lumped disturbances and achieved improved position tracking performance under high-frequency reference signals.

Overall, DOB-based control has evolved from conventional model-based disturbance compensation toward advanced observer structures with improved adaptability and estimation accuracy. For manufacturing equipment servo systems, DOB provides an effective approach for compensating load disturbances, friction

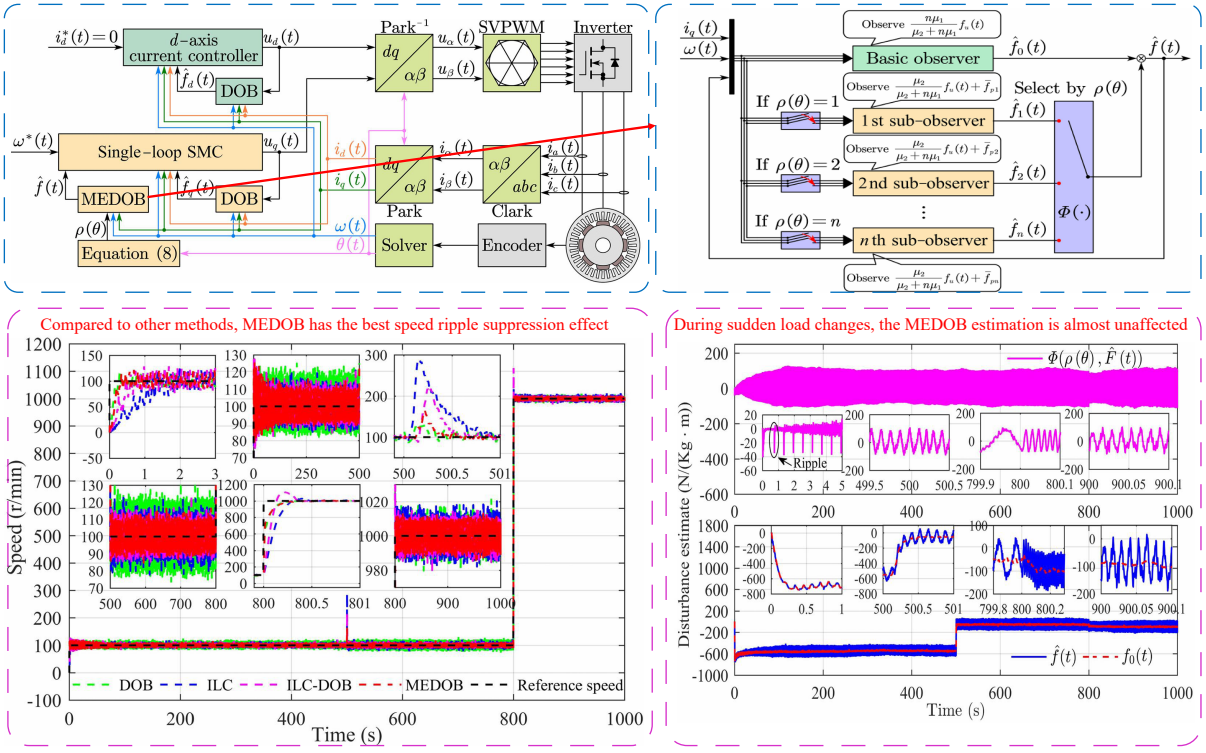


Fig. 23 Disturbance observer-based control framework and performance evaluation for PMSM servo systems. Reproduced with permission from Ref. [228], © 2026 IEEE.

effects, and modeling errors. Nevertheless, challenges remain in balancing disturbance estimation bandwidth, noise sensitivity, and model uncertainty. Future research should focus on developing high-bandwidth and low-noise disturbance observers with strong compatibility for industrial servo drive applications.

5.2.2 Active disturbance rejection control

Active disturbance rejection control (ADRC) [231–240] is an advanced disturbance compensation strategy that estimates and rejects both internal uncertainties and external disturbances without requiring an accurate mathematical model of the controlled system. Different from conventional disturbance observer-based methods, ADRC considers unknown dynamics, parameter variations, and external disturbances as a unified total disturbance, which is estimated by an extended state observer (ESO) and compensated through the control input. Due to its strong robustness and model independence, ADRC has been widely investigated in high-performance servo systems, especially for PMSM drives with nonlinear characteristics, load variations, and uncertain operating conditions. As illustrated in Fig. 24, the adaptive hybrid state feedback ADRC framework further enhances servo performance by integrating adaptive mechanisms with state feedback control, improving disturbance rejection and system adaptability while maintaining acceptable computational complexity.

