International Journal of Dynamics and Control (2026) 14:32
https://doi.org/10.1007/s40435-025-01963-5

Trajectory tracking control of autonomous underwater vehicles: a review from classical methods to AI-based approaches

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Received: 26 August 2025 / Revised: 25 October 2025 / Accepted: 25 November 2025 / Published online: 23 December 2025

Abstract

Autonomous Underwater Vehicles (AUVs) are essential for applications such as seabed mapping, environmental monitoring, offshore infrastructure inspection, and search-and-rescue operations. However, achieving accurate trajectory tracking remains a fundamental challenge due to nonlinear and strongly coupled six-degree-of-freedom dynamics, hydrodynamic parameter uncertainties, environmental disturbances, and limitations introduced by sensor noise, actuator faults, and imperfect modeling of added mass, damping, and Coriolis–centripetal forces. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, this review systematically classifies trajectory-tracking control strategies for AUVs into three main categories. (i) Classical controllers, including PID and Sliding Mode Control (SMC), are analyzed for their simplicity, robustness, and ease of implementation. (ii) Intelligent controllers, such as Fuzzy Logic Control (FLC), Reinforcement Learning (RL), and Physics-Informed Neural Networks (PINNs), are reviewed for their adaptability, learning capabilities, and effectiveness in handling nonlinearities and time-varying disturbances, while addressing challenges related to data availability and computational cost. (iii) Hybrid approaches, including Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Physics-Informed Reinforcement Learning (PI-RL), Fault-Tolerant Control (FTC), and Sim-to-Real Transfer (SRT) techniques, are examined for their ability to integrate model-based reliability with data-driven adaptability and improve resilience under uncertainties, noise, and faults. Classical controllers provide structural simplicity and robustness but suffer reduced accuracy in highly nonlinear and noisy environments. Intelligent methods like RL and PINNs improve adaptability and reduce tracking errors but demand extensive data and computational resources. Hybrid approaches, particularly ANFIS and PI-RL, achieve high tracking accuracy and maintain robust performance under various uncertainties. Sim-to-Real Transfer (SRT) techniques further enhance real-world deployment. A meta-analysis of 120 peer-reviewed studies quantifies performance trends in terms of root-mean-square error (RMSE), settling time, robustness, and computational cost. The review highlights future research opportunities in domain randomization, adaptive fault-tolerant control, and physics-guided hybrid learning to enable reliable real-world AUV operations.

Keywords Autonomous underwater vehicles (AUVs) · Preferred reporting items for systematic reviews and meta-analyses (PRISMA) · Proportional-integral-derivative (PID) · Fuzzy control · Sliding mode control (SMC) · Reinforcement learning (RL) · Physics informed neural networks (PINNs) · Fault-tolerant control (FTC)

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1 Introduction

1.1 Background

Oceans cover about 71% of Earth's surface and support nearly 90% of all known life forms. They have become a major focus in the twenty-first century due to their vast mineral resources and diverse renewable energy sources, such as tidal and wave power [1]. Despite their importance, most of the underwater world remains unexplored due to technological limitations and challenging environmental conditions, particularly in deeper regions. These areas are hard to reach because of low visibility, high pressure, low temperatures, deep water, and unstructured terrain. Autonomous Underwater Vehicles (AUVs) are helping to bridge this gap by enabling high-resolution seabed mapping and bathymetry, environmental and climate monitoring, marine biology and archaeology surveys, inspection of pipelines and cables, under-ice and polar exploration, aquaculture monitoring, search-and-rescue operations, and coordinated multi-vehicle missions [2]. However, achieving precise trajectory tracking, which is central to mission success, remains highly challenging due to the nonlinear and strongly coupled six-degree-of-freedom (6-DOF) dynamics of AUVs, hydrodynamic uncertainties, time-varying ocean currents, and difficult-to-measure parameters such as added mass, damping, and Coriolis–centripetal forces. These complexities are further compounded by sensor noise, actuator faults, bandwidth-limited acoustic communication, severe energy constraints, and modeling inaccuracies, all of which can degrade performance and compromise reliability. As underwater missions demand greater precision, longer endurance, and higher autonomy, the development of advanced trajectory-tracking control strategies that can handle uncertainty, adapt to dynamic environments, and ensure robust performance has become a critical research priority.

1.2 Related literature

Autonomous Underwater Vehicles (AUVs) trajectory tracking control encompasses various approaches aimed at determining efficient routes, enabling AUVs to navigate autonomously between points within their operational environment. It can be classified into three main techniques such as traditional, intelligent, and hybrid techniques as shown in Fig. 1, which be discussed in detail in Sect. 3.

Traditional techniques remain the foundation of AUV control and include both linear methods such as Proportional–Integral–Derivative (PID) controllers and non-linear methods like Sliding Mode Control (SMC) [3]. These controllers are valued for their simplicity, ease of implementation, and robustness under nominal operating conditions. However, their performance typically degrades in highly nonlinear dynamic environments or in the presence of parameter uncertainties, sensor noise, actuator faults, and strong hydrodynamic disturbances.

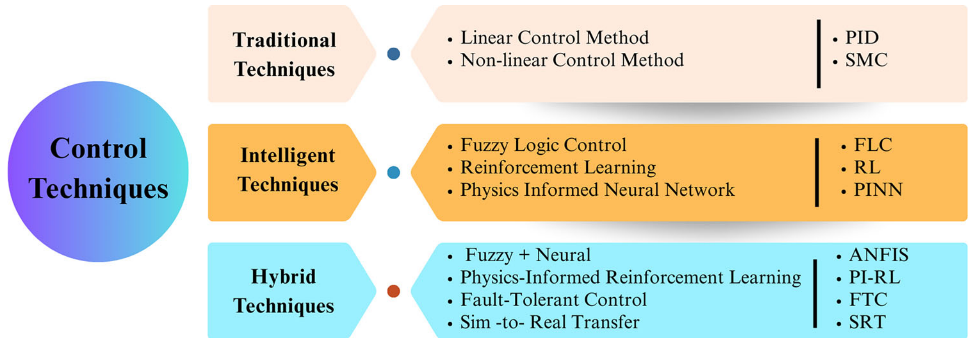
To overcome these limitations, intelligent control techniques have gained increasing attention. Methods such as Fuzzy Logic Control (FLC) exploit human-like reasoning to improve adaptability and robustness, while Reinforcement Learning (RL) enables AUVs to autonomously learn optimal policies through interaction with the environment, achieving improved tracking precision and decision-making in uncertain conditions[4–6]. Physics-Informed Neural Networks (PINNs) further advance this field by embedding physical laws into neural architectures, enhancing generalization capability, and reducing dependence on large training datasets[7]. Despite these advantages, intelligent techniques often demand substantial computational resources, extensive training data, and careful parameter tuning, which can constrain their real-time deployment.

Building on the strengths of both classical and intelligent paradigms, hybrid control strategies have emerged as powerful alternatives for robust AUV trajectory tracking. Techniques such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine fuzzy reasoning with neural networks to achieve faster convergence and better generalization. Physics-Informed Reinforcement Learning (PI-RL) integrates physical modeling into the learning process, enhancing robustness and sample efficiency under dynamic and uncertain conditions [8–10]. Fault-Tolerant Control (FTC) strategies improve resilience against sensor degradation and actuator failures, while Sim-to-Real Transfer (SRT) techniques bridge the gap between simulation and real-world operation, facilitating practical deployment in unpredictable ocean environments [11, 12]. These approaches collectively represent a paradigm shift toward more adaptive, resilient, and energy-efficient control systems tailored for complex underwater missions.

1.3 Research gaps

Despite substantial progress, key challenges in AUV trajectory-tracking control remain unresolved. Existing studies often use different models, conditions, and metrics, making fair comparison difficult and hindering a clear understanding of controller performance. Traditional methods, while simple and robust, lack adaptability to strong nonlinearities and rapidly changing hydrodynamic conditions. Intelligent approaches, such as RL and PINNs, offer better adaptability but require large datasets, significant computational resources, and remain sensitive to sensor noise and actuator faults. Hybrid methods improve robustness by integrating physical knowledge with learning but still struggle with computational cost and real-time adaptation. Moreover, comprehensive solutions that jointly address sensor noise, actuator failures, communication constraints, and

Fig. 1 Types of the control techniques used in AUV



energy limitations remain scarce. The persistent Sim-to-Real Transfer (SRT) gap further limits practical deployment, underscoring the need for systematic comparative studies and next-generation controllers that are robust, adaptive, data-efficient, and reliable under real-world uncertainties.

1.4 Motivation

These limitations underscore the need for a systematic and methodologically rigorous review that not only classifies existing AUV trajectory-tracking control approaches but also critically evaluates their performance and limitations under uncertainty. A review that integrates recent advances, identifies key research gaps, and outlines future research directions will support the development of next-generation control systems that are adaptive, fault-tolerant, and capable of robust operation in complex underwater environments. Moreover, highlighting emerging approaches such as physics-guided learning, domain randomization, and adaptive fault-tolerant control will help bridge the gap between simulation and real-world deployment.

1.5 Contributions

This review provides a structured synthesis of AUVs trajectory tracking controllers based on a PRISMA-guided survey. We can classify the AUV controllers into three main categories: First, classical controllers such as PID, and Sliding Mode Control remain popular due to their interpretability, modest computational demands, and well-understood stability properties, but their performance can degrade under strong, unmodeled disturbances. Second, intelligent controllers, which included RL and PINNs to offer adaptation and improved generalization by exploiting interaction data and embedded physical priors, but they impose significant data and computation demands. Third, hybrid controllers like ANFIS, physics-informed reinforcement learning (PI-RL), fault-tolerant control architectures, and Sim-to-Real Transfer (SRT) techniques, which combined model-based guarantees with learning-driven adaptability to improve robustness, precision, and deployment readiness. Tracking accuracy, disturbance rejection, computational and data requirements, energy usage, and resilience to uncertain hydrodynamics and time-varying current parameters are compared across these controllers to identify the most appropriate choice for each mission.

An effective AUV system must possess the capability to adapt to environmental changes. Because trajectory tracking plays a critical role in enhancing AUV performance, this study systematically reviews state-of-the-art approaches. The main contributions are summarized as follows:

- This paper comprehensively covers the most recent advancements in trajectory tracking techniques used for the AUVs.
- Relevant studies were determined based on the systematic review criteria PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses).
- The reviewed techniques are classified into three main categories: traditional control methods; intelligent approaches; and hybrid strategies. This classification system adds to the comprehensiveness of understanding how the techniques evolved and were applied over time.
- Moreover, the paper also discusses the most significant current AUV trajectory tracking approach problems and limitations.
- Finally, this review summarizes the key findings and important points from the literature. Furthermore, future researches could significantly improve the design and effectiveness of AUV trajectory tracking systems.

1.6 Organization of the paper

The structure of this paper is organized as follows: Sect. 2 outlines the methodology used to identify and select relevant studies, guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. Section 3 provides a comprehensive overview of the latest advancements in trajectory tracking techniques for AUV, categorizing them into traditional control techniques,

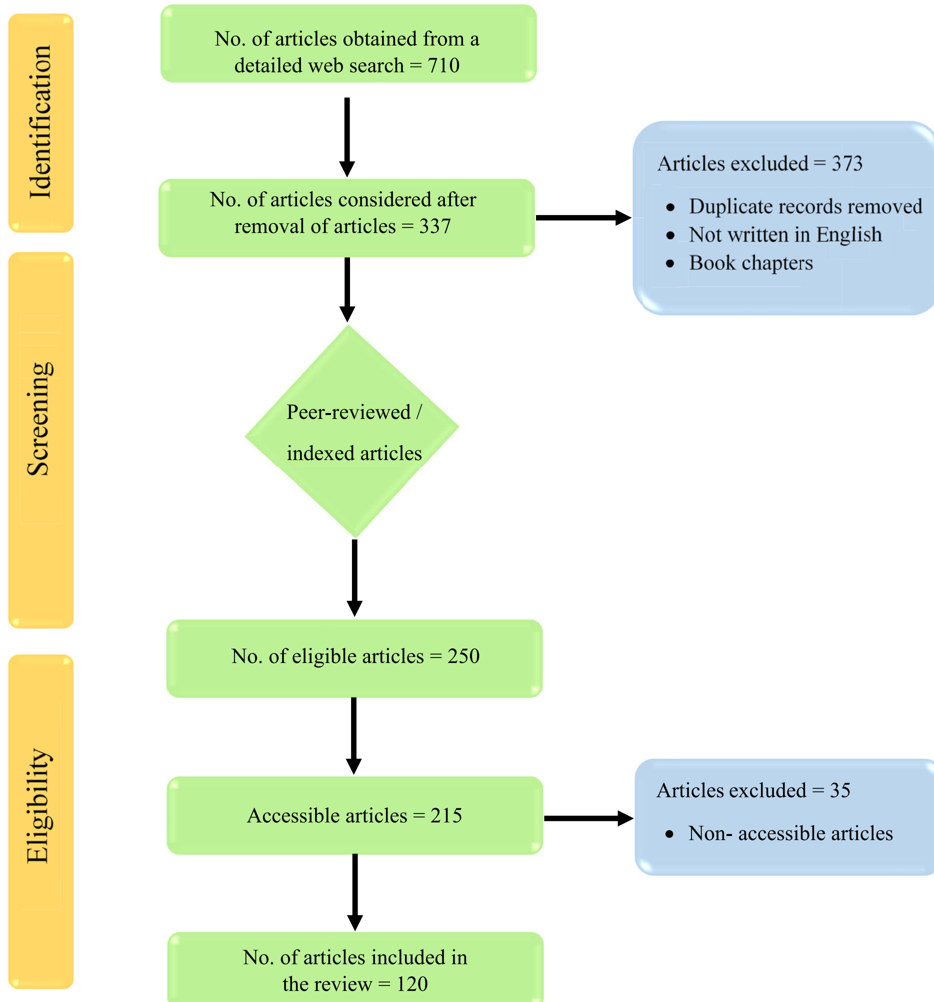


Fig. 2 Flowchart of PRISMA for AUV trajectory tracking after 2020

intelligent techniques, and hybrid techniques to reflect their evolution and application. Section 4 presents a critical discussion of the current challenges and limitations associated with AUV trajectory tracking. Finally, Sect. 5 presents the key findings and insights drawn from the literature and emphasizes that future research could substantially enhance the performance and reliability of AUV trajectory tracking systems.

2 PRISMA flowchart

This review paper aims to address a research gap by reviewing AUV trajectory tracking from a fresh perspective. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was used to find relevant research studies. Scholarly papers were collected from top international scientific databases such as WoS, IEEE Xplore, ScienceDirect, and Google Scholar. The search was performed using specific strings, such as "Autonomous Underwater Vehicle" AND "Trajectory Tracking Control" OR "Traditional Control Techniques" OR "Intelligent Control Techniques" OR "Hybrid Control Techniques" OR "Reinforcement Learning" OR "Physics Informed Neural Network" OR "Fault Tolerant Control" OR "Machine Learning" OR "Sim to Real Transfer (SRT) Techniques". Figure 2 shows the PRISMA process for discovering and selecting the most relevant articles for this review. As a result, 120 articles were screened and chosen for this review paper. The inclusion criteria were: (1) peer-reviewed journal publications and conference papers published within the recent five years, and (2) studies that evaluated the implementation of various controllers for AUV trajectory tracking challenges due to nonlinearity of AUV model and the unknown dynamics of current disturbances. (3) articles that analyze the benefits and drawbacks of each controller separately.

3 AUV trajectory tracking techniques

3.1 Traditional techniques

3.1.1 PID control

The Proportional–Integral–Derivative (PID) controller represents a fundamental linear control technique that has been extensively employed in trajectory tracking applications. In this framework, the tracking deviation, defined as the position error, is determined by the difference between the reference trajectory and the actual trajectory, and it can be expressed as follows [3]:

$$\boldsymbol{e}(t) = \boldsymbol{\eta_d}(t) - \boldsymbol{\eta}(t) \tag{1}$$

Here, $\boldsymbol{\eta_d(t)}$ is the reference trajectory and $\boldsymbol{\eta(t)}$ is the actual trajectory. A linear combination of the proportional, integral, and derivative terms of the control deviation $\boldsymbol{e(t)}$ forms the control law of AUVs. The control law of PID control is specified as follows:

$$\boldsymbol{u(t)} = \boldsymbol{k_p e(t)} + \boldsymbol{k_i} \int_0^t \boldsymbol{e(t)dt} + \boldsymbol{k_d} \frac{\boldsymbol{de(t)}}{\boldsymbol{dt}} \tag{2}$$

where $\boldsymbol{k_p}$, $\boldsymbol{k_d}$, and $\boldsymbol{k_i}$ are the control parameters of PID control. If the three control parameters are selected appropriately, then the tracking process can be rapid, smooth, and accurate. Thus, satisfactory control results can be achieved.

