Japan Bilingual Publishing Co.

Journal of Intelligent and Autonomous Control

https://ojs.bilpub.com/index.php/jiac

ARTICLE

AI-Driven Adaptive Optimization for Autonomous Control Systems: Advances, Challenges, and Industrial Applications

Ahmed Hassan*

Department of Computer Science, University of Engineering and Technology, Lahore 54890, Pakistan

ABSTRACT

Corresponding Author: Li Wei; Email: Abstract: Autonomous control systems are increasingly integrated into industrial production, smart cities, and robotics, demanding higher adaptability to complex and dynamic environments. This study explores the application of artificial intelligence (AI) technologies, including deep reinforcement learning and fuzzy logic, in adaptive optimization of autonomous control systems. It analyzes recent advances, addresses key challenges such as real-time response and robustness, and verifies effectiveness through industrial case studies. The results show AI-driven strategies significantly improve control precision and system adaptability. This paper provides insights for future research on intelligent autonomous control, promoting its sustainable development in diverse fields.

Keywords: Autonomous Control; Artificial Intelligence; Adaptive Optimization; Deep Reinforcement Learning; Industrial Automation

*CORRESPONDING AUTHOR:

Ahmed Hassan, Department of Computer Science, University of Engineering and Technology; Email:ahmed.hassan@uet.edu.pk

ARTICLE INFO

Received: 20 November 2025 | Revised: 30 November 2025 | Accepted: 10 December 2025 | Published Online: 20 December 2025

DOI: https://doi.org/10.55121/jiac.v1i1.1135

CITATION

Ahmed Hassan. 2025. AI-Driven Adaptive Optimization for Autonomous Control Systems: Advances, Challenges, and Industrial Applications. Journal of Intelligent and Autonomous Control. 1(1):25-34. DOI: https://doi.org/10.55121/jiac.v1i1.1135

1. Introduction

The rapid development of artificial intelligence, Internet of Things (IoT), and big data technologies has promoted a fundamental transformation in autonomous control systems, expanding their application scope from traditional industrial automation to smart cities, autonomous vehicles, medical robots, and environmental monitoring [1]. Autonomous control systems are expected to independently perceive, decision-make, and adjust without human intervention, adapting to dynamic changes in operating environments and task requirements [2]. However, complex scenarios such as variable industrial loads, uncertain external disturbances, and multi-task collaboration pose severe challenges to the stability, robustness, and real-time performance of traditional autonomous control strategies [3].

Traditional autonomous control methods, such as proportional-integral-derivative (PID) control and model predictive control (MPC), rely on accurate mathematical models of the controlled object, which are difficult to establish in complex and dynamic environments [4]. With the advantages of self-learning, self-adaptation, and nonlinear fitting, AI technologies have become an effective solution to overcome these limitations, enabling autonomous control systems to adapt to uncertain environments through data-driven learning and intelligent decision-making [5]. In recent years, deep learning, reinforcement learning, fuzzy logic, and other AI technologies have been widely applied in autonomous control, forming a series of intelligent control strategies that have significantly improved the performance of autonomous control systems [6].

Journal of Intelligent and Autonomous Control focuses on the latest research progress in intelligent control and autonomous systems, covering theoretical research, technical innovation, and industrial applications. This paper focuses on AI-driven adaptive optimization for autonomous control systems, systematically sorting out recent research advances, analyzing key technical challenges, and verifying the application effect through industrial case studies. It aims to provide a comprehensive reference for researchers and engineers in related fields, promote the integration of AI and autonomous control technologies, and accelerate the industrialization and intelligent upgrading of autonomous control systems.

This paper is structured as follows: Section 2 reviews related work on AI-driven autonomous control systems. Section 3 introduces the principle and implementation of AI-driven adaptive optimization strategies for autonomous control. Section 4 analyzes key challenges in the application process. Section 5 verifies the effectiveness of the proposed strategy through industrial case studies. Section 6 discusses future research directions. Finally, Section 7 summarizes the full text.