The improvement of ESO performance is one of the major research directions in ADRC-based servo control. Since the estimation accuracy of ESO directly affects disturbance compensation performance, researchers have proposed various improved observer structures to enhance disturbance tracking capability. Tang et al. [231] proposed a cascaded extended state observer-based speed controller for PMSM systems considering variable control gain and uncertain disturbances. By introducing a cascaded ESO structure, the proposed method improved disturbance estimation accuracy under complex operating conditions. Furthermore, Kang et al. [233] proposed an

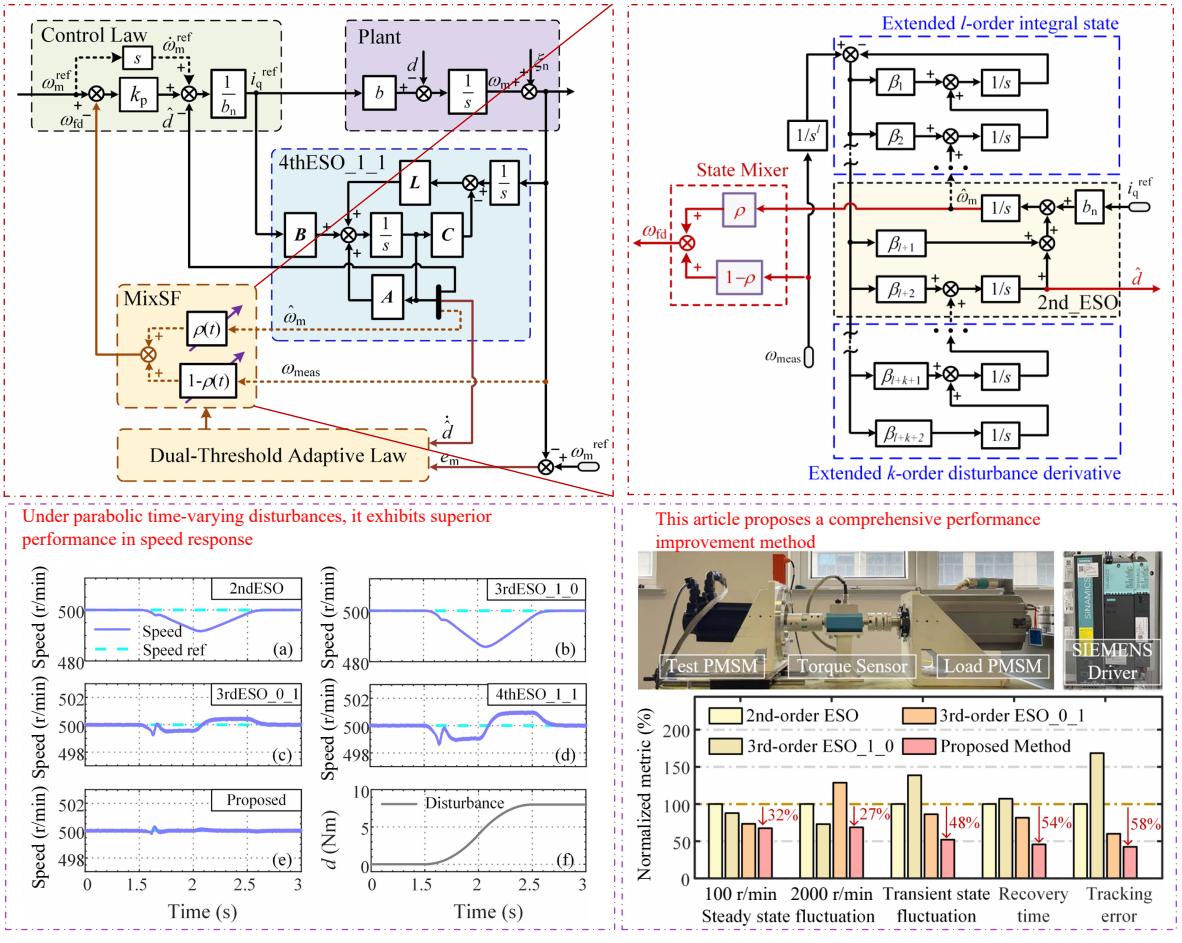


Fig. 24 Adaptive mixed-state feedback-based active disturbance rejection control for PMSM servo systems. Reproduced with permission from Ref. [237], © 2026 IEEE.

enhanced ADRC method combining an error-corrected cascaded ESO (EC-CESO) with an error-transformed adaptive RBF neural network. The EC-CESO improved aperiodic disturbance estimation, while the neural network was used to compensate periodic disturbances, achieving better speed regulation performance under complex disturbance conditions. These studies indicate that improving observer structures and combining different estimation mechanisms are effective approaches for enhancing ADRC performance in precision servo systems.