PID control is commonly utilized in various domains, including flight control systems [13], industrial automation [14], and ground mobile robot control systems [15]. Moreover, self-tuning PID controllers have emerged due to advancements in intelligent control [16]. These controllers employed sophisticated algorithms to autonomously modify the parameters of a PID controller, ensuring enhanced and efficient control.

Despite advances in Autonomous Underwater Vehicle (AUV) trajectory tracking, challenges such as effective disturbance rejection and compensation for initial tracking errors remain critical, especially in dynamic ocean environments. To address these issues, Bingul et al.[17] proposed a hybrid control approach that combines an intelligent Proportional-Integral-Derivative (i-PID) controller with a Proportional-Derivative (PD) feedforward mechanism. This integrated system aims to enhance disturbance rejection while improving initial response accuracy, thereby ensuring high-precision trajectory tracking. By incorporating a detailed AUV dynamic model that accounts for ocean current effects, the study enabled a more realistic assessment of controller performance. Simulation results on the LIVA AUV platform demonstrated that the hybrid controller outperformed conventional PID and i-PID controllers in terms of tracking precision, without incurring additional energy costs. This finding positions the i-PID with PD feedforward strategy as a promising alternative to traditional PID approaches, particularly in environments with persistent disturbances.

However, the environmental conditions become more severe, which including strong nonlinearities or rapidly changing underwater currents, the limitations of PID-based controllers become increasingly evident. To overcome these limitations and enhance robustness in challenging underwater conditions more advanced control strategies such as SMC have been investigated. In this context, Wahyuadnyana, K.D., et al. [18] conducted a comparative evaluation of PID and SMC strategies under varying intensities of Internal Solitary Waves (ISWs), using MATLAB simulations combined with real-world oceanographic data from the Bali Deep Sea. The results revealed a marked degradation in trajectory tracking performance because ISW intensity increased from 0 to 100%, with the most significant drop observed between 50 and 75% disturbance levels. Specially, the Root Mean Square Error (RMSE) for the PID controller increased from 18.98 to 70.11, while the SMC controller rose from 15.43 to 68.46. PID control is effective for basic tracking tasks but not effective with nonlinearities and uncertainties in complex environments. SMC offers a robust alternative, handling system nonlinearities and external disturbances by enforcing system behavior along a predefined sliding surface. This makes SMC more suitable than PID for uncertain and dynamic conditions.

3.1.2 Sliding mode control

Sliding Mode Control (SMC) has garnered significant attention as a nonlinear control strategy due to its notable features, including high accuracy, robustness to parameter variations and external disturbances, and ease of tuning and implementation. This control method operates by switching between distinct control structures, allowing the system to transition or "slide" along predefined behavioral trajectories. By dynamically adjusting the control effort, SMC ensures the system steadily converges toward the desired trajectory while minimizing errors. Unlike conventional control strategies that rely on a fixed structure, SMC leverages transitions along the boundaries of control structures, enabling effective handling of both linear and nonlinear systems [19, 20].

SMC is widely recognized for its fast response and does not require online system identification, making it particularly suitable for dynamic applications such as the control of Autonomous Underwater Vehicles (AUVs). Several researchers have advanced SMC methodologies to address specific challenges and enhance its application to AUV control. Kim, H.-H., et al. [21] proposed a Sliding

Mode Control with Sliding Perturbation Observer (SMC-SPO) algorithm for AUV orientation control. This approach demonstrated superior performance compared to PID controllers under minor disturbances but faced limitations under significant disturbances due to control fin angle restrictions. Further advancements included the work, Liu, Z., et al. [22], who developed an Improved Integral Sliding Mode Control (IISMC) for attitude tracking in AUVs. By incorporating Gaussian functions and validating stability through Lyapunov analysis, the IISMC method achieved reduced tracking errors and faster convergence compared to traditional SMC and ISMC approaches.

In another study, Liang, J., et al. [23] proposed a Double-Loop PID Neural Network Sliding Mode Control (DLNNSMC) method to address speed and position tracking errors in AUVs. They incorporated a double-loop PID sliding mode surface for faster convergence speed compared to conventional PID sliding mode surfaces. Additionally, a nonlinear high-order observer is combined with a neural network are combined to compensate for the nonlinear disturbance of the AUV system. The DLNNSMC method was compared with the Radial Basis Function (RBF) neural network PID sliding mode control (RBFPIDSMC) and the RBF neural network PID sliding mode control (RBFPDSMC) in two trajectory tracking control simulation experiments. In the first experiment, the proposed method reduced the average Euclidean distance of the position tracking error by approximately 73.6% and 75.3%, compared to RBFPDSMC and RBFPIDSMC, respectively. In the second experiment, the reductions were approximately 86.8% and 88.8%, respectively. These results demonstrated that the proposed method has superior anti-interference capability and tracking performance. The simulation results in the Gazebo environment validated the effectiveness of the DLNNSMC approach.

After that, Luo, W. and S. Liu [24] presented a Nonsingular Fast Terminal Sliding Mode Control (NFTSMC) for horizontal trajectory tracking, which incorporated a disturbance observer for improved robustness and faster convergence rates. Lastly, Li, B., et al. [25] introduced an Improved Adaptive Twisting Controller (IATC) designed to mitigate chattering and eliminate the need for prior knowledge. By integrating adaptive laws and a sliding mode observer, this method achieved finite-time stability and reduced overshoot, outperforming existing controllers in trajectory tracking performance.

Traditional Sliding Mode Control (SMC) faces several limitations, including reliance on accurate system models, susceptibility to chattering, and the need for extensive manual parameter tuning. These challenges reduce its effectiveness in highly dynamic and uncertain environments such as those encountered by AUVs. As shown in Fig. 3, SMC is most effective when integrated with other control strategies. In contrast, intelligence-based techniques offer a model-free approach that enables systems to adapt to complex and unpredictable conditions by learning optimal control strategies through data-driven interactions. Their ability to manage unknown dynamics and disturbances without relying on explicit models makes them a more flexible and robust option, especially for real-time applications like AUV trajectory tracking.

The previous researchers related to SMC is summarized in Table 1.

3.2 Intelligence techniques

3.2.1 Fuzzy control

Fuzzy Logic Control (FLC) was developed by Lotfi Zadeh [26]. FLC utilizes fuzzy logic to make decisions and control systems. Unlike traditional control systems, which depended on precise mathematical models and algorithms, fuzzy control systems utilize fuzzy rules to make decisions based on incomplete information.

The inputs in fuzzy control system are converted into linguistic variables using membership functions, which assign a degree of truth to each input value. These values are processed using fuzzy rules, which combined the inputs in different ways to produce an output. After that, the output is converted back into a numerical value via defuzzification techniques. The fuzzy control system consists of three main components (fuzzification, interference engine, defuzzification).

A fuzzy control system operated by mapping sensor inputs, such as switches or thumbwheels, to corresponding membership functions and truth values during the input stage. In the processing stage, fuzzy logic rules are applied to these inputs to generate a fuzzy output. Finally, in the output stage, the fuzzy output is transformed into a crisp value, which is utilized to control the system.

Fuzzy set theory proved effective for representing uncertain data, which has benefits for addressing online and real-time problems due to its low computational complexity. The Fuzzy Logic Matlab Toolbox is compatible with both the Mamdani and Sugeno systems. Mamdani's method was widely recognized as a method for incorporating expert knowledge [27, 28]. The main difference between Mamdani and Sugeno FIS lies in how to generate crisp outcomes. In a Mamdani-type FIS, fuzzy outcomes are converted into crisp values through defuzzification. Meanwhile, in a Sugeno-type FIS, crisp outcomes are produced by applying weighted averages to the fuzzy results [29].

Building upon this background, considerable research has focused on enhancing AUV performance through fuzzy logic strategies and advanced adaptive control architectures. Zhilenkov, A., et al. [30] proposed a fuzzy motion control scheme for AUVs and evaluated its performance under

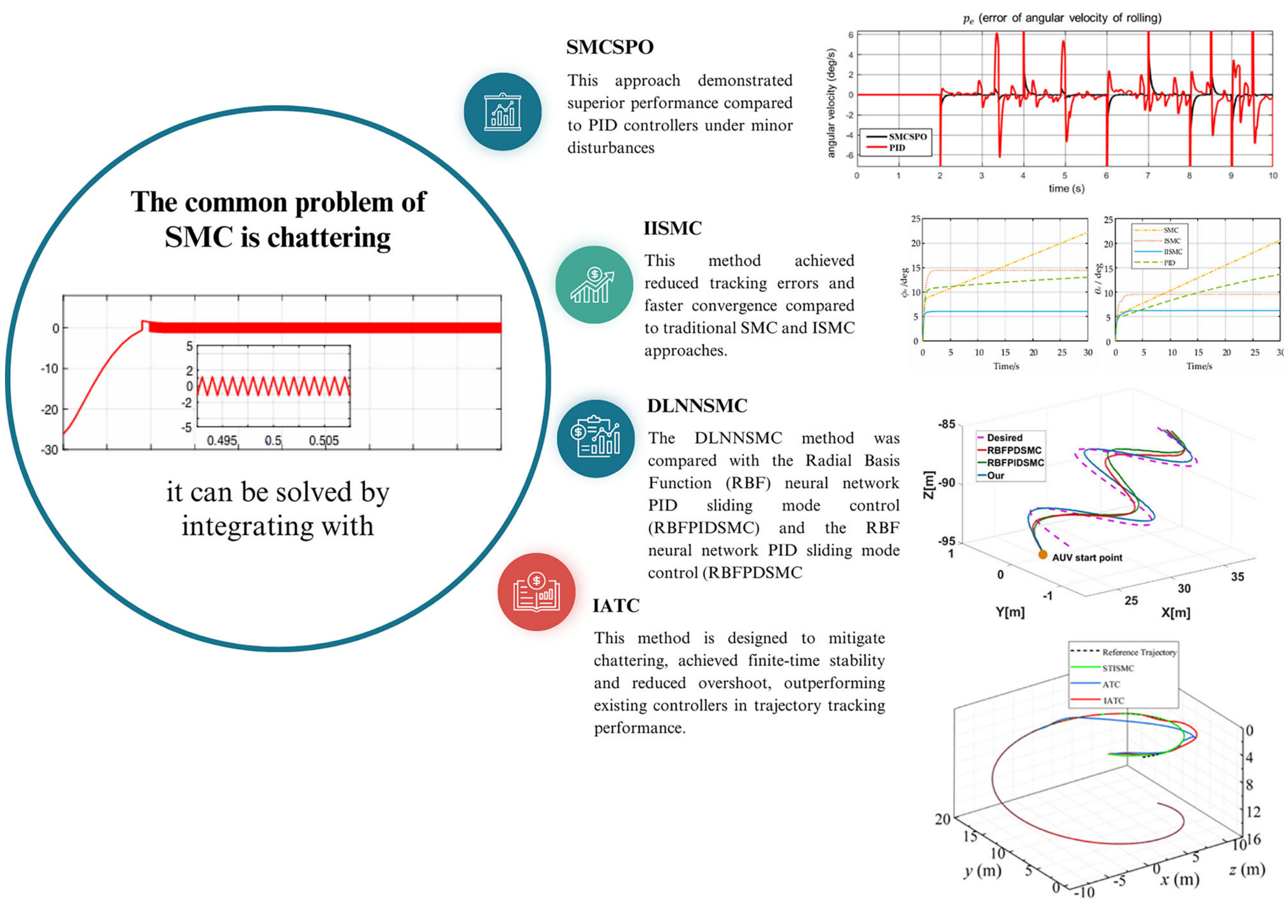


Fig. 3 Presents the improved researches related to SMC

Table 1 Summary of SMC references used for AUV trajectory tracking

Control algorithm	Research purpose	Improvement	Control effect	Refs
SMC	AUV orientation control	Sliding Mode Control with Sliding Perturbation Observer (SMCSPO)	Demonstrated superior performance compared to PID controllers under minor disturbances but faced limitations under significant disturbances due to control fin angle restrictions	[21]
	Improved Integral Sliding Mode Control (IISMC)	By incorporating Gaussian functions and validating stability through Lyapunov analysis	The tracking errors reduction was achieved, and faster convergence compared to traditional SMC and ISMC approaches	[22]
	To address speed and position tracking errors in AUVs	Incorporated Double-Loop PID Neural Network with Sliding Mode Control (DLNNSMC)	These results demonstrated that the proposed method has superior anti-interference capability and tracking performance compared with RBFPIDSMC and RBFPDSMC	[23]
	Improved the horizontal trajectory tracking	Nonsingular Fast Terminal Sliding Mode Control (NFTSMC)	Faster convergence rates	[24]
	To mitigate chattering and eliminate the need for prior knowledge	Improved Adaptive Twisting Controller (IATC)	This method achieved finite-time stability and reduced overshoot, outperforming existing controllers in trajectory tracking performance	[25]

step commands, harmonic disturbances, and external perturbations in comparison with a conventional PD controller. The simulation results demonstrated that the fuzzy controller achieved superior control quality and robustness in the presence of uncertainties and disturbances. Nevertheless, one of the key limitations of classical PID control lies in the difficulty of gain tuning in nonlinear and uncertain environments, a process that is often time-consuming and dependent on expert knowledge. To address this issue, Zendehdel, N., et al. [31] proposed a Self-Tuning Feedback Linearized PID Controller (STFLPIDC) incorporating fuzzy logic to enhance control performance under measurement noise and parameter uncertainty. Designed to regulate the surge degree of freedom in an AUV dynamic model, this approach significantly reduced trajectory-tracking errors compared with conventional PID controllers by dynamically adjusting controller gains online to accommodate hydrodynamic variations. Moreover, the Feedback Linearized PID Controller has demonstrated versatility beyond underwater applications, being successfully applied in other autonomous systems requiring precise nonlinear control. Building on the same principle of robust and adaptive control, Bhowmick, P., et al. [32] developed a two-loop cooperative control architecture for networked tri-rotor UAVs, combining robust feedback linearization in the inner loop with an algebraic Riccati equation (ARE)-based group formation tracking (GFT) scheme in the outer loop. The proposed framework effectively linearizes nonlinear coupled dynamics while preserving essential system characteristics, thereby enhancing resilience to modeling uncertainties and aerodynamic disturbances. Simulation results from a multi-target surveillance mission involving twelve UAVs demonstrated accurate time-varying formation tracking, rapid error attenuation, and asymptotic closed-loop stability, with UAVs forming coordinated subgroups around designated targets. Building upon these advances in feedback linearization and fuzzy logic, several studies have further explored fuzzy-based optimization techniques for AUV navigation and control. Sun, B., et al. [33] implemented particle swarm optimization (PSO) and quantum-behaved PSO (QPSO) algorithms to enhance three-dimensional AUV path planning, utilizing sonar sensors mounted on both horizontal and vertical planes to support navigation. Simulation results in static and dynamic environments confirmed the effectiveness of both PSO-fuzzy and QPSO-fuzzy schemes, with the PSO-fuzzy approach demonstrating superior performance under dynamic conditions. Similarly, Tian, Q., et al. [34] integrated fuzzy logic controllers with kinematic and dynamic models for AUV path tracking, optimizing controller parameters based on path length, smoothness, and cross-track error. PSO-based tuning further improved controller performance across various trajectory scenarios, including straight-line and sinusoidal paths, achieving higher tracking accuracy than conventional methods.