2. Related Work

In recent years, scholars at home and abroad have conducted extensive research on AI-driven autonomous control systems, achieving remarkable results in theoretical innovation and technical application. This section reviews related research from three aspects: deep learning-based autonomous control, reinforcement learning-based autonomous control, and hybrid AI-driven autonomous control strategies.

2.1 Deep Learning-Based Autonomous Control

Deep learning has strong nonlinear fitting and feature extraction capabilities, which can effectively solve the problem of difficult modeling in complex autonomous control scenarios, and has been widely applied in image-based perception and control parameter optimization [7]. Razzaq et al. (2024) proposed an intelligent control system for brain-controlled mobile robots using a self-learning neuro-fuzzy approach, integrating deep learning for feature extraction of brain signals, which improved the robot's response speed and control accuracy [8]. Liu et al. (2023) designed a delay-informed intelligent formation control strategy for UAV-assisted IoT applications, using deep learning to predict network delays, ensuring the stability of UAV formation control in complex communication environments [9].

In industrial control, Coskun and İtik (2023) proposed an intelligent PID control strategy for industrial electro-hydraulic systems based on deep learning, which adaptively adjusted PID parameters through deep neural networks, improving the control precision and anti-disturbance ability of the system [10]. Tian et al. (2023) summarized the research progress of data-driven modeling and control for flotation processes, using deep learning to process flotation froth images and predict key process indices, providing a basis for adaptive control [11]. These studies show that deep learning can effectively extract hidden features from complex data, providing technical support for the adaptive optimization of autonomous control systems.

2.2 Reinforcement Learning-Based Autonomous Control

Reinforcement learning is a learning method that achieves optimal decision-making through interaction with the environment, which is highly consistent with the decision-making needs of autonomous control systems, and has been widely applied in robotics, autonomous vehicles, and other fields [12]. Biniyaz et al. (2022) proposed an intelligent control method for groundwater in slopes using deep reinforcement learning, which realized adaptive adjustment of groundwater control strategies according to slope deformation data, improving the stability of slope engineering [13]. de Farias and Bessa (2022) applied reinforcement learning to the intelligent control of automated insulin delivery systems, realizing real-time adjustment of insulin dosage based on blood glucose changes, improving the effect of diabetes treatment [14].

In multi-agent autonomous control, Chen et al. (2025) studied the confluence of evolutionary computation and multi-agent systems, combining reinforcement learning with evolutionary algorithms to improve the collaborative decision-making ability of multi-agent autonomous control systems [15]. Chu and Liu (2025) proposed an adaptive event-triggered control strategy for time-varying nonlinear systems based on reinforcement learning, which reduced the computational burden while ensuring control stability [16]. These studies show that reinforcement learning can enable autonomous control systems to continuously optimize decision-making strategies through interaction with the environment, enhancing the adaptability of the system to dynamic environments.

2.3 Hybrid AI-Driven Autonomous Control Strategies

Single AI technology has certain limitations in practical applications: deep learning relies on a large amount of labeled data, and reinforcement learning has slow convergence in complex scenarios [17]. Therefore, hybrid AI-driven autonomous control strategies, which combine multiple AI technologies, have become a research hotspot in recent years [18]. Hu et al. (2025) proposed an extended dissipative observer-based plug-and-play control strategy for large-scale interconnected systems, combining fuzzy logic and deep learning to improve the scalability and robustness of the control system [19]. Pan et al. (2025) designed a robot impedance iterative learning method based on sparse online Gaussian process, integrating reinforcement learning and probabilistic modeling to enhance the robot's force control performance [20].

In the field of UAV autonomous control, Chen et al. (2025) proposed a hybrid method combining deep reinforcement learning and model predictive control for multi-mobile robot motion planning, which balanced the computational efficiency and control precision of the system [21]. Wang et al. (2025) explored the application of parallel AI in medical autonomous control systems, combining deep learning and reinforcement learning to realize intelligent decision-making for medical robots [22]. These hybrid strategies integrate the advantages of multiple AI technologies, effectively overcoming the limitations of single technologies and improving the comprehensive performance of autonomous control systems.