For servo systems with complex disturbance characteristics, recent studies have focused on the simultaneous rejection of periodic and nonperiodic disturbances. Wang et al. [234] proposed an enhanced ADRC framework combined with quasi-resonant control for PMSM speed regulation considering both aperiodic and periodic disturbances. In this method, ADRC was responsible for estimating and compensating unknown disturbances, while the quasi-resonant controller was introduced to suppress periodic harmonic disturbances caused by motor characteristics.

Another important research direction is enhancing ADRC adaptability through parameter tuning and intelligent optimization. Although it reduces dependence on accurate system models, its performance is highly influenced by observer bandwidth and controller parameters, which increases the difficulty of practical implementation. Lu et al. [236] proposed a load-adaptive PMSM drive system based on improved ADRC for manipulator joints. By introducing load adaptation mechanisms into the ADRC framework, the controller achieved better performance under varying load conditions. Beyond motor servo systems, ADRC has also been extended to complex manufacturing equipment applications. Hosseini et al. [239] proposed a high-accuracy online circular path compensation method for coordinated hexapod industrial robots by integrating PID-ADRC with trajectory compensation. A discrete-time ESO was employed to estimate synchronization errors, payload variations, and spindle-induced disturbances, improving machining trajectory accuracy.

Table 16 summarizes representative ADRC methods according to their main development directions, including observer enhancement, composite disturbance rejection, and adaptive/intelligent parameter optimization.

5.3 Predictive and intelligent control

Predictive and intelligent control methods address the increasing demands for precision, fast response, and adaptability in high-performance servo systems. MPC predicts future system behavior and optimizes control inputs under constraints, while learning-based methods improve adaptability through data-driven techniques such as neural networks and reinforcement learning. These approaches are particularly promising for servo systems with nonlinearities, parameter variations, and complex operating conditions.

5.3.1 Model predictive control

Model predictive control (MPC) [241–250] is an optimization-based control strategy that predicts the future behavior of a system through a dynamic model and determines the optimal control input by solving a finite-horizon optimization problem. Compared with conventional feedback controllers, MPC can explicitly consider system constraints, multivariable coupling, and future reference trajectories, making it attractive for high-performance servo systems. However, the practical application of MPC in servo drives is limited by the high computational burden caused by online optimization, especially for systems with high sampling frequencies. Therefore, recent research on MPC-based servo control mainly focuses on improving computational efficiency, enhancing tracking performance, and incorporating disturbance rejection mechanisms. As illustrated in Fig. 25, the improved finite control set model predictive control (FCS-MPC) servo brake control strategy demonstrates the capability of MPC-based methods to achieve fast dynamic response and coordinated optimization of multiple performance objectives in practical servo applications.

To reduce the computational complexity of online optimization, researchers have developed efficient MPC formulations and simplified solution methods. Stephens et al. [242] proposed an MPC framework for reference tracking on an industrial machine tool servo drive. By introducing a trajectory horizon into the MPC

Table 16 Summary of several ADRC based methods.

Strategy	Source	Computational burden	Model dependence	Noise sensitivity	Practical characteristics
ESO-based ADRC	Kang et al. [233], Tang et al. [231], Tan et al. [232], Liu et al. [240]	Medium	Low–medium	High with excessive observer bandwidth	Improved disturbance estimation; observer tuning required
Composite ADRC	Hu et al. [235], Wang et al. [234], Hosseini et al. [239]	Medium–high	Low–medium	Method-dependent	Handles periodic/nonperiodic disturbances; increased structural complexity
Adaptive and intelligent ADRC	Tan and Shi [237], Lu et al. [236], Wang et al. [238]	High	Data/adaptive-law dependent	Method-dependent	Reduces manual tuning; stability/computation challenges

formulation, the trade-off between tracking accuracy and online computational cost was achieved. The proposed method was implemented on an industrial machine tool servo system and demonstrated improved tracking performance compared with conventional cascaded PID control. For PMSM drives, Arpacik and Ankarali [243] investigated an efficient implementation of online MPC with field weakening operation for surface-mounted PMSMs. Their method reduced the computational requirements of MPC while maintaining effective control performance in high-speed operating regions.

FCS-MPC and explicit MPC (EMPC) have also been investigated to address the computational limitations of conventional MPC. Kawai et al. [245] applied finite control set model predictive control to servo brake motion in PMSM drives. By directly selecting optimal switching states without additional modulation stages, the proposed method achieved fast dynamic response and accurate motion control. In addition, Guo et al. [246] proposed an explicit model predictive control method for PMSMs based on multi-point linearization. By constructing explicit control laws at different operating points, the method reduced online computation while maintaining prediction accuracy under varying operating conditions.

Beyond computational efficiency, MPC has been increasingly applied to improve position tracking performance and handle complex servo systems dynamics. Wang and Liu [247] proposed a model predictive position control strategy for PMSM servo systems combined with a sliding mode observer. The sliding mode observer was introduced to estimate disturbances and improve robustness, while MPC optimized the position control process based on future system states.