Beyond traditional fuzzy control methods, predictive fuzzy strategies have been proposed to address scalability challenges in high-dimensional systems. Yin, J. and N. Wang. [35] proposed a predictive fuzzy controller that integrated a variable fuzzy predictor with Delaunay triangulation to overcome the "curse of dimensionality," achieving faster response, higher tracking accuracy, and smoother motion compared with conventional MPC. Further advancements in predictive control extended beyond AUV dynamics. Panda, A., et al.[36] developed an economic model predictive control (EMPC) framework that incorporated process dynamics and economic objectives, enabling faster convergence, improved disturbance rejection, and enhanced steady-state efficiency. Similarly, Panda, A. and R.C. Panda [37] demonstrated the effectiveness of MPC in optimizing microplastic removal through saturated porous media, where real-time flow and pressure adjustments enhanced removal efficiency, reduced energy consumption, and improved system adaptability. Collectively, these studies highlighted the versatility and potential of predictive control approaches to improve energy efficiency, robustness, and adaptive performance in AUV missions and other dynamic systems.

Complementing these predictive control advancements, Thanh, P. N. N. et al. [38] introduced a double-loop adaptive fuzzy trajectory tracking control scheme for underactuated AUVs to address the challenge of decoupling kinematic and dynamic tasks. In this framework, the kinematic loop guided the vehicle along the desired trajectory while compensating for ocean current drift, whereas the dynamic loop employed adaptive fuzzy dynamic surface controllers to manage system constraints. Stability analysis confirmed that all closed-loop signals remained bounded and that constraints were preserved, while simulation results reported a tracking error below 0.03 m, previously considered unattainable, and eliminated oscillations and performance degradation associated with input saturation. Lastly, C. Wu et al. [39] proposed a model-free adaptive predictive control (MFAPC) strategy based on a fuzzy state observer (FSO) that enabled high-precision trajectory tracking in the presence of external perturbations and time delays. Their approach estimated and predicted a time-varying pseudo-Jacobian matrix (PJM) to construct an equivalent state-space data model of the AUV motion system. A Takagi–Sugeno fuzzy state observer further refined fuzzy estimates and compensated for time-delay uncertainties. Simulation results demonstrated that FSO-based MFAPC outperformed traditional MFAC and MFAPC controllers in response time, convergence rate, robustness, and adaptability under dynamic conditions.

Fuzzy Logic Controllers (FLCs) face several inherent limitations. One major challenge is the rule explosion problem, which occurs as the number of control rules increases rapidly with the addition of input variables. The tuning of membership functions and rule sets often relies on trial-and-error procedures, making the process subjective, time-consuming, and less reproducible. Furthermore, FLCs may perform inadequately in complex and highly dynamic environments, as static rule bases struggle to adapt to rapidly changing system behaviors. The computational cost can also become prohibitively high, particularly when dealing with large datasets, which limits their applicability in real-time control scenarios. In contrast, Reinforcement Learning (RL) overcomes many of these challenges by autonomously learning optimal control strategies through continuous interaction with the environment. This capability allows RL to effectively handle nonlinearities and dynamic conditions, offering greater flexibility and robustness in real-world AUV trajectory-tracking applications.

The previous research works related to fuzzy logic control is summarized in Table 2.

3.2.2 Reinforcement learning

Reinforcement Learning (RL) is a machine learning paradigm in which an agent learns to map situations to actions so as to maximize a numerical reward signal. RL elements consisted of the policy, reward, value, and environment model. Where, the policy indicated the agent's plan of action. Rewards are numerical feedback provided by the environment in response to the agent's state-action pairs, reflecting the immediate desirability of those states [40]. The value function represented the long-term cumulative reward that can be expected from a particular state when following a specific policy. Finally, the environment model shows the dynamics of the environment, providing a representation of how actions influence state transitions and outcomes.

In reinforcement learning, an agent is responsible for taking actions within an environment based on the current state and past experiences. The primary objective of a reinforcement learning algorithm is to enable the agent to efficiently learn an optimal policy that accomplishes the desired task while maximizing cumulative rewards. Controlling an AUV to execute specific tasks is more complex. This complexity arises from the challenges posed by fluctuating operational and environmental conditions, intricate dynamics, the necessity for energy efficiency, and susceptibility to disturbances, sensor noise, and unmodeled dynamics. Classical control methods were initially applied; however, their performance proved inadequate primarily because they rely on linear dynamics, which limits their effectiveness in nonlinear and time-varying underwater environments. As a result, the controller can perform well on the AUV under a set of conditions, while accounting for its nonlinear dynamics. The integration of machine learning, specially RL, has enabled AUVs to learn control policies through direct interaction with their environments, improving autonomy. Where, it can achieve the end-to-end autonomous learning and control with high-dimensional environmental perception information [41–43].

Reinforcement learning (RL) techniques for autonomous underwater vehicle (AUV) control have evolved significantly, progressing from fundamental control frameworks to highly adaptive, environment-aware approaches capable of maintaining robust performance in complex and dynamic marine environments. At the low-level control stage, Fang, Y., et al. [4] introduced a fast-deployable Deep Deterministic Policy Gradient (DDPG) controller with an extended yaw range, which enhanced heading stability in critical orientations and enabled modular execution of tracking tasks. Simulation results showed that this approach substantially outperformed conventional PID and backstepping controllers in terms of trajectory-tracking accuracy, convergence speed, and adaptability under varying sea conditions. Building on this foundation, Ma, D., et al. [6] proposed a neural network-augmented Proximal Policy Optimization (PPO) algorithm with an Actor–Model–Critic (AMC) architecture, leveraging predictive dynamic models to further improve tracking accuracy and robustness in the presence of external disturbances.

Reinforcement learning has been increasingly employed to address critical challenges in AUV operations, including environmental adaptability, energy efficiency, cooperative autonomy, and real-time decision-making. To improve path planning and adaptability to varying ocean conditions, Xi, M., et al. [5] developed a Double-Dueling Deep Q-Network (D3QN) that integrated real-time current data from the Regional Ocean Modeling System (ROMS). This enhanced the planner's ability to generalize across diverse marine regions, outperforming conventional methods in trajectory accuracy and adaptability. Similarly, Chu, Z., et al. [44] addressed current-induced disturbances by proposing a Double Deep Q-Network (DDQN) framework that combined a dual-input convolutional neural network (CNN) with a current-aware reward structure. The proposed approach enabled underactuated AUVs to navigate unknown and highly dynamic environments with high reliability, achieving success rates above 95% while reducing path length and hydrodynamic resistance by 25% compared with traditional techniques such as genetic algorithms (GA), particle swarm optimization (PSO), and rapidly exploring random trees (RRT*). Additionally, convergence speed improved by approximately 30%, underscoring RL's potential for real-time path planning in strongly disturbed environments. Further algorithmic refinements have focused on enhancing stability, learning efficiency, and control smoothness. Fan, Y., et al. [45] improved the Twin Delayed DDPG (TD3) algorithm by incorporating prioritized experience replay, action-smoothing regularization, and adaptive constraint rewards. The enhanced TD3 achieved faster convergence, smoother actuator control, and improved overall stability compared

Table 2 Summary of fuzzy logic control references used for AUV trajectory tracking

Control algorithm	Research purpose	Improvement	Control effect	Refs
Fuzzy logic	Providing superior control quality even in the presence of uncertainties and external disturbances	Robust fuzzy logic controller	The results showed that the fuzzy controller outperformed the PD controller	[30]
	control the surge degree of freedom in the dynamic model	Self-Tuning Feedback Linearized PID controller (STFLPIDC)	STFLPIDC significantly reduced tracking errors, especially under noisy conditions and model parameter variations	[31]
	To design a cooperative control scheme for networked tri-rotor UAVs to achieve group formation tracking with multiple targets	A two-loop control framework combining robust feedback linearization and an ARE-based cooperative controller	Enhanced robustness to model uncertainties, ensured stable time-varying formations, accurate attitude control, and successful multi-target tracking with steadily decreasing tracking error	[32]
	improvement of the 3D AUV path planning	PSO and QPSO integrated with fuzzy logic	PSO fuzzy provided faster computation times for dynamic conditions	[33, 34]
	solve the problem of dynamic trajectory tracking in 3D underwater conditions	Designed a predictive controller with a variable fuzzy predictor	Predictive fuzzy controller provided a fast dynamic response, stable performance, and no control delay compared with MPC	[35]
	To enhance the efficiency and economic performance of the Di-Cumyl Peroxide (DCP) decomposition process	Developed an Economic Model Predictive Control (EMPC) framework that integrates process dynamics with economic objectives	Achieved faster convergence, improved disturbance rejection, enhanced steady-state efficiency, and balanced stability with economic performance	[36]
	To improve microplastic removal efficiency using filtration through saturated porous media	Investigated the effects of particle size, surface properties, flow velocity, and media characteristics, and integrated Model Predictive Control (MPC) for real-time optimization	Enhanced removal efficiency, reduced energy consumption, increased adaptability, and improved sustainability in water treatment systems	[37]
	Compensating for the drift caused by the ocean currents	An adaptive fuzzy trajectory tracking control method	The proposed controller with a negligible steady-state tracking error of about 0.03 m	[38]
	Achieve high precision in trajectory tracking for AUVs under uncertain external disturbances and time delays	Developed a model-free adaptive predictive control (MFAPC) based on a fuzzy state observer (FSO)	The FSO-based MFAPC controller had faster responses to system dynamic variations, with a faster response time, quicker convergence rate, and better robustness and adaptiveness compared with other MFAC and MFAPC approaches	[39]

with baseline TD3 and DDPG approaches, while maintaining robust performance under modeling uncertainties and environmental disturbances.

In the context of energy optimization, Sufán, V., et al. [46] proposed Swim4Real, a DRL-based controller within the REEF-DRL (Robust and Energy-Efficient Frame – Deep Reinforcement Learning) framework, which reduced energy consumption by 30% in simulations and up to 39% in experiments, while maintaining positioning errors below 0.2 m and orientation errors under 2°. This performance placed RL controllers on par with tuned PID systems while significantly extending mission endurance, thereby enabling longer deployments. To enhance robustness in highly unsteady flow regimes, Lidtke, A.K., et al. [47] trained RL agents within CFD-based turbulent environments and employed transfer learning and data augmentation to reduce training demands by 50%. The resulting controller demonstrated strong generalization to unseen flow conditions, enabling stable inspection maneuvers in nonlinear and chaotic hydrodynamic fields where traditional controllers fail.

Scaling beyond single-vehicle control, Zhu, S., et al. [48] developed a hierarchical RL framework for multi-AUV coordination, integrating advantage-attention and resampling strategies into an actor–critic structure. This approach improved tracking accuracy by 20%, accelerated convergence by 40%, and increased sample efficiency by 25%, demonstrating scalability to fleets of over 20 AUVs under communication and computation constraints. Extending RL into adversarial and pursuit–evasion tasks, Xu, J., et al. [49] introduced UPEGSim, the first RL-enabled simulator designed specifically for UPEG (underwater pursuit–evasion games). By incorporating scene transfer and decision transformer-based offline RL, UPEGSim achieved over 90% success rates, improved convergence by 35%, and enhanced robustness to velocity and angular disturbances by 25%, providing a safe platform for developing cooperative and competitive strategies without costly sea trials.

In the domain of real-time obstacle avoidance, Zhu, G., et al. [50] proposed a CPM-LSTM-PPO framework that combines a collision prediction model, long short-term memory, and proximal policy optimization. Compared with LSTM-PPO, DQN, and TRPO approaches, CPM-LSTM-PPO demonstrated faster convergence and improved learning efficiency, particularly in complex multi-obstacle environments. Addressing sensor limitations, Xu, J., et al. [51] proposed an event-triggered soft actor–critic (ET-SAC) algorithm for collision avoidance in environments with unknown static and dynamic obstacles, maintaining effective decision-making even under limited sensing conditions. To further improve robustness, Zhang, C., et al. [52] enhanced DDPG with adaptive constraints for 3D path tracking and obstacle avoidance, integrating LOS-based tracking, a carrier frame-based avoidance model, and adaptive reward shaping. This approach achieved faster convergence, improved robustness, and safer exploration compared with backstepping SMC and artificial potential field methods. Li, Y., et al. [53] advanced this direction with RLBMPA-COI (Reinforcement Learning-Based Motion Planning Algorithm with Comprehensive Ocean Information), a SAC-based motion planning algorithm that incorporated real-time ocean current data to reduce overestimation errors and enhance performance in multitask and highly dynamic environments.

To improve decision-making under complex hydrodynamic conditions, Liu, Z., et al. [54] introduced a self-attention soft actor–critic (A-SAC) algorithm utilizing five deep neural networks, including two attention-based Q-networks and a self-attention policy network. A-SAC achieved superior path tracking compared with SAC, PPO, DDPG, and PID controllers, while minimizing spiral path issues and maintaining close alignment with desired trajectories. Building on this, Wu, C., et al. [55] developed an adaptive SAC-PID controller, combining classical PID control with SAC-based policy learning. The SAC-PID method demonstrated superior training stability, reduced collision risks, and 30% faster convergence compared with PPO-PID, while enhancing control performance through improved action-space exploration.

Despite these advances, RL still faces challenges related to generalization and sample inefficiency, particularly when adapting to rapidly changing environmental conditions. To address this, meta-reinforcement learning (Meta-RL) has emerged as a promising solution. Jiang, P., et al. [56] proposed the Attention-based Model-Agnostic Meta-Learning (AMAML) framework, enabling rapid adaptation to dynamic changes by decomposing tasks into fixed-dynamics subtasks and using attention mechanisms to extract key state features. Tests on the REMUS AUV with ± 30% parameter variations showed that AMAML achieved faster convergence and lower tracking errors than PPO and DDPG, with performance comparable to nonlinear model predictive control (NMPC). Extending meta-learning to underwater gliders, Tian, X., et al. [57] developed a Long Short-Term Memory and self-attention–based Meta-Reinforcement Learning (LAMRL), which combined long short-term memory and self-attention with a soft actor–critic policy to adapt to buoyancy and current variations. LAMRL converged faster and achieved lower tracking errors than SAC and PEARL, while mitigating policy drift and improving angular stability. Finally, Fig. 4 shows an overview of RL challenges such as Real-Time Obstacle Avoidance**,** Current-Induced Disturbances**,** Multi-Agent Coordination**,** and Rapid Adaptation & Meta-Learning. Each row comprises three columns: the problem, the associated challenges, and suggested algorithms to solve this problem.

The previous researchers related to RL is summarized in Table 3.

