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The Current Status and Prospects of Reinforcement Learning in the Field of Automation Control

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Abstract: The implementation of Industry 4.0 and Intelligent Manufacturing 2035 plan promotes the transformation of the automation control field from traditional fixed strategies to autonomous and adaptive control. Reinforcement learning relies on the core advantages of trial and error learning and online adaptation to address the control challenges of nonlinear and uncertain systems, becoming a key support for technological upgrades in this field. This article combines authoritative industry data and practical application cases to systematically summarize its application status, analyze the adaptability, application scenarios, technological breakthroughs, and existing bottlenecks of automation control, explore the constraints of large-scale applications, and look forward to development trends. Research has found that reinforcement learning has been implemented in control scenarios such as industrial processes, robots, and intelligent energy. However, issues such as sample efficiency, robustness, and implementation costs still constrain its large-scale promotion. In the future, with the deep integration of algorithm optimization and industry, it will promote the development of automation control towards higher levels of intelligence.

Keywords: Reinforcement learning, Automated control, Application status, Technical bottlenecks, Development Prospects.

1. Introduction

Automation control is an indispensable core support technology in modern industry, robot research and development, intelligent energy regulation and other fields. Its development level directly affects the improvement of production efficiency and the pace of intelligent transformation in various industries. At present, industrial production is accelerating towards refinement, complexity, and flexibility. The dynamic fluctuations of production parameters in complex scenarios such as metallurgy and chemical engineering are becoming increasingly frequent. The drawbacks of traditional PID control and other conventional methods are becoming increasingly prominent. Not only is it difficult to adapt to nonlinear, multi constraint, and dynamically changing control requirements, but there are also obvious shortcomings in the adaptive ability of dynamic interference response and multi-objective collaborative control, as well as the control accuracy required for high-end production. It fails to meet the core requirements of high-quality and refined development in modern industry. As an important branch of machine learning, reinforcement learning has the core advantage of not requiring the construction of precise system mathematical models in advance [1]. It can autonomously iterate and optimize control strategies through real-time interaction between intelligent agents and control environments, which precisely compensates for the core deficiencies of traditional control methods and provides a new solution for technological upgrading in the field of automation control. According to the industry report released by Rongzhong Consulting in 2026, the market size of China's reinforcement learning industry will reach 26 billion yuan in 2024, with an average annual compound growth rate (CAGR) of 37%. Among them, the application in the field of automation control accounts for more than 40%, and has become the core scenario for the implementation of reinforcement learning technology. At present, the application of reinforcement learning in the field of automation control has made phased progress, and some scenarios have been implemented on a large scale. However, technical bottlenecks and difficulties in engineering implementation are still prominent. Based on this, this article systematically reviews the current application status of reinforcement learning in this field, deeply analyzes existing problems and constraints, and reasonably looks forward to future development prospects, providing practical references for research and engineering practice in related fields, and helping to promote the deep integration and high-quality development of reinforcement learning and automation control.

2. The Adaptability of Core Principles of Reinforcement Learning to Automation Control

The core logic of reinforcement learning lies in the dynamic collaboration of the four core elements of intelligent agents, environment, reward function, and strategy iteration. By forming a closed-loop mechanism of "perception-decision-feedback-optimization", it achieves the autonomous evolution of control strategies. Its core characteristics are highly compatible with the core requirements of adaptive, high-precision, and anti-interference automation control, laying a solid foundation for the deep integration of the two. In this mechanism, the intelligent agent captures the environmental state in real time and outputs control actions, while the environment provides feedback reward signals based on the action effects. The intelligent agent continuously iterates the strategy guided by the reward signals, ultimately achieving the optimal solution for the control objectives. It is particularly crucial that this process does not rely on precise mathematical models of the system, which precisely solves the core pain points of long modeling time and low accuracy in nonlinear and uncertain systems in traditional automation control - such systems are commonly found in industrial scenarios such as metallurgy and chemical engineering, and traditional modeling often struggles to keep up with the rhythm of parameter dynamic changes [2].

The research published in the Journal of Automation in

2025 clearly indicates that the model-free property of reinforcement learning can be adapted to over 70% of complex industrial automation control scenarios. These scenarios often involve difficulties such as multivariable coupling and parameter time-variation, and the online adaptive capability of reinforcement learning can reduce the control error of dynamic systems by 15% -30%. On the other hand, researchers have improved the state encoding mechanism of reinforcement learning through ResNet, which has increased the training speed of DQN algorithm by three times, further bridging the gap in real-time performance of reinforcement learning and making it more in line with the strict requirements of automation control for response speed [3]. Compared with traditional control methods, reinforcement learning has more prominent advantages in multi-objective collaborative control and dynamic interference response. Taking multi-parameter collaborative control in the metallurgical industry as an example, it can simultaneously balance production efficiency and environmental indicators, while traditional control methods often only focus on a single objective. This also provides strong support for the widespread application of reinforcement learning in the field of automation control.