For servo systems with uncertain dynamics and external disturbances, combining MPC with disturbance estimation and robust control methods has become an important research direction. Wang et al. [249] proposed a novel explicit MPC combined with dynamic sliding mode control (EMPC-DSMC) for elastic servo drive systems. By considering transmission torque constraints and disturbance rejection simultaneously, the proposed method improved control accuracy under flexible transmission conditions. Moreover, Dong et al. [250] developed a two-degree-of-freedom control method for permanent magnet synchronous linear motors based on MPC and an extended state observer (ESO). The MPC component improved trajectory tracking performance, while the ESO estimated and compensated lumped disturbances such as load variations and nonlinear force fluctuations.

Table 17 summarizes representative MPC-based control methods according to their main research focuses, including computational efficiency improvement, servo performance enhancement, and robustness improvement.

5.3.2 Learning-based intelligent control

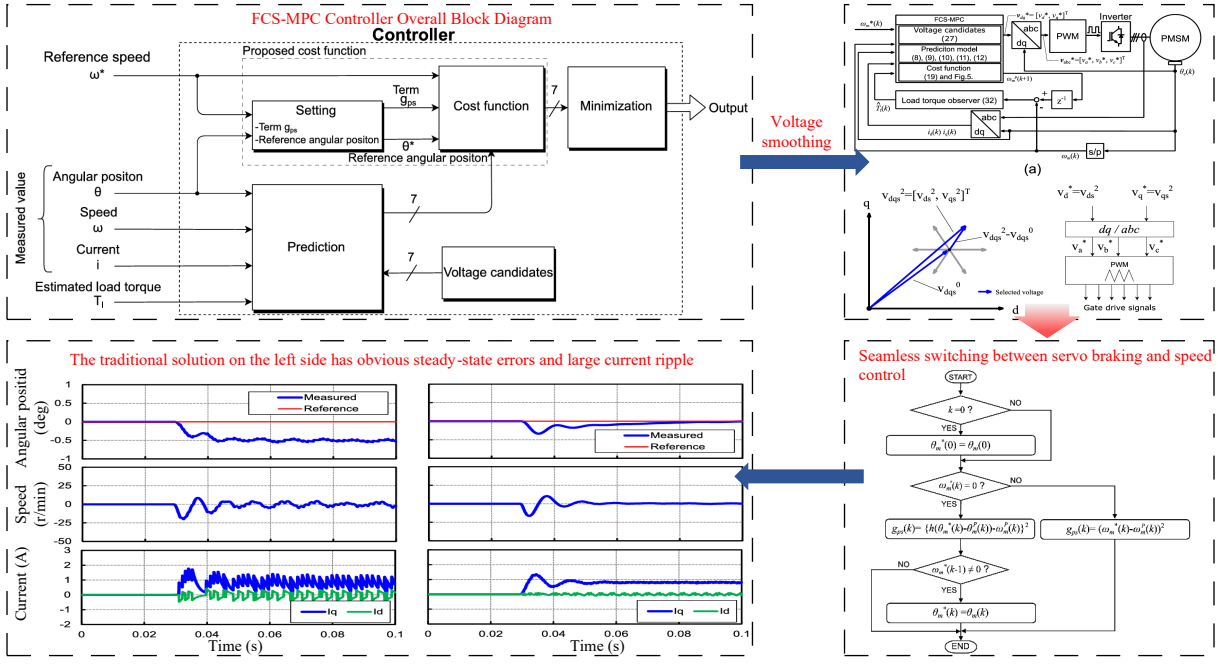


Fig. 25 Finite control set model predictive control framework for PMSM servo systems. Reproduced with permission from Ref. [245], ©2023 IEEE.

With the increasing requirements for ultra-high precision and repeatable motion in manufacturing equipment, conventional model-based control methods face difficulties in compensating for repetitive disturbances and unknown nonlinearities. Learning-based intelligent control methods [251–261] provide an alternative solution by utilizing historical operation data to improve control performance through iterative optimization. Unlike traditional feedback control, which mainly relies on current system information, learning-based approaches can extract useful information from previous operations and gradually reduce tracking errors. Among these methods, iterative learning control (ILC) and repetitive learning control (RLC) have been widely investigated in high-precision servo systems due to their effectiveness in handling periodic disturbances and repetitive trajectories. As illustrated in Fig. 26, the enhanced iterative learning control method achieves a balance between convergence speed and steady-state tracking accuracy by optimizing the learning process, enabling effective suppression of coupling disturbances and significant improvement in ultra-precision trajectory tracking performance.