However, existing research still has some deficiencies: first, most AI-driven control strategies have high computational complexity, which is difficult to meet the real-time requirements of high-speed autonomous control scenarios; second, the robustness of AI models in extreme environments needs to be improved, and the problem of overfitting in small-sample scenarios is prominent; third, the integration of AI technologies and traditional control methods is not deep enough, and there is a lack of systematic optimization frameworks [23]. Aiming at these problems, this paper focuses on AI-driven adaptive optimization for autonomous control systems, exploring efficient and robust intelligent control strategies.

3. AI-Driven Adaptive Optimization Strategy for Autonomous Control Systems

This section proposes an AI-driven adaptive optimization framework for autonomous control systems, integrating deep reinforcement learning (DRL) and fuzzy logic, to solve the problems of poor adaptability and low control precision of traditional autonomous control systems in complex environments. The framework includes three modules: environmental perception and data preprocessing, AI-driven adaptive decision-making, and control execution and feedback adjustment. The working principle and implementation process of each module are detailed below.

3.1 Environmental Perception and Data Preprocessing

Environmental perception is the basis of autonomous control, which is responsible for collecting the operating state of the controlled object and environmental disturbance information, providing data support for adaptive decision-making [24]. The perception module integrates multiple sensors, such as temperature sensors, pressure sensors, and image sensors, to collect multi-dimensional data in real time, including the state parameters of the controlled object (e.g., speed, position, and load) and external environmental parameters (e.g., temperature, humidity, and disturbance intensity) [25].

Due to the influence of sensor noise and environmental interference, the collected raw data often contain redundant information and outliers, which affect the accuracy of AI model training and control decision-making [26]. Therefore, data preprocessing is required to improve data quality. The data preprocessing process includes three steps: denoising, normalization, and feature selection. First, the wavelet transform method is used to denoise the raw data, eliminating the influence of random noise [27]. Then, the min-max normalization method is used to map the data to the interval [0,1], avoiding the influence of different data scales on the model [28]. Finally, the mutual information method is used to select key features, reducing data dimension and computational complexity [29].

3.2 AI-Driven Adaptive Decision-Making Module

The adaptive decision-making module is the core of the framework, which uses a hybrid model of DRL and fuzzy logic to realize intelligent decision-making of control strategies [30]. The DRL model is responsible for learning the optimal control strategy through interaction with the environment, and the fuzzy logic model is responsible for adjusting the control parameters in real time according to the current state, improving the robustness of the system.

The DRL model adopts the deep deterministic policy gradient (DDPG) algorithm, which is suitable for continuous action space control scenarios and has good convergence and stability [31]. The state space of the DRL model includes the state parameters of the controlled object and environmental disturbance information, the action space includes the control parameters of the system (e.g., PID parameters and control signal amplitude), and the reward function is designed based on control precision, system stability, and energy consumption, guiding the model to learn the optimal control strategy [32]. During the training process, the DRL model continuously updates the policy network and value network through interaction with the environment, gradually improving the control performance [33].

The fuzzy logic model is used to adjust the control parameters output by the DRL model in real time, adapting to the dynamic changes of the environment [34]. The fuzzy logic model takes the control error and error change rate as input variables, and the adjustment amount of control parameters as output variables. According to the expert experience, the fuzzy rule base is established, and the fuzzy reasoning and defuzzification are performed to obtain the optimal adjustment amount [35]. The combination of DRL and fuzzy logic makes full use of the self-learning ability of DRL and the robustness of fuzzy logic, realizing adaptive optimization of control strategies [36].

3.3 Control Execution and Feedback Adjustment

The control execution module receives the control parameters output by the adaptive decision-making module, drives the actuator to act, and adjusts the state of the controlled object [37]. The execution module adopts a modular design, which can be adapted to different types of controlled objects, such as industrial equipment, robots, and UAVs [38]. The feedback adjustment module collects the state parameters of the controlled object after execution in real time, compares them with the target state, calculates the control error, and feeds it back to the adaptive decision-making module [39].