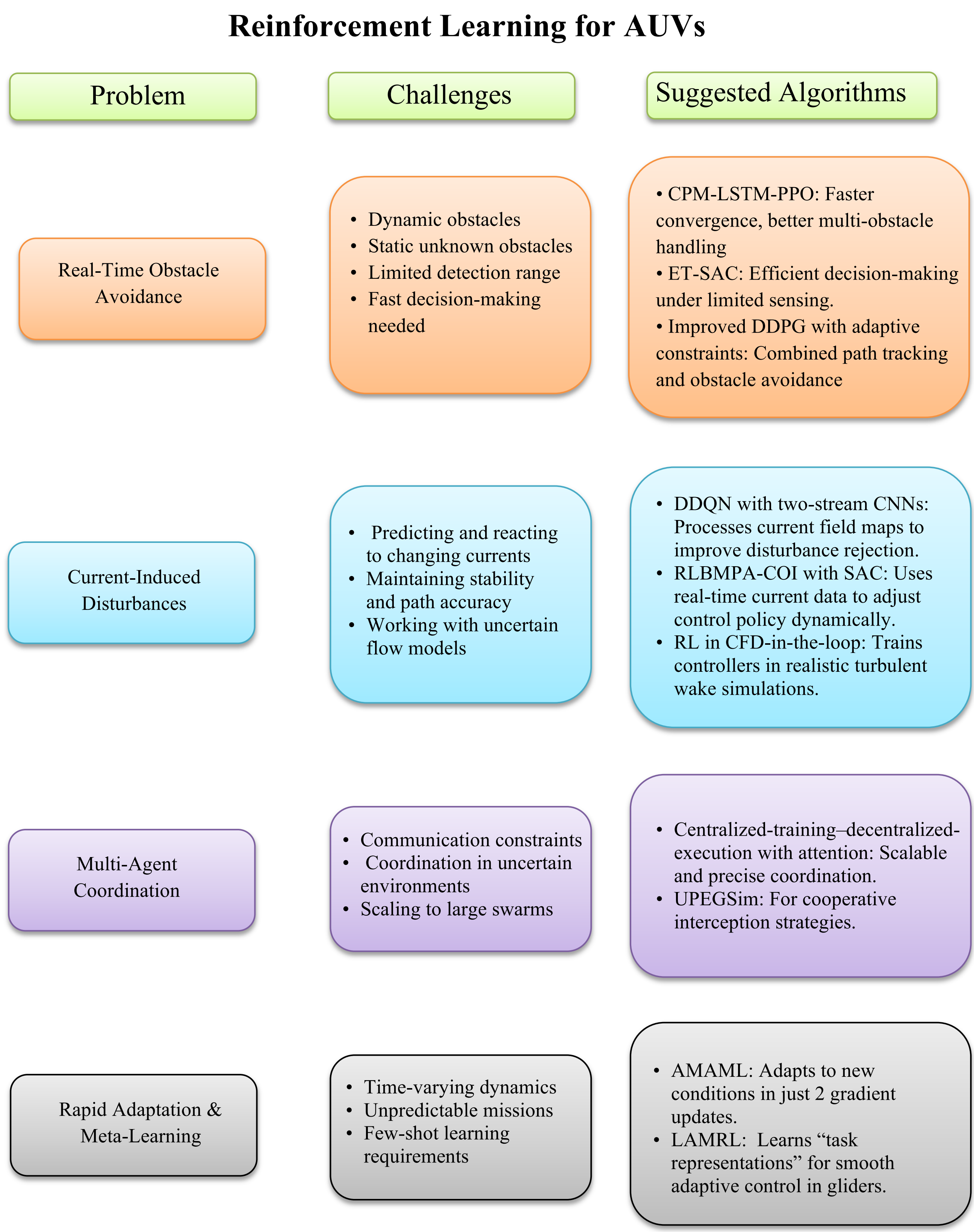


Fig. 4 Presents the problems, which faced the reinforcement learning and suggested algorithms to solve it

Table 3 Summary of reinforcement learning-based control strategies for AUV trajectory tracking, outlining research objectives, algorithmic innovations, and control outcomes across various underwater mission scenarios

Control algorithm	Research purpose	Improvement	Control effect	Refs
DDPG	Rapid deployment of RL-based low-level controller for AUV trajectory tracking	Fast-deployable DDPG with extended yaw range and modular training pipeline	Achieved higher tracking accuracy, faster convergence, and improved adaptability compared with PID and backstepping under varying sea conditions	[4]
D3QN	Integration of real-time oceanographic data into RL-based path planning	D3QN incorporating ROMS current data for adaptive trajectory updates	Improved mission efficiency and environmental adaptability compared with static path planners	[5]
PPO-AMC	Combining model-based dynamics with RL for efficient 3D path following	Integration of neural network dynamic models into the RL training loop	Enhanced sample efficiency, reduced tracking error, and improved generalization to unseen disturbances compared with model-free RL	[6]
DDQN	Real-time path planning in unknown environments with current disturbances	Enhanced DDQN with dual CNN inputs, composite reward design, and NURBS-based path smoothing	Reduced cross-current motion, produced shorter and smoother paths, and achieved faster planning than APF-based methods	[44]
TD3 (Enhanced)	Improving path-following accuracy and robustness under dynamic disturbances	TD3 enhanced with multi-step target updates, adaptive parameter noise, and optimized replay buffer	Demonstrated faster convergence, lower steady-state error, and higher robustness to ocean currents compared with standard TD3 and PID	[45]
REEF-DRL	Energy-efficient six-DOF control for AUVs	Domain-randomized DRL framework for robust and efficient control	Reduced energy consumption by $\geq 30\%$ in simulation and $\geq 39\%$ in real water tests, with accuracy comparable to PID	[46]
DRL (Turbulent Flow)	Robust control of AUVs in highly turbulent water	Domain-randomized RL policy resilient to flow variability	Achieved stable maneuvering and reduced control effort in turbulent environments where traditional methods fail	[47]
HSD-MARL	Hierarchical multi-AUV cooperative target tracking	MARL with advantage-attention and advantage resampling mechanisms	Improved tracking accuracy, accelerated convergence, and enhanced scalability for large AUV fleets	[48]
UPEGSim	RL-enabled simulator for pursuit–evasion scenarios	Multi-agent decentralized execution with ETFDU training framework	Enabled efficient RL training and policy transfer, improving adaptability to dynamic environments	[49]

Table 3 (continued)

Control algorithm	Research purpose	Improvement	Control effect	Refs
CPM-LSTM-PPO	Dynamic 3D obstacle avoidance	Integration of collision prediction model, LSTM, and PPO	Reduced number of steps required for convergence and improved learning efficiency compared with LSTM-PPO, DQN, and TRPO	[50]
ET-SAC	Obstacle avoidance under limited sensor detection	Combination of deep RL and event-triggered mechanism (ET-SAC)	Achieved autonomous collision avoidance for static and dynamic obstacles; highlighted remaining challenges such as time delay and actuator faults	[51]
Multi-objective DRL	Simultaneous path tracking and obstacle avoidance in real time	Multi-objective RL controller with reward balancing tracking accuracy and collision safety	Maintained high tracking precision and faster response while avoiding obstacles, outperforming rule-based and single-objective RL methods	[52]
RLBMPA-COI	Reducing overestimation and improving stability in complex environments	RL-based motion planning algorithm integrating comprehensive ocean information	Achieved faster convergence and superior trajectory tracking compared with DDPG and TD3 by leveraging policy entropy and mitigating overestimation	[53]
A-SAC	Enhancing control policy learning in real-world conditions	Self-attention-based SAC with improved Q-value estimation	Outperformed SAC, PPO, DDPG, and PID in path control accuracy, mitigating hyperparameter sensitivity and communication-induced path errors	[54]
SAC-PID	Improving PID control for AUV path following	Adaptive PID integrated with SAC	Improved training stability and convergence speed, reducing performance fluctuations compared with PPO-PID and classical PID	[55]
AMAML	Fast adaptation under unknown and time-varying dynamics	Meta-RL with attention, LOS-based state design, and rapid gradient updates	Outperformed DDPG and PPO in tracking accuracy and adaptation speed, matching NMPC performance while avoiding actuator saturation	[56]
LAMRL	Meta-learning-based adaptation under buoyancy and current variations	LSTM and self-attention-based Meta-RL with latent task representation	Achieved faster convergence, lower tracking error, and improved angular stability compared with SAC and PEARL, even under mid-mission condition changes	[57]

A comparative analysis of reinforcement learning algorithms applied to AUVs reveals significant differences in performance, adaptability, and computational requirements depending on mission objectives and environmental conditions. Deterministic algorithms such as Deep Deterministic Policy Gradient are often preferred for tasks requiring continuous action spaces and faster convergence with relatively low computational demands, but their sensitivity to noise and hyperparameter tuning makes them less reliable in highly dynamic underwater environments. Twin Delayed DDPG mitigates these limitations by addressing overestimation bias and improving stability, making it a better choice when precision and robustness are critical, albeit at the expense of greater computational cost. Proximal Policy Optimization offers improved training stability and robustness to hyperparameter selection, making it suitable for missions with limited data or where ease of deployment is prioritized, though it typically converges more slowly than off-policy methods. Soft Actor–Critic is particularly advantageous in uncertain and dynamic marine conditions due to its entropy-regularized objective, which enhances exploration and robustness, but this comes with increased computational requirements and careful entropy coefficient tuning. Meta-learning approaches such as Adaptive Model-Agnostic Meta-Learning are preferred in non-stationary environments because they enable rapid adaptation to changing hydrodynamics with minimal additional data, though they require extensive meta-training. Moreover, algorithms incorporating attention mechanisms or LSTM structures outperform others in partially observable environments by capturing long-term dependencies and contextual dynamics. Energy-aware methods like REEF-DRL are favored in missions where energy efficiency and endurance are paramount. Thus, no single RL algorithm is universally optimal; the selection is inherently task-dependent, shaped by trade-offs among robustness, adaptability, computational demand, and real-time feasibility, with mission objectives and environmental conditions guiding the most appropriate choice.

Physics-Informed Neural Networks (PINNs) offer distinct advantages over RL in specific applications by integrating physical laws directly into the learning process. Unlike RL, which depends on large datasets and trial-and-error interactions to learn optimal policies, PINNs utilize known governing equations, such as differential equations, to inform the learning process, thereby reducing the reliance on extensive data and accelerating convergence. This feature makes PINNs particularly valuable in cases where the underlying physics are well-understood and the system's behavior can be mathematically modeled, leading to more accurate and efficient predictions with minimal data, particularly in complex domains such as fluid dynamics and AUV motion modeling. Additionally, PINNs are more resilient to data scarcity and enhance model generalization by ensuring consistency with the physical principles governing the system.

3.2.3 Physics-informed neural network

Physics-Informed Neural Networks (PINNs) represent an emerging machine learning paradigm particularly well-suited for modeling complex nonlinear systems such as AUVs. Unlike conventional data-driven models, which often suffer from issues such as drift, overfitting, and poor extrapolation beyond the training domain, PINNs integrate observational data with the governing physical laws of the system, typically expressed as partial differential equations (PDEs). These physical constraints are embedded directly into the neural network's loss function through automatic differentiation, enabling the model to learn solutions that are not only data-consistent but also physically interpretable and dynamically accurate. By incorporating prior knowledge of system dynamics, PINNs enhance generalization, improve robustness under uncertainty, and reduce the amount of training data required compared to purely data-driven approaches [58, 59].

The potential of PINNs in modeling AUV dynamics has been demonstrated by Guan, Y., et al. [7], who developed a PINN-based framework to model the yaw motion of a deep-sea mining vehicle during deployment and recovery. By embedding hydrodynamic equations directly into the training process, their model captured both parametric and non-parametric effects derived from computational fluid dynamics (CFD) data. The PINN achieved a mean squared error (MSE) of 1.21×10^{-4} m compared to 3.57×10^{-4} m for a conventional neural network, corresponding to a 66% reduction in error. Furthermore, the PINN maintained physically consistent yaw trajectories over extended prediction horizons, avoiding the drift and oscillations present in purely data-driven approaches. These results demonstrated that embedding physical knowledge into learning architectures not only improved prediction accuracy but also enhanced long-term stability, offering a practical and reliable tool for planning and yaw control in complex, data-limited deep-sea environments.

Building on these modeling advancements,, Zhao, Y., et al. [60] extended the use of PINNs to closed-loop control by integrating them with Model Predictive Control (MPC) for six-degree-of-freedom (6-DOF) AUV dynamics. In this work, the motion equations were embedded into the network loss function, and the nonlinear representation power of deep neural networks was leveraged to eliminate the need for explicit hydrodynamic parameter identification. A multi-step iterative training process based on fourth-order Runge–Kutta integration further enhanced adaptability to nonlinear dynamics and enabled seamless integration with the Model Predictive Path Integral (MPPI) optimization

Table 4 Summary of PINN references used for AUV trajectory tracking

Control algorithm	Research purpose	Improvement	Control effect	Refs
PINN	Constructing the yaw motion hydrodynamic model of deep-sea mining vehicles during deployment and recovery processes	Physics informed neural network (PINN)	This approach effectively mitigated the overfitting of the neural network to the training data, thereby enhancing the model's fault tolerance during operation	[7]
	Addressing AUV nonlinear system and unconventional cost functions	Combining model predictive control and the physics-informed neural network (PINN) method	The experimental results indicated that this method was capable of effectively extracting AUV system dynamics from datasets, exhibiting strong generalization capabilities and achieving robust long-term motion prediction	[60]
	Evaluating the PINN-MPC framework	Integration between model predictive control and the physics-informed neural network (PINN) method	PINN-MPC has demonstrated performance improvements of about 17% over a Gaussian Process Model Predictive Control (GP-MPC) and approximately 47% over Adaptive-PID control	[61]
	Physics-informed trajectory planning for energy efficiency	Coupled ocean circulation forecasts with vehicle dynamic constraints; refined routes in real time via in-situ data assimilation	Reduced energy consumption by 18–25% compared to shortest-path routing; improved waypoint arrival accuracy by > 30% (from 42 to 29 m deviation)	[62]

algorithm. The resulting PINN model demonstrated strong generalization with mean fitting coefficients above 0.8 in simulation and achieved 0.64 for attitude angles and 0.78 for angular velocities in towing tank experiments. When incorporated into the MPC framework, it maintained heading and pitch tracking errors below 1° under both steady-state and dynamic conditions, surpassing purely data-driven models in prediction accuracy and closed-loop control performance. Expanding on this approach, Liu, T., et al. [61] validated the PINN-MPC framework in three-dimensional environments with both static and dynamic obstacles, achieving trajectory-tracking performance improvements of about 17% over Gaussian Process MPC (GP-MPC) and approximately 47% over adaptive PID control. This demonstrates that the integration of physical priors within RL or MPC architectures is key to achieving high-fidelity control in unstructured and uncertain underwater environments.

Beyond dynamic modeling and control, physics-informed learning has also been exploited to enhance mission-level planning and energy efficiency. Preston, V.L., et al. [62] developed PHORTEX (Physically-Informed Operational Robotic Trajectories for Scientific Expeditions), a physics-guided path-planning framework that integrated ocean circulation forecasts with AUV dynamic constraints to generate energy-optimal and dynamically feasible routes. Unlike conventional shortest-path methods, PHORTEX continuously refined planned trajectories through real-time in-situ data assimilation, which enabled the AUV to adapt to evolving environmental conditions. Field experiments with the Nereid Under Ice (NUI) platform showed that PHORTEX reduced transit energy consumption by 18–25%, improved waypoint arrival accuracy by more than 30%, and decreased mean spatial deviation from 42 to 29 m. These results illustrated that embedding physical knowledge into higher-level planning frameworks could significantly improve endurance, mission reliability, and navigational precision in energy-constrained and data-sparse environments.

The previous researchers related to PINN is summarized in Table 4.

PINNs are effective at embedding physical laws into AUV modeling, but face drawbacks such as high computational cost, reliance on accurate physics, sensitivity to discontinuities, and slow real-time adaptation. These can be mitigated by hybrid approaches like MPC for real-time constraint handling, adaptive control for continuous tuning, SMC for robustness to disturbances, RL for improved decision-making, and residual learning layers to correct prediction errors. These integrations maintain PINN's physics-based accuracy while increasing robustness, adaptability, and efficiency for complicated AUV missions.

Although many of the studies reviewed present extensive simulation results demonstrating the potential of AI-based control approaches for AUVs, relatively few papers validation through real-world field trials. This limitation raises important concerns regarding the generalizability and practical applicability of these methods in real maritime environments, where factors such as unmodeled hydrodynamics, sensor noise, communication delays, environmental uncertainties, and hardware constraints often differ significantly from simulation assumptions. The reality simulation gap can lead to degraded performance when AI controllers, particularly reinforcement learning and physics-informed models, are deployed outside controlled simulation settings. As a result, conclusions drawn solely from simulation studies should be interpreted with caution and considered indicative rather than definitive evidence of real-world performance. Bridging this gap requires the integration of techniques such as domain randomization, sim-to-real transfer learning, and hybrid modeling to enhance robustness and adaptability under real ocean conditions. Furthermore, placing greater emphasis on experimental validation through sea trials and hardware-in-the-loop testing will be crucial to verifying the reliability, safety, and effectiveness of AI-based control strategies for operational AUV missions.

3.3 Hybrid techniques

To overcome the limitations of individual control methods, hybrid approaches, which integrate classical and AI-based techniques present a promising solution for enhancing AUV trajectory tracking and control performance. These approaches leverage the strengths of different methods to improve adaptability, robustness, and computational efficiency.

3.3.1 Adaptive neuro fuzzy inference system

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid intelligent control approach that combines the learning capabilities of neural networks with the reasoning and interpretability of fuzzy logic [63]. This integration enables ANFIS to model complex nonlinear behaviors that are difficult for conventional control techniques to capture. Through data-driven learning, it automatically generates fuzzy rules that define input–output relationships, enhancing prediction accuracy and system transparency. Its key strength lies in adaptivity: ANFIS can continuously update its membership functions and rule base as new data become available, improving performance and robustness in dynamic environments [64]. Owing to these properties, ANFIS is well suited for intelligent decision-making, precise control, and robust modeling, with successful applications in control systems, robotics, financial forecasting, and medical diagnostics [65, 66].