Iterative learning control is particularly suitable for manufacturing equipment because many industrial processes, such as CNC machining, wafer positioning, and precision motion control, involve repetitive motion patterns. The basic principle of ILC is to update the control input based on tracking errors obtained from previous iterations, thereby improving the control accuracy cycle by cycle. Kitayoshi and Fujimoto [251] proposed a precision-oriented iterative learning control

Table 17 Summary of several mpc based methods.

Strategy	Source	Computational burden	Model dependence	Constraint handling	Practical characteristics
Efficient MPC	Arpacik and Ankarali [243], Zhang et al. [244], Kawai et al. [245], Guo et al. [246]	Medium	High	Yes	Reduced online computation; simplification may reduce prediction accuracy
Performance-oriented MPC	Stephens et al. [242], Wang and Liu [247], Zhang et al. [248]	High	High	Yes	Strong tracking/coordination capability; sensitive to model accuracy
Robust/Hybrid MPC	Wang et al. [249], Dong et al. [250]	High	Medium–high	Yes	Improved disturbance robustness; increased design and computation

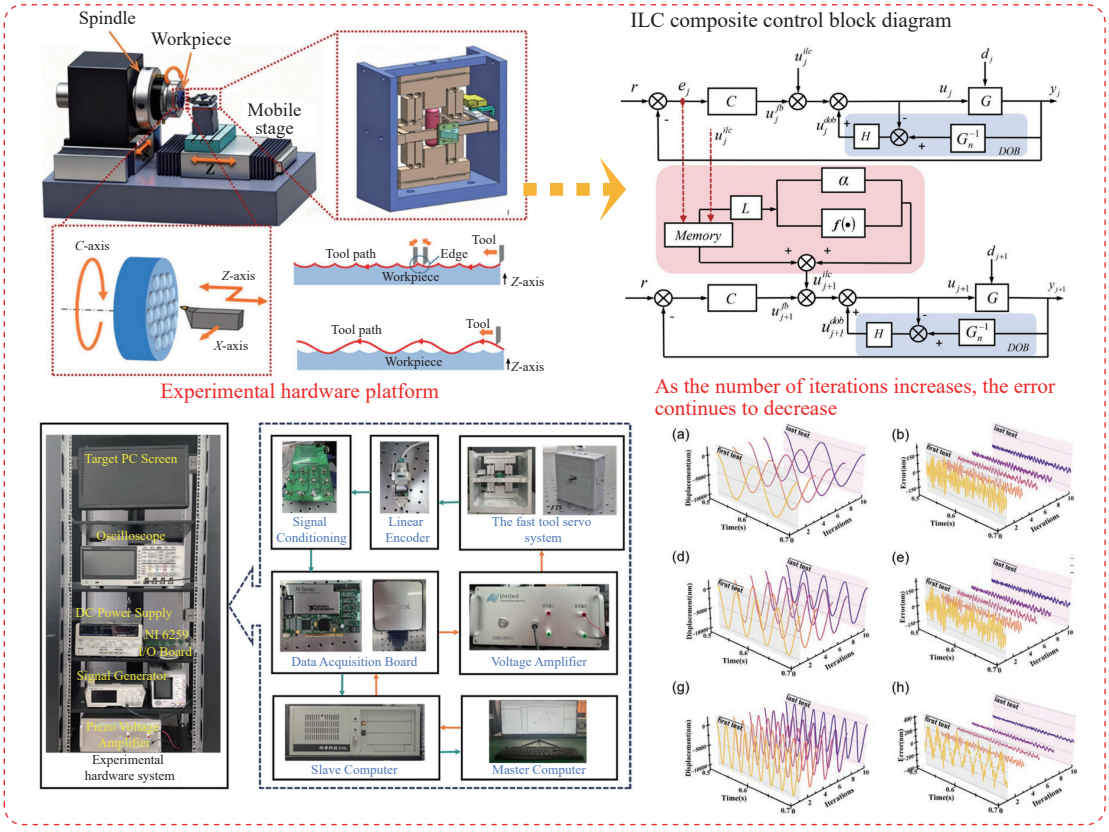


Fig. 26 Advanced servo control framework integrating iterative learning control and disturbance compensation. Reproduced with permission from Ref. [254], © 2026 Springer Nature.

method combined with robust feedback control for high-accuracy positioning systems. By integrating learning compensation with robust feedback, the proposed method achieved high positioning accuracy while maintaining disturbance rejection capability.

To improve the applicability of ILC under uncertain operating conditions, researchers have introduced disturbance observers, adaptive mechanisms, and robust control techniques into learning frameworks. Conventional ILC mainly focuses on repetitive disturbances and may suffer from degraded performance when system parameters vary or non-periodic disturbances exist. Jing et al. [254] proposed an enhanced iterative learning control method combined with a disturbance observer for trajectory tracking of fast tool servo systems. The disturbance observer was employed to estimate non-repetitive disturbances, while ILC compensated periodic tracking errors, resulting in improved trajectory tracking accuracy.