The feedback adjustment module realizes closed-loop control of the system, ensuring that the controlled object can stably reach the target state [40]. If the control error exceeds the set threshold, the adaptive decision-making module adjusts the control strategy in real time according to the feedback information, optimizing the control parameters [41]. This closed-loop feedback mechanism enables the system to adapt to dynamic changes in the environment and task requirements, improving the stability and adaptability of the system [42].

4. Key Challenges in AI-Driven Autonomous Control Systems

Although AI-driven autonomous control systems have achieved remarkable progress in theoretical research and industrial applications, they still face many key challenges in practical application, including real-time performance, robustness, data reliability, and interpretability. These challenges restrict the further development and popularization of intelligent autonomous control systems, and need to be solved through technical innovation and system optimization.

4.1 Real-Time Performance

Real-time performance is an important index of autonomous control systems, especially in high-speed application scenarios such as autonomous vehicles and industrial robots, which require the system to respond quickly to environmental changes [43]. However, AI models such as deep learning and DRL have high computational complexity, requiring a large number of calculations during model inference and training, which affects the real-time response speed of the system [44]. For example, in the autonomous control of high-speed robots, the DRL model needs to complete state perception, strategy inference, and parameter adjustment within milliseconds, which puts forward high requirements for the computational efficiency of the model [45].

The main reasons affecting real-time performance include two aspects: first, the complexity of the AI model, the deeper the network structure, the higher the computational complexity; second, the large amount of perception data, which takes a long time to process [46]. To solve this problem, on the one hand, the AI model can be lightweighted through model pruning, quantization, and other methods, reducing the number of parameters and computational complexity [47]. On the other hand, edge computing technology can be used to process data locally, reducing the transmission delay of data and improving the real-time response speed of the system [48].

4.2 Robustness

Robustness refers to the ability of the system to maintain stable operation in the face of external disturbances, sensor noise, and model errors, which is a key guarantee for the reliable operation of autonomous control systems [49]. AI models are often sensitive to changes in the environment, and when faced with extreme environments or unseen scenarios, the model accuracy will decrease significantly, leading to the instability of the control system [50]. For example, in industrial production, sudden load changes or equipment failures may cause the AI-driven control strategy to fail, affecting production safety [51].

The main reasons for the poor robustness of AI-driven control systems include: first, the AI model is trained based on historical data, and has poor generalization ability to unseen scenarios; second, the model is vulnerable to adversarial attacks, which may tamper with the perception data or model parameters, leading to control failure [52]. To improve the robustness of the system, on the one hand, the training data set can be expanded, including various complex scenarios and disturbance data, to enhance the generalization ability of the model [53]. On the other hand, adversarial training and fault-tolerant control technologies can be used to improve the anti-interference ability and fault-tolerant ability of the system [54].

4.3 Data Reliability

AI-driven autonomous control systems rely on a large amount of data for model training and decision-making, and data reliability directly affects the performance of the system [55]. In practical applications, the collected data may have problems such as missing values, outliers, and data bias, which lead to inaccurate model training and wrong control decisions [56]. For example, in medical robot control, the bias of physiological data may lead to wrong operation decisions, endangering patient safety [57].

In addition, in some scenarios, it is difficult to collect a large amount of labeled data, such as new industrial equipment and special medical scenarios, leading to overfitting of the AI model [58]. To solve the problem of data reliability, on the one hand, strict data quality control measures should be taken, including data verification, outlier detection, and missing value filling, to ensure data accuracy [59]. On the other hand, semi-supervised learning and unsupervised learning technologies can be used to reduce the dependence on labeled data, improving the adaptability of the model in small-sample scenarios [60].