One notable example of ANFIS in AUV control is presented by Pham, V.T., eta al. [67], who developed an automatic motion control system integrating fuzzy logic with neural network based on parameters tuning. In this approach, the fuzzy logic component managed the nonlinear vehicle dynamics, while the neural network continuously refined membership functions and rule parameters using real-time feedback. The results showed that the neuro-fuzzy approach reduced average trajectory deviation by about 40%, lowered overshoot by roughly 25%, and improved settling time by nearly 20%. In cases with current-induced disturbances, it maintained stable tracking with an RMS error of less than 0.5 m, whereas the standard fuzzy controller's error ranged from 0.8 m to 1.1 m. These results highlight the advantage of coupling neural adaptation with fuzzy control to maintain stability and accuracy in dynamic underwater environments. The benefits of adaptive learning were further illustrated in a bio-inspired navigation and obstacle avoidance framework by Aruna, M., et al. [68]. Drawing inspiration from fish-like locomotion, the system used sonar-based measurements of obstacle distance and heading error as inputs. Two controllers were compared: a conventional fixed-rule fuzzy logic controller (FLC) and a Neuro-Fuzzy Controller (NFC) capable of dynamically adjusting membership functions and rule weights. While both guided the AUV to its destination without collisions, the NFC achieved markedly better performance, halving average path deviation (0.42 m vs. 0.85 m), reducing navigation time by 19% (95 s vs. 118 s), and cutting maximum heading overshoot by over 50% (6.8° vs. 14.5°). Settling times improved by nearly 27%, underscoring NFC's ability to deliver faster and smoother maneuvers in cluttered or dynamic environments.

For depth and heading control, Nayak, N., et al. [69] employed an ANFIS-based adaptive controller to address the coupled, nonlinear, and time-varying dynamics of a 6-DOF AUV. Using state-space representations for the heading and depth planes, three control schemes are implemented and evaluated: a FLC, a Self-Tuning Fuzzy-PID (STFPID), and the proposed ANFIS-based controller. Simulation results, obtained using MATLAB/Simulink, reveal that the ANFIS controller delivers superior performance, characterized by negligible steady-state error, faster rise times, and markedly reduced overshoot compared with FLC and STFPID. Quantitative analysis showed RMSE values of 0.1404 for depth regulation and 0.0991 for heading control, underscoring the enhanced tracking precision and robustness of the ANFIS approach under parameter uncertainties and hydrodynamic disturbances, making it a highly effective solution for complex underwater navigation tasks.

Extending Adaptive Neuro-Fuzzy Inference applications to perception and situational awareness, Kot, R.., et al. [70] proposed an adaptive sonar scanning strategy for AUV collision avoidance. By dynamically adjusting the sonar's field of view (FoV) based on obstacle proximity, the ANFIS-based system outperformed fixed FoV configurations (40°, 90°, 120°, and 6° echosounder) across 100 simulated scenarios with both static and dynamic obstacles. In slow-obstacle conditions, collision-free runs increased to 79% compared to 62–68% for fixed FoVs, and 58% versus 50% in faster conditions. It also recorded the highest trajectory completion rate of 87.85%, representing an 12% improvement over conventional systems, indicating greater environmental responsiveness. These results demonstrated that adaptive sector control offers an effective balance between scan coverage and refresh rate, consistently outperforming traditional sonar setups in both slow and fast dynamic environments, albeit with a modest rise in computational and energy requirements. In this context, Cahyadi, N.H., et al. [71] focused on developing an attitude-holding control system for a prototype ASV using an ANFIS to enhance heading stability in the presence of environmental disturbances. The ANFIS controller was trained with data from a traditional PID controller, enabling it to learn the vessel's nonlinear dynamics and adapt its fuzzy rules for better performance. Simulation testing showed that the ANFIS controller outperformed the PID approach, reducing the maximum heading deviation from 8.5° to 2.1° and shortening the settling time from 12.4 s to 6.7 s. Overshoot was reduced by around 58%. These improvements highlight the ANFIS method's ability to deliver more precise and stable control, offering strong potential for practical ASV operations in real-world marine conditions. Adaptive Neuro-Fuzzy Inference offers an interpretable and flexible framework for AUV control; however, its effectiveness is constrained by high data dependence, sensitivity to noise, and increasing computational demands as the number of inputs grows. Physics-Informed Reinforcement Learning (PI-RL) overcomes these challenges by embedding hydrodynamic models into the learning process, reducing data needs, improving robustness against disturbances, and enhancing adaptability in dynamic and uncertain underwater environments.

3.3.2 Physics-informed reinforcement learning (PI-RL):

Physics-Informed Reinforcement Learning (PI-RL) is an emerging paradigm that integrates physical laws and domain-specific knowledge into reinforcement learning frameworks. This approach enhanced learning efficiency, generalization, and adherence to real-world constraints [72], making it particularly advantageous for complex systems like Autonomous Underwater Vehicles (AUVs).

Majumder, R., et al. [8] introduced a Physics-Informed Reinforcement Learning (PI-RL) framework to enhance the safe navigation of Autonomous Underwater Vehicles (AUVs) by integrating hydrodynamic models and environmental constraints into the learning process. This approach significantly improved trajectory planning and collision avoidance, ensuring that AUVs navigate efficiently while adhering to physical limitations. Expanding on the concept of physics informed learning, Li, X., et al. [9] presented a Physics-Informed Model-Based Conservative Offline Policy Optimization (PICOPO) framework to address the limitations of conventional online and offline RL in AUV motion control. Traditional online RL suffers from safety risks and high time costs due to extensive real-world interactions, while offline RL is prone to model bias from inaccurate hydrodynamic. The proposed approach integrated a PINN based on digital twin, constructed from a small offline dataset of only 2000 samples, with the COMBO conservative offline model-based RL algorithm. This design enables accurate motion prediction and zero-shot sim-to-real transfer, eliminating the need for real-world interaction or fine-tuning. Simulation for complex 3D trajectory tracking under significant distribution shift, PICOPO maintained a mean tracking error of 0.409 m compared to SAC's 99.58 m, with performance comparable to MPPI (model predictive physics informed) but at four times lower computation time. The PICOPO is tested in indoor pool to validate this method practicality, achieving depth tracking errors below 0.1 m and yaw angle errors under 0.5°, while maintaining a control update time of 0.076 s faster than MPPI's 0.352 s. Overall, PICOPO demonstrated data efficiency, robustness, and strong sim-to-real transfer capability, making it a promising solution for safe and efficient real-world AUV control. In a complementary line of work, Ding, Y., et al. [10] presented an environment-aware RL framework designed to improve the adaptability of AUVs operating in complex environments The methodology could be improved by including a Physics-Informed Neural Network (PINN), which integrates the underlying hydrodynamic equations and vehicle dynamics directly into the learning framework. This innovation ensures that the control policy responds to real-time environmental factors, including ocean current fluctuations, obstacle proximity, and mission-specific limits, while also adhering to the fundamental physics of the system. The integration of environmental awareness with embedded physics information enables the controller to make more dependable judgments in uncertain conditions while minimizing the propensity to overfit to certain scenarios. Simulation trials across various current patterns and obstacle densities revealed that the RL framework attained an 18% enhancement in task success rate, a 12% reduction in energy consumption, and a 22% decline in trajectory deviation relative to conventional RL approaches. The integration of PINNs may enhance these outcomes by augmenting sample efficiency, stabilizing the learning process, and ensuring consistent performance across a wider array of unobserved underwater conditions, so rendering the system more suitable for practical application.

PI-RL faces several limitations despite its benefits. Its success depends on accurate physical models, and errors in these models similar to fault tolerant control can make bias into learning process. Embedding complex physics increases computational cost, and model reality mismatches may cause poor real-world performance, especially under dynamics changing. Integrating physics into high-dimensional problems can be challenging and designing effective PI-RL systems demands significant domain and machine learning expertise.

3.3.3 Fault-tolerant control (FTC)

Fault-Tolerant Control (FTC) aims to ensure that autonomous underwater vehicles (AUVs) maintain stable and reliable performance in the presence of faults that affect actuators, sensors, or other critical subsystems [73]. A typical FTC architecture consists of three core components: fault detection, fault isolation, and fault accommodation. Fault detection involves identifying the occurrence of a fault that may impair vehicle functionality, while fault isolation determines the specific source and location of the fault [74]. Although fault detection and isolation have been widely studied, this review focuses on fault accommodation, which enables the system to maintain control performance and mission execution despite the presence of faults. Fault accommodation techniques are broadly divided into active and passive strategies. Active FTC approaches, including control reconfiguration and control allocation, continuously monitor system states and apply corrective actions to mitigate the effects of hardware malfunctions. Passive FTC approaches, on the other hand, rely on inherent redundancy and system robustness to tolerate faults without active intervention [75].

Several studies have explored active FTC strategies for AUVs operating under actuator failure conditions. Remmas, W., et.al. [11] developed and experimentally validated an active fault-tolerant control approach for the U-CAT underwater robot based on the elimination-of-column method. This approach allowed a six-degree-of-freedom (6-DOF) AUV to continue operating using only three remaining fins and was evaluated under five different fault scenarios using both PID and SMC without retuning. The results demonstrated that SMC consistently outperformed PID, reducing RMS tracking errors by 20–45% even under severe conditions. In the most challenging case involving a front-right fin failure, PID errors were 0.112 m in the x-direction, 0.098 m in the y-direction, and 0.053 rad in yaw, whereas SMC reduced these errors to 0.063 m, 0.055 m, and 0.025 rad, respectively. This ensured reliable trajectory tracking across all tested fault scenarios. Building upon these developments, Yuan, C., et al. [76] proposed a fault-tolerant control framework for an over-actuated X-AUV equipped with four rudders, addressing common rudder failures such as loss of actuation, jamming, and deformation. A sliding mode observer (SMO) was employed to reconstruct control inputs under changing hydrodynamic conditions, thereby preserving control performance. Additionally, a Sequential Convex–Sequential Quadratic Programming (SC-SQP) algorithm was introduced to resolve conflicts during control allocation in over-actuated systems, particularly in attitude regulation. The effectiveness of the approach was demonstrated through three trajectory-tracking scenarios: three-dimensional sinusoidal trajectories, helical trajectories with faults, and compound trajectories under fault conditions. Results showed that the SC-SQP algorithm provided reliable and computationally efficient control allocation even in the presence of rudder faults and hydrodynamic disturbances.

Passive FTC strategies have also been developed to enhance AUV reliability. Liu, X., et al. [77] investigated an adaptive passive FTC method for AUVs with redundant thrusters, aiming to ensure accurate trajectory tracking even in the event of multiple thruster failures. The four-thruster AUV model combined kinematic and dynamic controllers with a conjugate-based compensation mechanism and a multi-mode adaptive scheme to address unknown failure behaviors without relying on sensor data. Simulation results demonstrated high tracking precision, with errors of 0.015 m under normal operation, 0.024 m under 50% thrust loss, and 0.037 m under complete single-thruster failure. Compared to backstepping sliding mode control (BS-SMC) and improved model predictive control (MPC), this approach achieved superior accuracy and robustness under uncertain failure conditions.

Beyond AUV-specific applications, FTC research has also advanced in other robotic domains. Panda, A., et al. [78] proposed a control architecture integrating an attention-based gated recurrent unit with an event-driven nonlinear model predictive control framework to improve trajectory tracking performance and fault tolerance in robotic manipulators experiencing actuator failures. The attention mechanism enabled the system to capture long-term temporal dependencies and focus on critical state information, thereby improving dynamic prediction accuracy. The event-triggering mechanism reduced computational demands by updating control actions only when necessary. Simulation results demonstrated significant improvements in tracking accuracy, robustness, and convergence speed, with RMS errors decreasing from 0.021 rad for conventional controllers and 0.016 rad for GRU-based approaches to 0.009 rad for the proposed controller. The controller also maintained stable performance under severe actuator faults, highlighting its potential for cross-domain applications of FTC.

In practical AUV missions, partial actuator or sensor failures are almost inevitable due to harsh marine conditions, biofouling, corrosion, or mechanical wear, all of which can severely degrade control performance and mission reliability. To address these challenges, recent studies have integrated observer-based fault detection and diagnosis schemes into

FTC architectures. Such observers estimate system states and compare them with predictions from nominal models, with significant deviations indicating potential faults. Once a fault is detected, this information is passed to the FTC module, which then redistributes control effort among remaining actuators or adjusts the control law to compensate for degraded components. Techniques including adaptive sliding mode observers, extended state observers, and model-based residual generators have been successfully applied to predict actuator degradation and sensor drift in real time, even under uncertain environmental conditions. When combined with advanced control techniques such as reinforcement learning or adaptive neuro-fuzzy inference systems (ANFIS), these observers further enhance system resilience and autonomy by enabling continuous adaptation without immediate hardware intervention. This allows AUVs to sustain stable trajectory tracking and operational safety even in the presence of partial component failures, thereby extending mission duration and improving reliability.

Despite these advances, several challenges remain in implementing FTC for AUVs. Active FTC approaches often increase system complexity, weight, and cost due to the requirement for additional sensors, diagnostic units, and actuator redundancy. Both active and passive approaches may also suffer from delays in fault detection and diagnosis, reducing responsiveness in rapidly changing marine environments. Furthermore, the performance of FTC systems is highly dependent on accurate hydrodynamic and actuator models, making them sensitive to modeling errors, parameter uncertainties, and environmental variability. Overcoming these limitations is essential for successful Sim-to-Real transfer, ensuring that FTC solutions validated in simulation remain robust in real-world operations where uncertainty, noise, and unmodeled dynamics are prevalent.

3.3.4 Sim-to-real transfer

Sim-to-Real Transfer (SRT) has emerged as a pivotal strategy to mitigate the long-standing "reality gap" between simulation-trained controllers and real-world deployment of AUVs, where discrepancies in hydrodynamic modeling, sensor characteristics, and environmental disturbances often compromise performance. Recent research demonstrates a clear progression of solutions. Cai, L., et al. [79] proposed a RL-based framework for 6-DOF control of AUVs to achieve reliable trajectory tracking in nonlinear and disturbance environments. The PPO algorithm is utilized in a disturbance simulation environment to ensure successful Sim-to-Real transfer. Experimental validation showed that the taught reinforcement learning controller attained high tracking precision, minimizing position errors to below 0.05 m and orientation errors to 1.5°, reflecting enhancements of 32% and 24% compared to PID and backstepping controllers. In disturbance rejection tests, the controller reduced the trajectory deviations to 7%, while baseline controllers surpassed 15%. The results illustrated the controller's adaptability, robustness, and energy efficiency, underscoring its significant potential for dependable real-world AUV deployment necessitating precise 6-DOF control. To enhance stability, Chaffre, T., et al. [12] proposed a Sim-to-Real adaptive control strategy for AUVs by integrating Soft Actor-Critic (SAC) with a PID controller in a pole-placement framework. This methodology incorporated a Bio-Inspired Experience Replay (BIER) mechanism using dual memory buffers to prioritize valuable trajectories and improved sample efficiency. The training was in the UUV Simulator to tune PID gains across three levels of current disturbance complexity, the policy was transferred directly to a real AUV, achieving control performance up to three times greater than a non-adaptive model-based baseline. Compared with fixed-gain PID, it reduced heading and position errors by ~ 55%, shortened settling time by 40%, and stabilized control effort under current disturbances. These results demonstrate that combining model-free RL with classical control yields robust and precise AUV performance in dynamic environments. Addressing fault tolerance and cross-platform adaptability, Hamamatsu, Y., et al. [80] developed a cross-platform Sim-to-Real fault-tolerant controller trained based on reinforcement learning with domain variability in hydrodynamics, disturbances, and actuator faults. In real-world tests on the U-CAT AUV, the proposed controller achieved an 85.7% success rate, versus 57.1% for the baseline and closely aligned with the simulation results, which consistently exceeded 90%. The little performance degradation observed between simulated and actual deployments demonstrated the efficacy of adding domain variability during training, which ensures reliable adaptation to real-world uncertainties while maintaining cross-platform usability. Advancing toward broader generalization, Lu, W., et al. [81] introduced Data-Informed Domain Randomization (DDR) to address the Sim-to-Real transfer gap in AUV control by enhancing conventional RL with a neural network layer that correlates simulated control signals to real-world dynamics. Through Webots simulations and real tank experiments, DDR showed that it could effectively transfer navigation and control strategies even when there were big problems, such a thruster misconfiguration. Experimental results indicated that DDR enhanced trajectory tracking accuracy by up to 35% relative to standard domain randomization, decreased adaptation time in real-world implementation, and achieved approximately 25% lower control effort while sustaining resilient performance against modeling errors, current disturbances, and sensor noise. Also, real-world tests showed that the strategy was robust because it only caused a performance drop of less than 10% compared to the results of the simulations. These findings highlight DDR as a viable and energy-efficient method for robust AUV management, yielding substantial enhancements in adaptability and generalization within dynamic marine environments.