Robust learning strategies have also been explored to enhance convergence performance and disturbance rejection ability. Liu et al. [256] proposed a robust ILC scheme for PMSM torque ripple suppression via adaptive sliding mode control. In this method, ILC was utilized to compensate periodic torque ripple, while adaptive sliding mode control handled parameter uncertainties and external disturbances. This combination improved robustness compared with conventional PI-ILC structures. Moreover, Li et al. [257] proposed a set-membership approach for enhancing projection-based ILC. By introducing prior information constraints into the learning process, the proposed method improved convergence robustness under measurement noise and uncertainty. In addition, Chen et al. [258] developed a prescribed-time robust repetitive learning control method for PMSM servo systems, which guaranteed rapid convergence within a predefined time while maintaining robustness against disturbances.

Besides traditional ILC structures, data-driven learning feedforward compensation has attracted increasing attention in precision motion systems. Song et al. [261] proposed a variable-gain robust data-driven feedforward learning method with force ripple compensation for wafer stages. By adjusting learning gains according to system conditions, the proposed method improved compensation accuracy while maintaining robustness against disturbances. This type of data-driven learning method provides a promising direction for precision manufacturing equipment where accurate dynamic models are difficult to obtain.

Table 18 summarizes representative learning-based intelligent control methods according to their main research directions, including iterative/repetitive learning control, robust and adaptive learning control, and data-driven learning compensation.

6 Future Prospects and Trends

With the continuous advancement of high-performance manufacturing, future manufacturing equipment will impose increasingly stringent requirements on servo systems, including higher positioning accuracy, faster dynamic response, stronger adaptability, and enhanced autonomous operation capability. Although significant progress has been achieved in servo system identification, parameter optimization, and advanced control technologies, several challenges remain in practical applications. For example, accurate identification under time-varying operating conditions, efficient parameter commissioning for complex systems, and robust control under uncertain environments still require extensive theoretical development and engineering efforts. The rapid development of artificial intelligence (AI) provides new opportunities for addressing these challenges. However, AI should not be regarded as a replacement for existing servo technologies; instead, it should serve as an auxiliary tool to enhance the capabilities of conventional model-based methods. By integrating AI techniques with physical models, engineering knowledge, and real-time system information, future servo systems are expected to achieve improved perception, optimization, and decision-making capabilities while maintaining reliability and interpretability. Fig. 27 illustrates how AI technology serves as a key enabler, enhancing the capabilities of servo systems in areas such as sensing, dynamic

Table 18 Summary of several learning based control methods.

Strategy	Source	Computational burden	Model/data requirement	Task dependence	Practical characteristics
ILC/RLC	Zhao et al. [255], Kitayoshi and Fujimoto [251], Tsurumoto and Ohnishi [252], Shi et al. [259], Fei et al. [253]	Low–medium	Repeated-cycle error data	High repetition dependence	Very effective for repetitive trajectories; weak against non-repetitive disturbances
Robust and Adaptive Learning	Jing et al. [254], Li et al. [257], Chen et al. [258], Liu et al. [256], Yang and Li [260]	Medium–high	Repetitive data + online feedback	Medium	Improved robustness/adaptability; more complex stability design
Data-driven Learning Compensation	Song et al. [261]	Medium–high	High-quality operational/training data	Data-dependent	Reduced model dependence; generalization and data quality remain issues

modeling, optimization, and intelligent control, thereby elevating the performance of manufacturing equipment. By integrating AI technology with servo systems identification, parameter optimization, and advanced control strategies, next-generation servo systems are poised to achieve higher precision, greater adaptability, and autonomous operational capabilities in high-performance manufacturing equipment.

6.1 AI-enabled intelligent and online system identification

Accurate system identification is fundamental to high-performance servo control because it provides dynamic information for modeling, parameter tuning, compensation, and control design. Existing methods have achieved substantial progress in friction, inertia, and load estimation, but many still rely on offline experiments, simplified models, or predefined excitation trajectories. Their applicability can therefore be limited under continuously varying manufacturing conditions, particularly when friction, inertia variation, transmission uncertainties, and external disturbances are strongly coupled.