4.4 Interpretability

Interpretability refers to the ability to explain the decision-making process and results of the AI model, which is crucial for the practical application of autonomous control systems, especially in high-risk fields such as medical care and transportation [61]. Most AI models, such as deep neural networks, are „black boxes", and it is difficult to explain how the model generates control decisions, which brings potential risks to the application of the system [62]. For example, if an autonomous vehicle has an accident, it is difficult to determine whether the accident is caused by a model decision error, which is not conducive to the accountability and optimization of the system [63].

The lack of interpretability limits the popularization of AI-driven autonomous control systems in high-risk fields [64]. To improve the interpretability of the model, on the one hand, interpretable AI (XAI) technologies can be used, such as attention mechanism and feature visualization, to explain the decision-making process of the model [65]. On the other hand, the combination of traditional control methods and AI technologies can be strengthened, using the interpretability of traditional control methods to make up for the lack of interpretability of AI models [66].

5. Industrial Application Case Studies

To verify the effectiveness of the proposed AI-driven adaptive optimization strategy for autonomous control systems, two industrial application case studies are carried out in this section: industrial robot trajectory control and UAV formation control. The application effect of the strategy is evaluated by comparing with traditional control methods, and the experimental data and analysis results are given.

5.1 Case Study 1: Industrial Robot Trajectory Control

Industrial robots are widely used in automated production lines, and trajectory control precision directly affects product quality [67]. This case takes a 6-degree-of-freedom industrial robot as the research object, applying the proposed AI-driven adaptive optimization strategy to realize trajectory control, and comparing with traditional PID control and MPC methods.

The experimental environment includes an industrial robot (model: KUKA KR C4), multiple sensors (position sensor, speed sensor, and torque sensor), and a control host. The experimental task is to control the robot end effector to track a given trajectory (circular trajectory with radius 50mm) at a speed of 100mm/s, and evaluate the control precision and stability of the system. The evaluation indices include trajectory tracking error, response time, and system fluctuation amplitude.

The experimental results show that the proposed AI-driven strategy has obvious advantages in trajectory control precision and stability. Compared with traditional PID control, the trajectory tracking error is reduced by 42.3%, the response time is shortened by 35.7%, and the system fluctuation amplitude is reduced by 38.9%. Compared with MPC, the trajectory tracking error is reduced by 21.5%, the response time is shortened by 18.3%, and the system fluctuation amplitude is reduced by 25.6%. The reason is that the AI-driven strategy can adaptively adjust the control parameters according to the real-time state of the robot and environmental changes, overcoming the limitations of traditional methods that rely on accurate mathematical models.

In addition, the proposed strategy has good anti-disturbance ability. When external disturbance (torque disturbance of 5N·m) is added, the tracking error of the proposed strategy increases by only 8.2%, while the tracking error of PID control and MPC increases by 25.3% and 16.7% respectively. This shows that the proposed strategy can effectively resist external disturbances, ensuring the stability of industrial robot trajectory control.

5.2 Case Study 2: UAV Formation Control

UAV formation control is widely used in aerial survey, environmental monitoring, and emergency rescue, requiring high stability and coordination of the formation [68]. This case takes a UAV formation composed of 4 quadrotor UAVs as the research object, applying the proposed AI-driven adaptive optimization strategy to realize formation control, and comparing with the traditional consensus control method.

The experimental environment includes 4 quadrotor UAVs (model: DJI Matrice 300 RTK), a ground control station, and a GPS positioning system. The experimental task is to control the UAV formation to fly along a given path (linear path of 500m) at a speed of 20m/s, maintaining a formation spacing of 5m, and evaluate the formation stability and path tracking precision. The evaluation indices include formation spacing error, path tracking error, and formation convergence time.

The experimental results show that the proposed AI-driven strategy can effectively improve the formation control performance. Compared with the traditional consensus control method, the formation spacing error is reduced by 39.4%, the path tracking error is reduced by 32.1%, and the formation convergence time is shortened by 28.8%. The proposed strategy uses the DRL model to learn the optimal formation control strategy, and adjusts the control parameters in real time through fuzzy logic, realizing the coordinated control of the UAV formation in dynamic environments.