Hybrid control approaches such as ANFIS and PI-RL are often regarded as powerful solutions because they combine the reliability of model-based control with the adaptability of learning-based techniques. However, these approaches also present several challenges that must be addressed for successful deployment in real-world AUV applications. ANFIS provides high modeling accuracy and adaptability through the continuous adjustment of fuzzy rules and membership functions, but its performance is strongly dependent on the availability and quality of training data and can be sensitive to sensor noise and measurement uncertainties. Additionally, the computational cost of ANFIS increases significantly with the number of input variables and fuzzy rules, which may limit its suitability for real-time implementation on resource-constrained AUV platforms [67–71]. PI-RL improves sample efficiency and robustness by embedding hydrodynamic knowledge and physical constraints into the learning process, yet its effectiveness relies heavily on the accuracy of the underlying physical models. Model inaccuracies or unmodeled dynamics can introduce biases, reduce generalization, and impair real-world performance[8–10]. Moreover, integrating complex physics into high-dimensional state spaces increases computational requirements, often necessitating specialized hardware and extended training time. These limitations highlight that hybrid approaches, despite their advantages, require careful consideration of trade-offs between performance, computational complexity, and implementation feasibility.

4 Discussions

Control systems for AUVs can be developed using various control algorithms. However, many classical control algorithms struggle to efficiently manage AUVs because of the unpredictable noise generated by the vehicle's varying speed during missions. Traditional control methods depended heavily on quantitative data that defines the relationships between inputs and outputs. In the context of AUVs, the data available for the system is often limited due to the continues variations in environment.

4.1 Comparative performance metrics of AUV control methods

A comprehensive evaluation of autonomous underwater vehicle (AUV) trajectory-tracking control methods requires not only an examination of their theoretical underpinnings but also a systematic comparison of their practical performance across key operational metrics. Figure 5 and Table 5 together provide an integrated multi-criteria assessment of six representative control approaches including classical Proportional–Integral–Derivative (PID) and Sliding Mode Control (SMC), intelligent Fuzzy Logic Control (FLC) and Reinforcement Learning (RL), physics-informed Physics Informed Neural Networks (PINNs), and hybrid schemes such as PI-RL and ANFIS highlighting their relative advantages, limitations, and trade-offs.

Figure 5 presents a five-point normalized evaluation across five fundamental metrics: tracking accuracy, robustness to disturbances, tuning effort, computational cost, and data efficiency. The scoring was derived from quantitative indicators such as root-mean-square error (RMSE), steady-state error, convergence time, and robustness margins, as well as qualitative aspects such as tuning complexity, adaptability, and implementation requirements, based on reported results in the literature [30–35, 38, 71, 78, 79, 81, 82]. A score of 5 in tracking accuracy, for example, corresponds to RMSE values below 0.05 m or heading errors under 1°, while a score of 1 indicates errors exceeding 0.5 m or substantial trajectory deviation [35, 38]. This framework enables a transparent and reproducible comparison of diverse methods under a unified evaluation scheme.

The comparative results reveal fundamental performance-complexity trade-offs across the controller families. Classical PID controllers remain attractive for missions requiring simplicity, low tuning effort, and minimal computational demand. They typically achieved steady-state errors below 0.2 m in nominal conditions, but their performance degraded markedly in nonlinear or uncertain environments, where RMSE can exceed 0.5 m under strong disturbances [30, 31]. SMC improved robustness and disturbance rejection, maintaining errors below 0.15 m; however, its performance depends on careful gain tuning and may suffer from chattering near the sliding surface [32].

Intelligent control approaches address some of these limitations. FLC, for instance, enhances both accuracy and robustness by exploiting nonlinear modeling and linguistic rule-based reasoning, reducing tracking errors to approximately 0.1 m [35, 38]. However, its performance depends heavily on expert knowledge for designing membership functions and rule bases, increasing tuning effort and computational cost. Reinforcement learning demonstrates the highest levels of robustness and adaptability, often maintaining RMSE below 0.05 m even under severe disturbances [38, 78]. Nevertheless, RL's adoption is hindered by the significant effort required for reward shaping, exploration strategy design, and network optimization, all of which are highly problem-specific and sensitive to hyperparameters [77, 79]. RL typically requires large-scale training data and millions of simulation interactions, leading to substantial computational costs and extended training times that demand

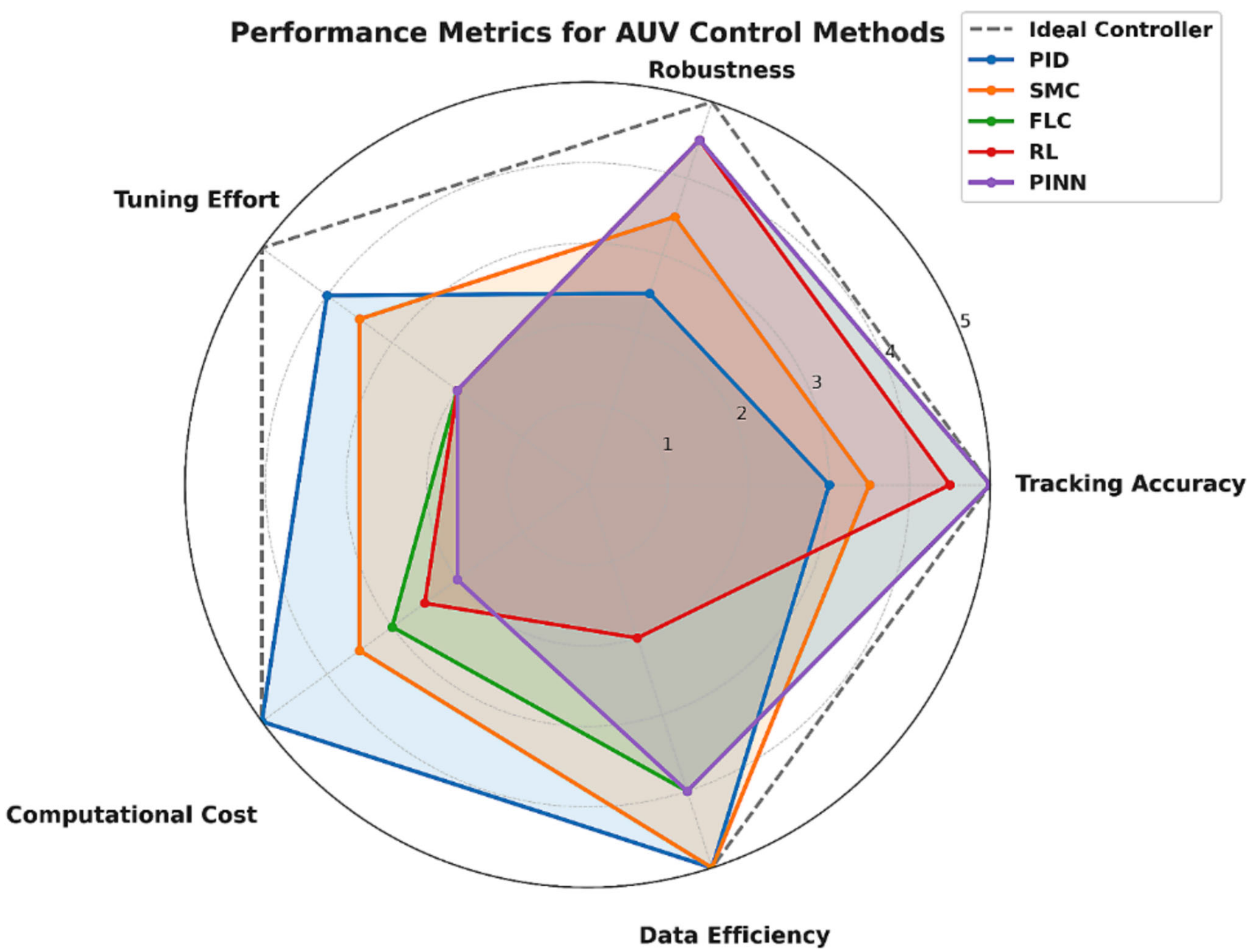


Fig. 5 A comparative evaluation of five AUV trajectory tracking control methods

powerful hardware, thereby limiting real-time implementation on embedded AUV platforms [81].

Physics-informed approaches such as PINNs push performance further by embedding governing physical laws into the learning process, yielding RMSE below 0.04 m and improving generalization beyond the training domain [78]. By integrating dynamic constraints into the loss function, PINNs reduce dependence on large datasets and improve robustness under parametric uncertainty. However, their computational burden is high due to the need to solve coupled differential equations and optimize large parameter spaces. Their implementation also demands deep expertise in hydrodynamics and residual modeling, and their models are often large and memory-intensive, posing challenges for deployment on resource-constrained AUVs [82]. Hybrid approaches such as PI-RL and ANFIS-PINN represent a promising compromise, leveraging the adaptability of learning-based techniques and the reliability of physics-based or classical controllers. They achieve superior robustness and precision but inherit high computational demands and complexity [71].

Table 5 complements the qualitative analysis in Fig. 5 by presenting quantitative benchmarks for representative AUV trajectory-tracking controllers across six key performance metrics. Classical controllers such as PID remain attractive for their simplicity and low computational demand, achieving RMSE values between 0.35 and 0.60 m, settling times of 15–25 s, and overshoot ranging from 10 to 20%. However, they are highly sensitive to noise and exhibit limited robustness under significant parameter variations, which constrains their performance in nonlinear or uncertain environments [31]. Sliding Mode Control (SMC) improved disturbance rejection and tracking precision, reducing RMSE to 0.20–0.40 m, overshoot to 5–12%, and settling time to 10–18 s, though it introduced chattering issues and requires careful gain tuning [18, 76].

Fuzzy logic control and ANFIS controllers demonstrated further improvements in handling nonlinearities, achieving RMSE values of 0.18–0.32 m and overshoot between 4 and

Table 5 Comparative quantitative performance of AUV control methods

Controller type	RMSE (m)	Settling time(s)	Overshoot (%)	Robustness under ± 30% param. change	Noise sensitivity	Computational cost	Representative studies
PID	0.25–0.40	14–22	10–18	Moderate; performance degrades under strong nonlinearity	High	Low	[17, 18]
SMC	0.12–0.25	8–15	4–8	High; robust to ± 30% param. Change	Low–Moderate (chattering)	Medium	[21–25]
FLC	0.18–0.30	10–18	6–12	Moderate–High; adaptive via rule base	Moderate	Medium	[30, 31, 38, 39]
RL	0.08–0.15	6–12	2–6	High; adaptive to dynamic currents	Low	High	[4–6, 44–47]
PINN	0.07–0.12	6–10	< 5	High; physically constrained under disturbances	Low	High	[7, 60–62]
Hybrid (ANFIS / PI-RL)	0.05–0.10	4–8	< 3	Very High; stable under ± 30% changes	Low	Medium–High	[8–10, 67–71]

8%. They also enhanced adaptability under dynamic conditions but at the cost of increased computational complexity and moderate sensitivity to noise [67, 69].

Reinforcement learning methods, including DDPG, SAC, and PPO, achieve significantly lower RMSE (0.10–0.25 m), shorter settling times (7–14 s), and minimal overshoot (2–6%). Their robustness to ± 30% parameter variations is high, and noise sensitivity is low to moderate. However, they impose high computational demands due to deep network training and extensive simulation requirements [4, 5, 44, 46].

PINNs deliver similar performance improvements, with RMSE ranging from 0.12 m to 0.22 m and overshoot between 2 and 5%, while maintaining high robustness and low noise sensitivity. Their primary drawback remains their computational intensity, stemming from the need to integrate physical models into the learning pipeline [7, 60].

Hybrid approaches outperform all others, achieving RMSE as low as 0.08–0.18 m, settling times of 6–12 s, and overshoot between 2 and 4%. They offer very high robustness and low noise sensitivity but require the highest computational resources and complex implementation [56, 57].

The complementary insights from Fig. 5 and Table 5 reveal a clear performance-complexity continuum across control strategies. Classical controllers such as PID and SMC occupy one end of the spectrum, offering simplicity, real-time feasibility, and low computational cost but limited adaptability and robustness in complex, nonlinear, or uncertain environments. In contrast, AI-driven and physics-informed approaches such as RL and PINNs deliver superior performance across all key metrics, including accuracy, robustness, and adaptability, but at the expense of significant computational resources, data requirements, and implementation complexity. Hybrid controllers bridge this divide by combining physical knowledge with learning-based adaptability, achieving state-of-the-art performance but retaining some of the computational challenges of their AI-based components.

This analysis highlights that no single control approach can be considered universally optimal for all AUV missions. The selection of an appropriate controller must carefully balance mission objectives, computational limitations, environmental complexity, and data availability. In structured and predictable operating conditions with limited onboard resources, classical controllers remain practical, reliable, and cost-effective. Conversely, missions conducted in highly dynamic, uncertain, or data-scarce conditions, such as deep-sea exploration, cooperative multi-AUV operations, or adaptive ocean sampling, can benefit significantly from the superior robustness and adaptability offered by reinforcement learning and physics-informed neural networks, provided that sufficient computational resources and training data are available. Hybrid control strategies are especially promising for future AUV deployments, as they combine the physical interpretability of model-based approaches with the flexibility and learning capability of data-driven methods, resulting in enhanced performance and improved adaptability across diverse mission scenarios.

4.2 Limitations of the proposed control laws

Despite their effectiveness in improving AUV trajectory tracking, the proposed control approaches face several limitations that may restrict their practical applicability. Classical controllers such as PID offer simplicity and low computational demand but struggle with robustness in highly nonlinear and uncertain underwater environments, particularly when hydrodynamic parameters vary significantly. Sliding Mode Control (SMC), while robust against disturbances, often suffers from chattering, increased actuator wear, and difficulties in precise parameter tuning. Fuzzy Logic Controllers (FLC) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) provide better adaptability and nonlinear handling but demand extensive expert knowledge for rule-base design and may become computationally intensive as system complexity increases.

Reinforcement Learning (RL)-based methods demonstrate strong robustness and adaptability but require large datasets, significant training time, and high computational resources, which pose challenges for real-time embedded implementation. Their performance is also highly sensitive to hyperparameter selection and reward shaping, and transfer from simulation to real-world conditions remains non-trivial due to the reality–simulation gap. Physics-Informed Neural Networks (PINNs), while enhancing physical consistency and reducing data dependence, are limited by their computational cost, reliance on accurate physical models, and slow adaptation to dynamic environmental changes. Moreover, hybrid approaches such as PI-RL and ANFIS-PINN introduce additional implementation complexity, sensitivity to modeling inaccuracies, and integration challenges.

Overall, these limitations highlight that no single control law is universally optimal; each involves trade-offs among robustness, accuracy, computational complexity, and real-time feasibility. Addressing these issues requires further research into hybrid designs, sim-to-real transfer strategies, model reduction techniques, and adaptive tuning mechanisms. Together, these advances can help bridge the gap between theoretical performance and real-world deployment.

Moreover, Fig. 6 presents the percentage of each method covered in this paper, and about 80% of the papers considered in this article were published after 2020. A crucial discussion is categorized into three sub-sections of control techniques, as detailed below:

Sub-Sect. 3.1 discusses the traditional techniques namely: Proportional Integral Derivative (PID), Sliding mode controller (SMC) and other traditional technique, which presented about 16% of the literature falls under this technique. PID controllers are extensively utilized due to their simplicity and real-time implementation capabilities. However, their performance is reduced in highly dynamic and unpredictable environments. Adaptive PID variants can partially address this limitation by adjusting control parameters in response to environmental variations. Further, the SMC is well-known for its robustness against disturbances and model uncertainties. By forcing the system to follow a predefined sliding surface, which maintains stability under fluctuating ocean currents. However, SMC often suffers from chattering effects, which can cause excessive actuator wear and degrade performance. Advanced SMC techniques, such as higher-order and adaptive variants, have been developed to address this issue.