Future identification research should move from isolated parameter estimation toward online multi-parameter characterization supported by artificial intelligence. By learning relationships among operating conditions, system states, and dynamic parameters from operational data, AI-assisted methods can complement

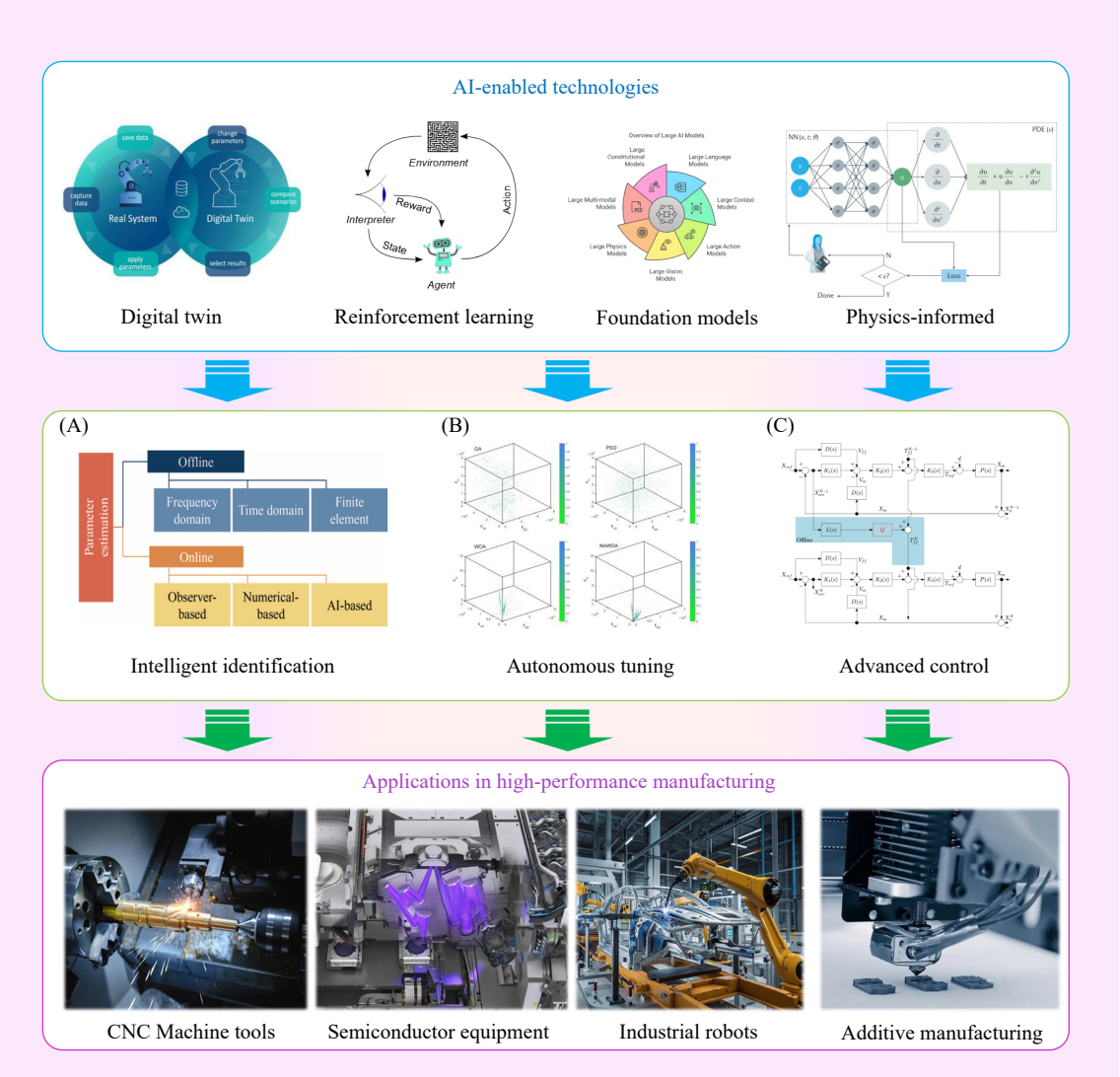


Fig. 27 AI-driven evolution of servo systems for high-performance manufacturing. (A) Reproduced with permission from Ref. [262], © 2024 China Machinery Industry Information Institute. (B) Reproduced from Ref. [263], © 2026 by the authors. Published by MDPI under the terms of the CC BY 4.0 license. (C) Reproduced with permission from Ref. [251], © 2026 IEEE.

conventional model-based identification and improve adaptation to changing conditions. Their integration with digital twins and physics-informed models may further enable continuous updating of servo-system characteristics while preserving physical consistency.

However, purely data-driven identification remains limited by interpretability, generalization, and reliability under unseen operating conditions. Future frameworks should therefore combine mechanism-based models, engineering constraints, and data-driven methods rather than replacing physical modeling. Such hybrid approaches are more suitable for providing reliable dynamic information for servo systems operating under complex and time-varying manufacturing conditions.

6.2 AI-assisted autonomous servo parameter optimization

Servo parameter tuning determines the trade-off among tracking accuracy, dynamic response, vibration suppression, and robustness, and therefore remains essential for high-performance manufacturing. Existing approaches, including empirical tuning, model-based methods, and optimization-based strategies, have improved controller commissioning and performance. However, increasing system complexity, varying operating conditions, and conflicting objectives make it difficult for fixed or manually adjusted parameters to remain effective across different manufacturing tasks.