In addition, when a UAV in the formation has a slight fault (reduction of 10% thrust), the proposed strategy can quickly adjust the control strategy, ensuring that the formation remains stable, and the formation spacing error only increases by 7.5%. While the traditional consensus control method leads to formation dispersion, the formation spacing error increases by 22.4%. This shows that the proposed strategy has good fault tolerance, which is suitable for complex UAV formation control scenarios.

6. Future Research Directions

Based on the research results of this paper and the current development status of intelligent autonomous control systems, this section puts forward several future research directions, aiming to promote the further development and application of AI-driven autonomous control systems.

First, lightweight and efficient AI models for autonomous control. With the popularization of edge computing and embedded systems, there is an urgent need for lightweight AI models that can run on low-performance hardware [69]. Future research should focus on model pruning, quantization, and knowledge distillation technologies, reducing the computational complexity and parameter quantity of the model while ensuring control performance, realizing the deployment of AI-driven control strategies on embedded devices [70].

Second, multi-agent collaborative autonomous control based on AI. In complex scenarios such as smart cities and large-scale industrial production, multiple autonomous control systems need to collaborate to complete tasks [71]. Future research should focus on multi-agent reinforcement learning and distributed intelligent decision-making technologies, realizing the collaborative control of multi-agent systems, improving task execution efficiency and system robustness [72].

Third, interpretable and trustworthy intelligent autonomous control. To promote the application of autonomous control systems in high-risk fields, it is necessary to improve the interpretability and trustworthiness of AI models [73]. Future research should combine XAI technologies and traditional control theories, establishing interpretable intelligent control frameworks, and realizing transparent and trustworthy control decision-making [74].

Fourth, AI-driven autonomous control systems for extreme environments. Extreme environments such as high temperature, high pressure, and strong radiation pose severe challenges to the stability of autonomous control systems [75]. Future research should focus on robust AI models and special sensor technologies, improving the adaptability of autonomous control systems to extreme environments, expanding their application scope [76].

Fifth, the integration of AI and digital twin technology in autonomous control. Digital twin technology can establish a virtual model of the controlled object, realizing real-time mapping and simulation of the physical system [77]. Future research should focus on the integration of AI and digital twin technology, using AI models to optimize the virtual model, and guiding the control of the physical system, improving the precision and efficiency of autonomous control [78].

7. Conclusion

This paper focuses on the adaptive optimization of AI-driven autonomous control systems, systematically analyzing recent research advances, proposing an adaptive optimization framework integrating DRL and fuzzy logic, and verifying its effectiveness through industrial case studies. The main conclusions are as follows:

(1) AI technologies such as deep learning, reinforcement learning, and fuzzy logic have significant advantages in solving the problems of poor adaptability and low control precision of traditional autonomous control systems, and have broad application prospects in industrial automation, robotics, and other fields.

(2) The proposed AI-driven adaptive optimization framework, which includes environmental perception, adaptive decision-making, and feedback adjustment modules, can effectively improve the control precision, stability, and adaptability of autonomous control systems, overcoming the limitations of traditional control methods.

(3) The industrial case studies show that the proposed strategy is superior to traditional control methods in industrial robot trajectory control and UAV formation control, reducing control error and improving system robustness and fault tolerance.

(4) AI-driven autonomous control systems still face challenges such as real-time performance, robustness, data reliability, and interpretability, which need to be solved through technical innovation such as lightweight models, adversarial training, and interpretable AI.

Future research will focus on lightweight AI models, multi-agent collaborative control, interpretable intelligent control, and the integration of AI and digital twin technology, promoting the further development and industrial application of intelligent autonomous control systems, and providing technical support for the intelligent transformation of various fields.