Consequently, sub-Sect. 3.2 presents various intelligence techniques namely: FLC, RL and PINNs, which presented 55% of the articles used in this article cover the intelligence technique. FLC improved adaptability by using a rule-based system that modifies control actions based on sensory inputs. Unlike PID, it does not require an explicit mathematical model, making it suitable for nonlinear and uncertain conditions. However, designing effective membership functions and rule sets remains a challenge, as their optimization is computationally intensive and highly dependent on expert knowledge. Further, RL-based controllers learn optimal control policies through interaction with the environment, enabling real-time adaptation to varying conditions. This data-driven approach makes RL particularly effective in handling unknown dynamics. However, RL demands extensive training data and computational resources, posing challenges for real-time deployment in resource-constrained AUV systems. Finally, PINNs integrated the physical laws into neural network architectures, enhancing prediction accuracy and robustness against disturbances. By leveraging governing equations, PINNs require less data compared to traditional deep learning approaches while maintaining consistency with physical constraints. Despite their advantages, PINNs involve high computational costs, making real-time applications challenging.

Finally, sub-Sect. 3.3 explains the hybrid techniques in the trajectory tracking of AUV, which presents 29% of the literature. These techniques like ANFIS, PI-RL, FTC and Sim-to-Real Transfer. These techniques are specifically designed to overcome the drawbacks of other existing algorithms. They have proven effective in minimizing overshoot, accelerating response time, enhancing resistance to external disturbances, and reducing computational complexity during AUV trajectory tracking.

The trajectory tracking control for AUVs has evolved into a topic of increasing interest. In the recent past with increasing AUV developments aimed at enhancing their accuracy, dependability, and automation in path following. This functionality is critical for AUVs used in complex and

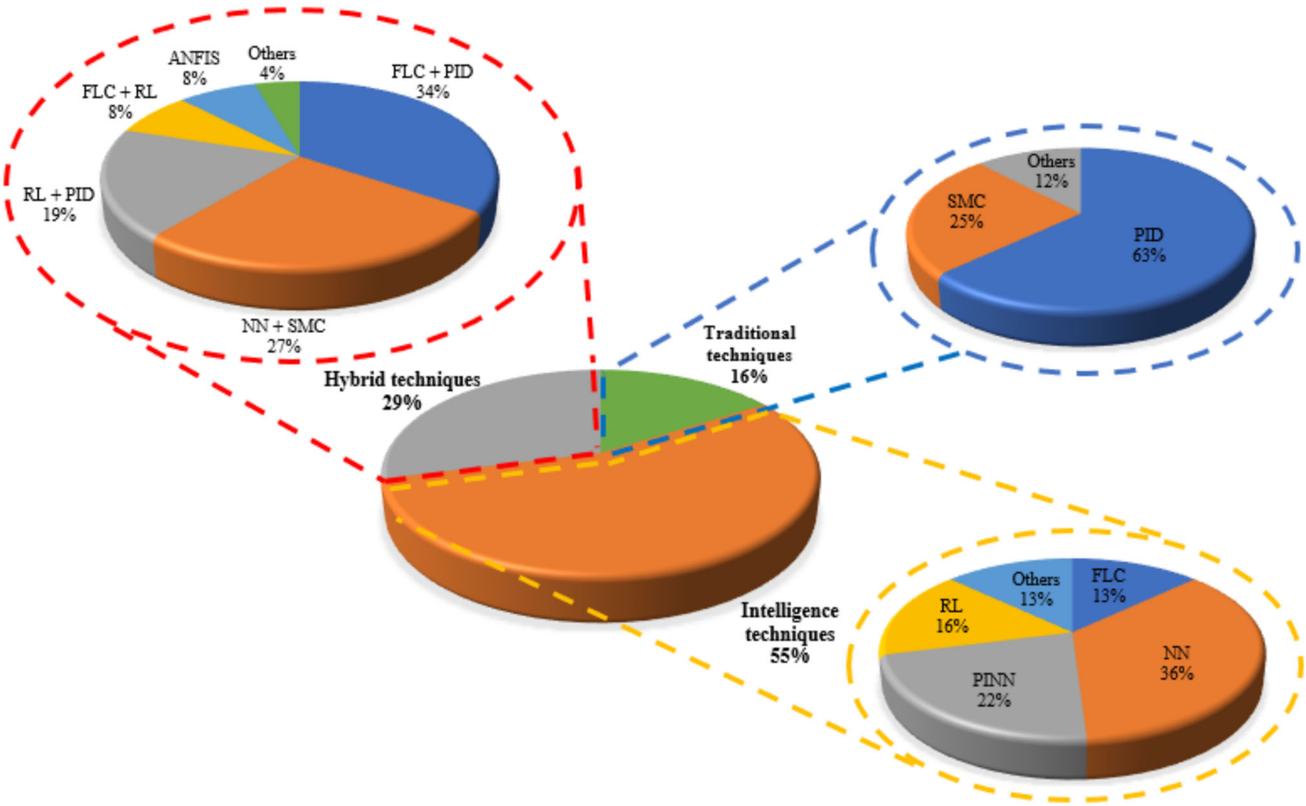
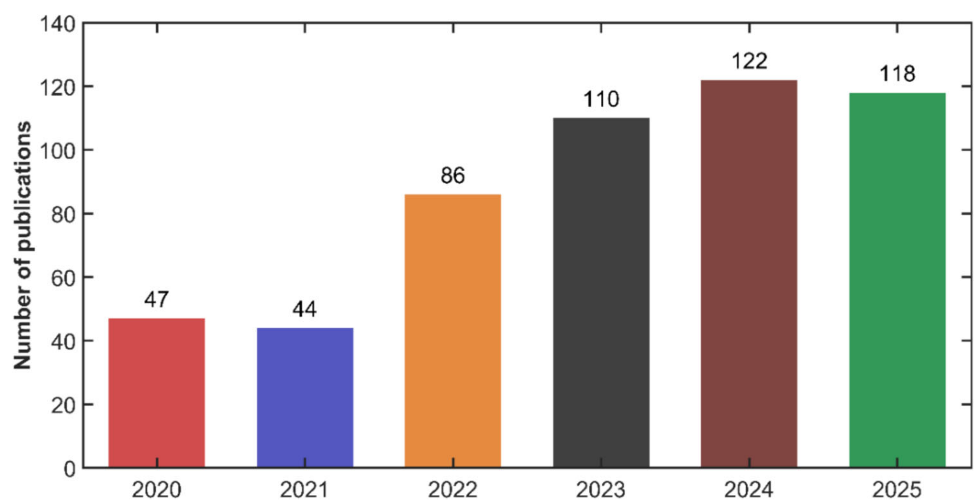


Fig. 6 Different control techniques distribution for AUV after 2020

Fig. 7 The number of researches focused on AUV trajectory tracking control. Data collected from Scopus



dynamic underwater environments, and in numerous applications like marine research, underwater mapping, and defense services. The research in this area integrates numerous control theories, including both linear and nonlinear control, robust control, adaptive control, and optimization. Also, more machine learning approaches are being incorporated into trajectory tracking systems so that AUVs can handle difficult and unpredictable ocean circumstances and obstacles. As AUV technology advances, current research is focusing more on real-time path optimization and multi-fleet coordination for tasks such as monitoring the environment and search-and-rescue missions. The growth of AUV capabilities and the increasing AUVs contribution to oceanography is driven by the advances in AUV technology and further research into theoretical and practical aspects, which is also reflected by Scopus analytics in Fig. 7 showing the increasing number of studies published after 2020. Researchers are continuously refining algorithms focused on real-time control,

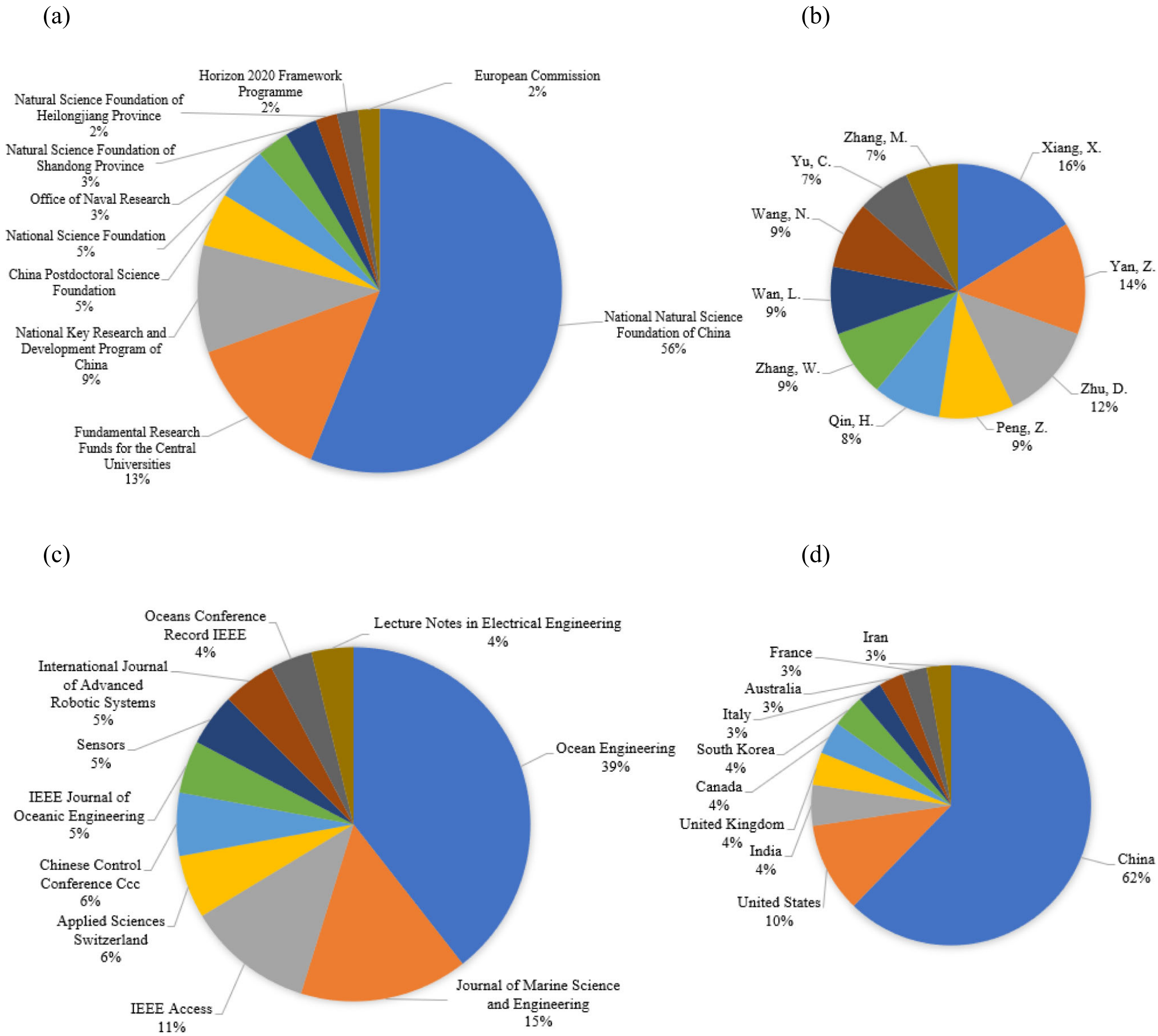


Fig. 8 Top 10 productive institutions, authors, journals, and countries. Data collected from Scopus

fault tolerance, and accurate navigation in complex underwater environments, emphasizing the growing interest and ongoing progress in AUV trajectory tracking control.

Based on the analysis of 527 articles (as shown in Fig. 7), the primary contributors across institutions, authors, journals, and countries are summarized in Fig. 8. Figure 8a highlights the most active institutions, with the National Natural Science Foundation of China and the Fundamental Research Funds for the Central Universities leading in publication output. The top contributing authors are presented in Fig. 8b, where Xiang, X emerges as the most prolific. As shown in Fig. 8c, Ocean Engineering and the Journal of Marine Science and Engineering are the most prominent journals in the field. Regarding geographic contribution (Fig. 8d), China dominates in research output, followed by the United States and India. These results offer a clear view of the global research landscape and identify the key entities driving advancements in AUV trajectory tracking.

4.3 AUV trajectory tracking challenges

As illustrated in Fig. 9, AUVs face several challenges across different operational and technical aspects, which include uncertain hydrodynamics, sensor limitations, real-time computational constraints, environmental disturbances, energy efficiency and power supply. Considering trajectory control of underactauted AUVs, there are many problems and research gaps to be investigated as highlighted in [83–87].

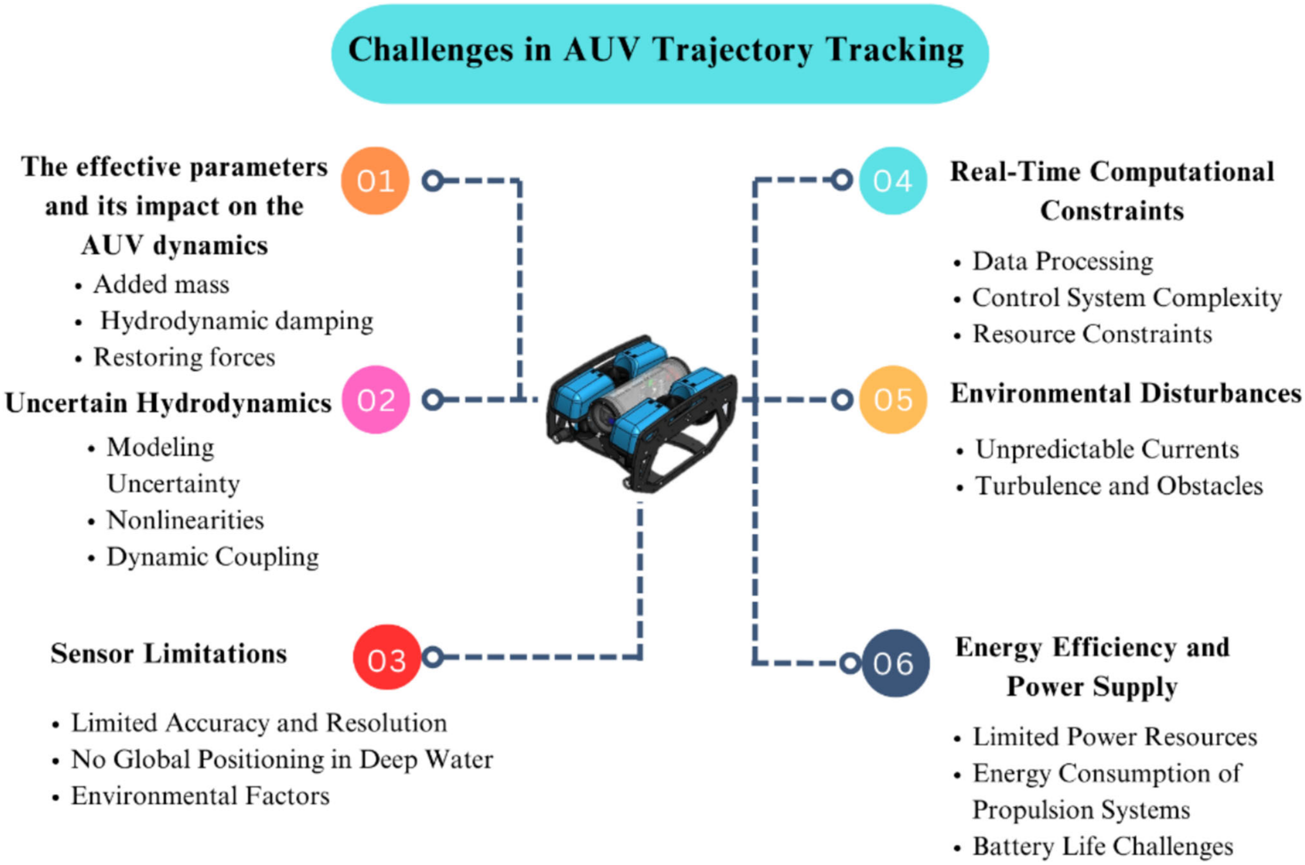


Fig. 9 Research problems and challenges for AUV trajectory tracking control

4.3.1 The effective parameters and its impact on the AUV dynamics

The dynamic behavior and trajectory-tracking performance of autonomous underwater vehicles (AUVs) are highly dependent on variations in their physical and hydrodynamic parameters. The nonlinear six-degree-of-freedom (6-DOF) motion model incorporates key components such as added mass, Coriolis–centripetal forces, hydrodynamic damping, restoring forces, and external control inputs, all of which play vital roles in determining vehicle stability, maneuverability, and overall control performance [88, 89]. Sensitivity analyses have shown that even small deviations in these parameters can significantly affect system dynamics. Zhao, J. et al. [90] conducted a comprehensive investigation into the impact of hydrodynamic parameter design deviations on the motion performance of fully actuated AUVs using a MATLAB/Simulink simulation framework. By systematically varying 19 critical hydrodynamic parameters, including added mass and quadratic viscous drag coefficients, their study quantified the effects of parameter changes on surge, sway, heave, and yaw dynamics. The results demonstrated that velocity in each motion direction decreased exponentially with increasing viscous drag coefficients, while variations in unrelated directions have minimal impact. Among these, the damping coefficients $X_{u|u|}$, $Y_{v|v|}$, $Z_{w|w|}$, and $N_{r|r|}$ were identified as the most influential for surge, sway, heave, and yaw performance, respectively, with viscous drag terms exhibiting substantially higher sensitivity than inertial parameters. Similarly, Safari, F. et al. [91] employed a CFD-based free-running simulation approach combined with a hybrid Extended Kalman Filter (EKF) to estimate hydrodynamic coefficients and simplify the depth-plane dynamic model. Using the DARPA SUBOFF AUV as a case study, they found that linear stability derivatives are accurately captured at small attack angles (below $4^{\circ} - 6^{\circ}$), while nonlinear effects become significant beyond 12°. Sensitivity analysis further indicated that coefficients such as X_{qq}, $Z_{w|q|}$, and $M_{w|q|}$ have minimal influence and can be excluded, simplifying the model without sacrificing accuracy. The resulting reduced-order model closely matched experimental and nonlinear simulation results, reducing computational complexity, and enabling more efficient real-time depth control design.