Future tuning strategies should therefore move from fixed offline settings toward adaptive and multi-objective optimization frameworks that incorporate operating-condition information and identified system dynamics. Different manufacturing tasks impose different priorities: high-speed machining emphasizes transient response and settling time, whereas ultra-precision applications place greater emphasis on tracking accuracy, vibration suppression, and long-term stability. AI-assisted tuning may further support parameter recommendation and optimization by learning relationships among operating conditions, system responses, and suitable controller parameters, while evolutionary and reinforcement-learning methods can provide additional tools for handling complex multi-objective optimization problems.

Practical deployment, however, requires careful consideration of computational cost, safety constraints, interpretability, convergence reliability, and stability guarantees. Purely data-driven tuning may produce inappropriate parameter combinations when data are insufficient or operating conditions differ from those represented during training. Future research should therefore emphasize hybrid frameworks that combine AI-based optimization with control-theoretic constraints, physical models, and engineering knowledge, with the goal of reducing manual commissioning effort while maintaining reliable and verifiable closed-loop performance.

6.3 Foundation model-driven intelligent control frameworks

Advanced control strategies have improved servo performance in disturbance rejection, robustness, prediction, and adaptation. However, future manufacturing equipment will operate under increasingly complex nonlinearities, variable loads, disturbances, and precision requirements. Existing methods such as DOB, ADRC, MPC, and learning-based control are effective for specific tasks but often depend on predefined models, structures, or task-specific tuning, which may limit flexibility under rapidly changing conditions.

Foundation models may provide higher-level support through knowledge representation, multi-source information fusion, operating-condition recognition, and decision assistance. However, they should not replace conventional current-, velocity-, or position-loop controllers, since hard real-time servo control requires deterministic latency, stability guarantees, and reliable execution. A more practical role is as a supervisory layer for anomaly diagnosis, strategy selection, parameter recommendation, and control-module coordination, while deterministic controllers retain responsibility for high-frequency closed-loop control.

Future research should therefore focus on hybrid architectures combining foundation models with mechanism-based control, digital twins, and engineering constraints. Key challenges include inference latency, closed-loop stability, reliability under unseen conditions, decision safety, and interpretability. Appropriate constraints and fallback mechanisms to verified conventional controllers are essential, making supervisory assistance and adaptive decision support more realistic near-term roles than direct high-frequency servo-loop execution.

6.4 Integrated intelligent servo systems for high-performance manufacturing

The future development of servo systems should emphasize the integration of identification, parameter tuning, and advanced control into complete engineering solutions rather than isolated algorithmic improvements. The practical value of AI-assisted identification, automated tuning, and foundation-model-supported control depends on their compatibility with existing servo architectures, real-time hardware, and manufacturing processes. Future systems should therefore integrate

sensing, modeling, optimization, control, and supervisory functions within a unified framework.

Engineering implementation must also account for platform-specific requirements. CNC machine tools emphasize contour tracking, vibration suppression, and robustness to cutting disturbances; semiconductor equipment requires ultra-precision positioning, low-noise operation, and rapid settling; industrial robots prioritize multi-axis coordination and task-dependent adaptability; and additive manufacturing systems require stable path tracking, layer positioning, and deposition consistency. These differences indicate that integrated servo solutions should be tailored to specific manufacturing platforms rather than designed as universal architectures.

Further progress is required in real-time computation, hardware deployment, digital-twin integration, and standardized evaluation. Combining mechanism-based models, AI-assisted methods, and manufacturing knowledge may provide a practical balance among intelligence, reliability, and interpretability. Continued integration and validation on representative manufacturing equipment will be essential for translating emerging servo technologies into deployable high-performance systems.

7 Conclusions

Servo systems are key enabling components of high-performance manufacturing equipment, with their performance strongly influencing motion accuracy, dynamic response, process stability, and operational reliability. This review systematically summarizes recent advances in system identification, parameter tuning, and advanced control, and discusses their roles in improving servo performance under nonlinearities, parameter variations, disturbances, and changing operating conditions. Overall, future servo systems will require closer integration of accurate system modeling, adaptive parameter optimization, and advanced control while maintaining real-time performance, stability, and engineering reliability. The combination of mechanism-based models, artificial intelligence, foundation models, and digital twins offers promising opportunities for developing more intelligent and integrated servo systems. Continued progress in algorithm integration, hardware implementation, and experimental validation will be essential for translating these technologies into practical high-performance manufacturing applications.

Data availability No datasets were generated or analyzed for this work.

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Competing interests The authors declare no conflicts of interest.

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