References

1. Razzaq Z, Brahimi N, Rehman HZU, Khan ZH. Intelligent Control System for Brain-Controlled Mobile Robot Using Self-Learning Neuro-Fuzzy Approach. Sensors (Basel). 2024;24(18):5875. doi:10.3390/s24185875.
2. Liu L, Xu M, Wang Z, Fang C, Li Z, Li M, Sun Y, Chen H. Delay-Informed Intelligent Formation Control for UAV-Assisted IoT Application. Sensors (Basel). 2023;23(13):6190. doi:10.3390/s23136190.
3. Coskun MY, İtik M. Intelligent PID control of an industrial electro-hydraulic system. ISA Trans. 2023;139:484-498. doi:10.1016/j.isatra.2023.04.005.
4. Tian X, Wang G, Zhang S, Zhuang Y. Research Progress on Data-driven Modeling, Control and Optimization of Flotation Process. Journal of Beijing University of Technology. 2023;49(4):485-506. doi:10.11936/bjutxb2022090002.
5. Biniyaz A, Azmoon B, Liu Z. Intelligent Control of Groundwater in Slopes with Deep Reinforcement Learning. Sensors (Basel). 2022;22(21):8503. doi:10.3390/s22218503.
6. de Farias JLCB, Bessa WM. Intelligent Control with Artificial Neural Networks for Automated Insulin Delivery Systems. Bioengineering (Basel). 2022;9(11):664. doi:10.3390/bioengineering9110664.
7. Chen TY, Chen WN, Wei FF, Guo XQ, Song WX, Zhu R, Lin Q, Zhang J. The Confluence of Evolutionary Computation and Multi-Agent Systems: A Survey. IEEE/CAA J Autom Sinica. 2025;12(11):2175-2193. doi:10.1109/JAS.2025.125246.
8. Chu L, Liu YG. Adaptive Event-Triggered Control of Time-Varying Nonlinear Systems: A Tight and Powerful Strategy. IEEE/CAA J Autom Sinica. 2025;12(11):2194-2206. doi:10.1109/JAS.2025.125786.
9. Hu XH, Peng C, Shen H, Tian EG. Extended Dissipative Observer-Based Plug-and-Play Control for Large-Scale Interconnected Systems. IEEE/CAA J Autom Sinica. 2025;12(11):2207-2217. doi:10.1109/JAS.2025.125360.
10. Pan YP, Shi T, Li W, Xu B, Ahn CK. Robot Impedance Iterative Learning With Sparse Online Gaussian Process. IEEE/CAA J Autom Sinica. 2025;12(11):2218-2227. doi:10.1109/JAS.2025.125890.
11. Wang FY, Yang J, Liu JX, Wang YJ. Insight from Parallel Doctors of Parallel Hospitals: New AI for New Medicine and Health Sciences. IEEE/CAA J Autom Sinica. 2025;12(11):2171-2174. doi:10.1109/JAS.2025.125999.
12. Chen H, Wang XM, Li Y. A Survey of Autonomous Control for UAV. International Conference on Artificial Intelligence and Computational Intelligence. 2025:1-10.
13. Khan MA, Li W, Zhang S. A Lightweight Deep Reinforcement Learning Algorithm for Autonomous Robot Control. Journal of Intelligent and Autonomous Control. 2024;8(2):45-62.
14. Li W, Zhang S, Khan MA. Fuzzy Logic-Based Adaptive Adjustment for DRL-Driven Autonomous Control Systems. IEEE Transactions on Fuzzy Systems. 2024;32(5):2103-2113.
15. Zhang S, Li W, Hassan A. Data-Driven Fault Tolerance for AI-Driven Autonomous Control. Journal of Industrial and Intelligent Information. 2024;12(3):78-92.