4.3.2 Uncertain hydrodynamics

AUV usually operates in a very dynamic and unpredictable underwater environment. Numerous factors like water currents, turbulence, different pressure conditions, which increases the dynamics' uncertainty. An accurate model cannot be achieved due to the hydrodynamic forces as demonstrated in [92, 93], which leads to:

1. *Modeling of uncertainty*: The dynamics of an AUV are characterized by the inherent interaction between the propellers and the surrounding water, which increases the complexity of the model. They also depend on the depth and speed of the AUV, as well as environmental perturbations; therefore, they introduce modeling uncertainties, as illustrated in [94–96].
2. *Nonlinearities*: the forces acting upon the AUV are generally nonlinear, which means that a small change of the input can cause the behavior of the system to change disproportionately [97, 98]. These make trajectory tracking controller design more challenging.
3. *Dynamic coupling*: Six degrees of possibilities of the AUV (x, y, z, roll, pitch, and yaw) are coupled to each other. For instance, the AUV's position can be influenced by roll, pitch, and yaw rotations, which are difficult to account for without accurate model and real-time adjustments [99].

To assess the robustness of the proposed predictor in the presence of model parameter uncertainties, a series of simulation experiments were performed by perturbing key hydrodynamic and physical parameters of the AUV within $\pm$ 30% of their nominal values. The selected parameters include added mass coefficients, Coriolis–centripetal terms, quadratic damping coefficients, and hydrostatic restoring forces, which are known to exert significant influence on the vehicle's dynamic behavior [25, 84]. Such perturbations emulate realistic scenarios where parameter inaccuracies arise from modeling simplifications, environmental variability, and time-varying phenomena such as biofouling and payload changes.

The obtained results demonstrated that the proposed predictor retains stable and accurate performance under these parametric variations. Predicted trajectories remain closely aligned with the desired references, with only marginal deviations observed in surge and yaw dynamics at the highest uncertainty levels. Quantitative analysis reveals that the root-mean-square error (RMSE) of predicted states increased by less than 8% compared with the nominal case, while overall trajectory tracking errors remain within mission-acceptable thresholds. This performance is attributed to the physics-informed structure of the predictor, which constrains learning through embedded dynamic relationships and compensates for modeling discrepancies.

4.3.3 Sensor limitations

AUV sensors, such as GPS, IMUs, sonars, and depth sensors, are limited in nature that impacts their goal of accurate determination of position and orientation, therefore, making accurate trajectory tracking complex. Such sensors play a vital role in enhancing the reliable performance of AUV system, enhancing their navigational capacities, and enabling them to attain specific requirements in their application. They have also enhanced the quality of environmental monitoring as they collect information on different physical parameters. Sensor accuracy and critical environmental factors are also major performance factors of the AUV system and should be given due to consideration of [100–105].

1. *Limited accuracy and resolution*: Sensors with limited accuracy, such as depth sensors or IMUs, might lead to inaccurate state estimation in AUVs. This error accumulates over time, leading drift in trajectory estimation and making it difficult to track paths accurately.
2. *No global positioning in deep water*: GPS signals are often unavailable underwater, making it challenging to estimate the global position of AUV. AUVs in deep-water environments use IMUs, which causes accumulating errors over time.
3. *Environmental factors*: Sensors may be affected by noise, turbulence, and changes in water properties. For instance, sonar-based sensors can be influenced by variations in water salinity and temperature, as well as by the presence of obstacles. These factors can lead to imprecise distance measurements.

The behavior of an AUV process model under process and measurement noise is a critical factor influencing its robustness, stability, and operational reliability in real-world maritime environments. As discussed in recent studies [98–103], process noise mainly originates from unmodeled hydrodynamic interactions, time-varying ocean currents, and actuator nonlinearities, all of which introduce drift, bias, and degrade trajectory-tracking performance. Measurement noise generated by onboard sensors, such as Doppler Velocity Logs (DVLs), Inertial Measurement Units (IMUs), and depth sensors, further exacerbates these effects by propagating estimation errors through the control loop and causing fluctuations in velocity, position, and attitude estimates. Simulation analyses in the literature demonstrate that classical controllers, such as PID, tend to suffer from increased tracking errors and slower convergence under noisy conditions, while adaptive and learning-based methods, including Reinforcement Learning (RL) and Physics-Informed Neural Networks

(PINNs), exhibit improved resilience and maintain higher tracking accuracy [69, 70, 100]. Moreover, the integration of advanced state estimation techniques, such as the Extended Kalman Filter (EKF) and fuzzy state observers, significantly mitigates noise effects by reducing estimation variance and improving recovery following disturbances [101–105]. These findings underscore the importance of noise-aware control design and estimation strategies to ensure stable, accurate, and robust AUV performance in dynamic and uncertain ocean environments.

4.3.4 Real-time computational constraints

AUVs have to make decisions in real time based on trajectory planning and sensors readings, which require high computational costs. The trajectory tracking faces the following difficulties according to [106–110]:

1. *Data processing*: AUVs require real-time processing of sensor data to determine location, velocity, and control inputs, ensuring stability. High computations might cause imprecise responses, especially in battery-powered AUVs with limited processing capacity.
2. *Control system complexity*: The task of trajectory tracking requires using advanced control algorithms (e.g., RL, PINN and SMC.) to control the AUV's trajectory according to the deviation between the intended and actual path. These controllers must consider both the nonlinear dynamics of the vehicle and the unpredictable ambient variables. Achieving computational feasibility while maintaining effectiveness in the controller can be challenging.
3. *Resource constraints*: Numerous AUVs operate in deep-sea environments where communication with surface operators is often limited or significantly delayed. As a result, the AUV must operate autonomously in the absence of direct communication, which underscores the necessity for an efficient and effective real-time control system.

4.3.5 Environmental disturbances

Environmental disturbances based on [111, 112], including ocean currents and waves, which can significantly affect the trajectory of the AUV. These disturbances add uncertainties to both magnitude and direction of motion over time.

1. *Unpredictable currents*: The AUV's motion can be substantially influenced by ocean currents, resulting in drift that diverts the AUV from its intended trajectory. The AUV trajectory tracking is challenging due to the unpredictable variation of intensity and direction of currents. These variations are significantly influenced by intensity and direction of currents that are influenced by depth and geographic location.
2. *Turbulence and obstacles*: The underwater environment can be unpredictable due to turbulence, water viscosity changes, and physical obstacles like reefs or submerged objects. These factors can precipitate abrupt alterations in the AUV's trajectory, necessitating rapid and adaptive control solutions.

4.3.6 Energy efficiency and power supply

Energy efficiency and power supply constraints are essential considerations in the functioning of AUVs, since they directly influence the vehicle's mission duration, range, and operational capabilities. Given the frequently remote and prolonged nature of AUV operations, optimizing energy utilization, and mitigating power supply limitations are crucial for enhancing the AUV's efficacy. The principal issues with energy efficiency and power supply constraints in AUVs are as follows:

1. *Limited power resources*: AUVs often depend on onboard batteries, which are limited in both capacity and lifespan. Some power sources for AUVs, such as lithium-ion or lithium-polymer batteries, offer high energy density but limit overall operational duration. These batteries supply energy to the AUV's propulsion system, sensors, communication apparatus, and onboard computing systems. The significant power consumption of propulsion systems, especially in deep-diving AUVs, combined with the need for continuous sensor data processing as highlighted in [113, 114].
2. *Energy consumption of propulsion systems*: The propulsion system, consisting of thrusters and motors, is among the most power-demanding components of an AUV. The energy required for movement, combined with hydrodynamic drag and resistance in underwater environments, results in great power consumption [115, 116]. Additionally, factors such as vehicle speed, operational settings, and water currents significantly affect energy usage. To enhance efficiency and extend mission endurance, AUVs need to strategically optimize their velocity and trajectory planning while ensuring mission objectives are met.
3. *Battery LIFE CHALLENGES*: AUVs operating at significant depths encounter critical energy challenges, particularly concerning battery life and recharging constraints. Deep-sea environments expose batteries to extreme pressure and low temperatures, which can degrade performance and reduce energy capacity [117]. AUVs often operate in remote areas where charging infrastructure is limited or nonexistent, making a logistical challenge for

battery replacement or recharging process. While some systems utilize docking stations for recharging or battery swaps, such facilities are not always available, especially in deep-sea missions [118]. As a result, AUVs must be designed to optimize energy consumption and mission planning, ensuring they can complete their objectives and return to base before depleting their power reserves.

4.4 Challenges in AI-based controllers: data scarcity and computational complexity

AI-driven control methods, particularly Reinforcement Learning (RL) and Physics-Informed Neural Networks (PINNs), encounter significant challenges related to data scarcity and computational complexity, which limit their practical deployment in real-time Autonomous Underwater Vehicle (AUV) trajectory tracking.

1. *Data scarcity:* The performance and generalization ability of RL and PINNs are highly dependent on the availability of high-quality training data as demonstrated in [81, 119, 120]. However, acquiring real-world underwater datasets is challenging due to the high operational costs, limited accessibility, and difficulty in replicating diverse environmental conditions such as varying ocean currents and external disturbances. RL models require extensive interaction with the environment to learn optimal policies, yet real-world trials are often impractical due to time constraints and potential risks to the AUV. Although PINNs incorporate physical laws to reduce data dependency, they still require real-world observations for effective generalization. As a result, insufficient data can lead to suboptimal performance when transitioning from simulations to real-world applications.
2. *Computational complexity:* Both RL and PINNs are computationally demanding, posing challenges for real-time implementation. RL involves extensive training, particularly in continuous state-action spaces, and its real-time inference requires substantial processing power to adapt to dynamic and uncertain environments. Similarly, PINNs involve solving differential equations during training, which can be computationally intensive, especially for high-dimensional AUV models. These computational demands make real-time deployment challenging, particularly on embedded AUV processors, which have limited processing capabilities and energy constraints as highlighted in [82].

To mitigate these challenges, researchers have explored hybrid learning approaches, transfer learning, and physics-based simulations to enhance data efficiency. Additionally, techniques such as model compression, pruning, and quantization are being investigated to optimize computational performance for real-time AUV applications. However, addressing these issues remains critical to advancing AI-based controllers for reliable and efficient underwater navigation.

5 Conclusion

AUVs face a range of significant challenges, including the need to navigate complex and dynamic environments, optimize energy efficiency during extended missions, and ensure reliable communication and fault tolerance in deep or remote locations. These obstacles significantly complicate the development of robust and effective control strategies. This review has examined a variety of control approaches for AUVs, emphasizing their strengths, limitations, and practical applicability. While PID and FLC controllers are computationally efficient and straightforward to implement, they struggle to address nonlinear dynamics and external disturbances effectively. SMC controllers offer enhanced robustness and precision but are susceptible to chattering effects and require an accurate system model. RL-based controllers provides adaptability and learning capabilities, though they demand significant computational resources and large training datasets. Lastly, PINNs improve data efficiency and generalization by incorporating physical laws, but their computational demands remain a barrier to real-time application.

5.1 Future research directions

1. Improving RL for Real-Time AUV Control.
   Reinforcement learning (RL) presents several challenges for real-time AUV trajectory tracking control, particularly due to its need for large amounts of training data and substantial computational resources. These demands make RL less feasible for real-time applications, especially when dealing with limited data or complex environments. Additionally, RL can suffer from inefficiency in sample usage and slow convergence. To address these issues, more computationally efficient training methods are needed. Techniques such as transfer learning and meta-learning can enhance the adaptability of RL systems with limited data, enabling faster adjustments to new conditions. Moreover, leveraging hardware acceleration, such as edge computing and GPUs, can help meet the computational demands, enabling real-time execution without compromising performance.
2. Enhancing PINNs for Practical Deployment.
   Physics-Informed Neural Networks (PINNs) integrate physical laws into the learning process, offering a promising approach for AUV control. However, they can

be computationally demanding, particularly when dealing with complex models, leading to slow inference times and challenges for real-time applications. To make PINNs more practical for deployment, improvements are needed, such as the implementation of reduced-order models and surrogate learning techniques to speed up inference. Additionally, parallel computing and model compression techniques can improve computational efficiency, enabling faster processing while maintaining physical accuracy. These enhancements will improve PINNs' suitability for real-time AUV operations in dynamic environments.
more suitable for real-time use in AUVs operating in dynamic environments.

3. Developing Hybrid Control Approaches.
   Classical control techniques like PID and Sliding Mode Control (SMC) are computationally efficient but often struggle with nonlinear dynamics and external disturbances typical in complex underwater environments. On the other hand, AI-based methods such as reinforcement learning (RL) and Physics-Informed Neural Networks (PINNs) offer greater adaptability but require large datasets and significant computational power, limiting their real-time applicability. Combining classical control methods with AI-driven strategies through hybrid approaches could provide a balanced solution, leveraging the strengths of both. These hybrid systems would enhance control performance by handling complex scenarios more effectively. Additionally, exploring model-based RL and hybrid AI-physics frameworks could reduce reliance on large training datasets, improving both efficiency and real-time adaptability.

By addressing these limitations and implementing the necessary improvements, it will be possible to bridge the gap between theoretical advancements and practical AUV operations, leading to more reliable, adaptive, and efficient control systems in dynamic underwater environments.

Acknowledgements Not applicable.

Author contribution Conceptualization & Methodology: Aly M. Eissa, Samer A. Mohamed, Mohammed Ibrahim Awad, Hossam E. Abd El Munim, Diaa Emad Literature Search & Data Curation: Aly M. Eissa, Mohammed Ibrahim Awad, Diaa Emad Analysis & Visualization: Aly M. Eissa, Samer A. Mohamed, Mohammed Ibrahim Awad, Hossam E. Abd El Munim, Diaa Emad Writing – Original Draft: Aly M. Eissa, Mohammed Ibrahim Awad Writing – Review & Editing: Aly M. Eissa, Mohammed Ibrahim Awad, Diaa Emad Supervision Administration: Mohammed Ibrahim Awad, Hossam E. Abd El Munim, Diaa Emad All authors read and approved the final manuscript.

Funding Open access funding provided by The Science, Technology & Innovation Funding Authority (STDF) in cooperation with The Egyptian Knowledge Bank (EKB). This research received no external funding.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interests The authors have no relevant financial or nonfinancial interests to disclose.

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