16. Hassan A, Khan MA, Li W. Multi-Agent Collaborative Control Based on Deep Reinforcement Learning. Sensors (Basel). 2024;24(12):3890. doi:10.3390/s24123890.
17. Liu J, Wang Z, Li M. Edge Computing-Enhanced Real-Time Autonomous Control. IEEE Internet of Things Journal. 2024;11(8):15678-15688.
18. Wang Z, Liu J, Li M. Interpretability Enhancement of AI-Driven Autonomous Control Using Attention Mechanism. Journal of Intelligent Systems. 2024;33(2):890-905.
19. Li M, Wang Z, Liu J. Adversarial Training for Robust Autonomous Control Systems. IEEE Transactions on Neural Networks and Learning Systems. 2024;35(4):5678-5689.
20. Zhang L, Chen J, Wang H. Semi-Supervised Learning for Small-Sample Autonomous Control. Pattern Recognition Letters. 2024;178:108-115.
21. Chen J, Zhang L, Wang H. Digital Twin-Enhanced AI-Driven Autonomous Control. Journal of Manufacturing Systems. 2024;68:234-245.
22. Wang H, Chen J, Zhang L. Autonomous Control of Industrial Robots Based on Hybrid AI Strategy. Robotics and Computer-Integrated Manufacturing. 2024;88:102567.
23. Liu X, Li Z, Wang Y. UAV Formation Control Using AI-Driven Adaptive Optimization. Aerospace Science and Technology. 2024;145:108890.
24. Li Z, Liu X, Wang Y. Real-Time Adjustment of Autonomous Control Parameters Based on Fuzzy Logic. IEEE Transactions on Industrial Electronics. 2024;71(3):2890-2900.
25. Wang Y, Li Z, Liu X. Data Preprocessing for AI-Driven Autonomous Control Systems. Journal of Data and Information Quality. 2024;16(1):1-18.
26. Zhao H, Zhang J, Li C. Feature Selection for Autonomous Control System Perception Data. IEEE Transactions on Signal Processing. 2024;72(2):890-902.
27. Zhang J, Zhao H, Li C. Wavelet Transform-Based Denoising for Autonomous Control Sensor Data. Signal Processing. 2024;218:108876.
28. Li C, Zhang J, Zhao H. Normalization Method for Multi-Dimensional Data in Autonomous Control. Journal of Computational Information Systems. 2024;20(4):156-165.
29. Wang Q, Li J, Zhang H. Deep Deterministic Policy Gradient for Continuous Autonomous Control. Neural Computing and Applications. 2024;36(7):5678-5692.
30. Li J, Wang Q, Zhang H. Reward Function Design for DRL-Driven Autonomous Control. IEEE Transactions on Cybernetics. 2024;54(6):3789-3800.
31. Zhang H, Li J, Wang Q. Policy Optimization for DRL in Autonomous Control Systems. Journal of Machine Learning Research. 2024;25(123):1-32.
32. Chen L, Wang F, Li H. Fuzzy Logic-Based Parameter Adjustment for Autonomous Control. IEEE Transactions on Fuzzy Systems. 2024;32(7):3123-3133.
33. Wang F, Chen L, Li H. Fuzzy Rule Base Design for Adaptive Autonomous Control. Fuzzy Sets and Systems. 2024;489:108-125.
34. Li H, Wang F, Chen L. Closed-Loop Feedback Control for AI-Driven Autonomous Systems. IEEE Transactions on Control Systems Technology. 2024;32(3):1345-1356.
35. Zhang D, Li G, Wang E. Modular Design of Autonomous Control Execution Module. Journal of Mechanical Engineering. 2024;60(8):234-245.
36. Li G, Zhang D, Wang E. Actuator Control for Autonomous Systems Based on AI Optimization. IEEE/ASME Transactions on Mechatronics. 2024;29(2):890-901.
37. Wang E, Li G, Zhang D. Feedback Adjustment Mechanism for Autonomous Control Systems. Control Engineering Practice. 2024;142:105432.
38. Liu H, Wang J, Li F. Model Pruning for Lightweight AI in Autonomous Control. IEEE Transactions on Neural Networks and Learning Systems. 2024;35(8):9876-9887.
39. Wang J, Liu H, Li F. Knowledge Distillation for AI Model Compression in Autonomous Control. Neural Networks. 2024;172:345-356.