3. The Main Application Scenarios of Reinforcement Learning in the Field of Automation Control

The application scenarios of reinforcement learning in the field of automation control have achieved diversified industrial application expansion. Among them, the three major fields of industrial processes, robots, and intelligent energy have become the most mature directions for current applications due to their high technological adaptability and urgent landing needs. Combined with actual test cases and authoritative quantitative data in various fields, their practical application value and technological superiority in automation control optimization can be intuitively confirmed. In industrial process control, the application of multi-parameter coupling in complex production scenarios such as metallurgy and chemical engineering is most widely implemented. A large steel enterprise has integrated reinforcement learning technology into blast furnace control process optimization, and alleviated the constraint conflict between clinker strength and coke ratio through dynamic weight allocation strategy, reducing the conflict coefficient from 0.72 to 0.34 and the coke ratio exceeding standard rate by 12% year-on-year; A well-known automotive parts company relies on reinforcement learning to achieve precise control of welding robots, compressing the takt time of a single device from 12 seconds to 8.7 seconds, saving over 2 million US dollars in annual production costs.

In the field of robot automation control, reinforcement learning technology has a particularly significant effect on improving the flexible operation capability and path planning efficiency of robots. The research results released by arXiv platform in 2025 show that the adaptive PID control method based on the fusion of hierarchical meta learning and reinforcement learning can improve the average control accuracy of Franka Panda robotic arm by 16.6% [4], reduce the control error of high-load joints by 80.4%, and the model can be effectively trained in only 10 minutes, greatly improving the engineering practicality of reinforcement learning in industrial robot automation control. In the field of intelligent energy control, the integration of reinforcement learning and digital twin technology has become a new direction for implementation. A large metallurgical steel plant has built an intelligent scheduling model for energy systems through reinforcement learning, combined with digital twin technology to replay and mine historical operation data, reducing the demand for RL model training data by 80% and improving the overall energy utilization efficiency of the plant by more than 10% [5]. This implementation model further expands the application boundary of reinforcement learning in process industry energy automation control, providing replicable engineering experience for the intelligent upgrading of energy regulation in various industries.

4. Technological Breakthroughs and Existing Bottlenecks of Reinforcement Learning in Automation Control Applications

In recent years, reinforcement learning technology has rapidly iterated and upgraded, and its engineering application in the field of automation control has achieved multiple key technological breakthroughs, laying a solid technical foundation for the industrial implementation of this technology. The end-to-end industrial RL development methodology continues to improve, relying on refined processing technologies such as sensor calibration and multi-source data synchronization to achieve industrial data standardization. After applying this methodology in a Toyota factory, the correlation of production data increased to 0.89, significantly optimizing the training convergence effect of reinforcement learning models. The deep integration of digital twins and reinforcement learning effectively solves the pain points of difficult sample acquisition and high trial-and-error costs in industrial scenarios. After applying this fusion technology, an oil drilling rig enterprise reduced equipment control response time by 50% and greatly improved on-site control efficiency. At the same time, the innovative development of multi-agent reinforcement learning technology has achieved a breakthrough in collaborative control of multiple devices on complex production lines. A certain electronic manufacturing enterprise has adopted the MA-DDQN algorithm to optimize equipment scheduling, reducing the equipment path collision rate from 47% to 11%, increasing the comprehensive utilization rate of equipment by 19%, and significantly improving production efficiency.

At the same time as technological breakthroughs, it is necessary to be aware that the practical implementation of reinforcement learning in the field of automation control still faces many explicit technical bottlenecks [6], which directly restrict its large-scale industrial applications. Firstly, the sample efficiency is low, and the dynamism and complexity of industrial scenarios result in a 3-5 times higher sample demand for reinforcement learning algorithms compared to ideal laboratory environments, directly driving up the cost of technology implementation and model training for enterprises; Secondly, the robustness is insufficient. In complex interference industrial sites, the robustness of reinforcement learning control strategies is 18.9% lower than that of traditional PID control, which is prone to control system instability and cannot meet the high-precision control requirements of high-end manufacturing; Thirdly, real-time performance needs to be improved. Low latency control scenarios such as electricity market bidding require scheduling decisions to be completed within 1 second, while existing reinforcement learning algorithms require 0.5 seconds for backpropagation, which is difficult to fully match the strict requirements of real-time control. The efficiency of algorithm execution still needs further optimization [7].

5. The Main Factors Affecting the Large-Scale Application of Reinforcement Learning in the Field of Automation Control

The large-scale application of reinforcement learning in the field of automation control is not solely based on technological breakthroughs, but is also constrained by multiple factors such as cost investment, talent supply, industry standards, and data security. Various factors are intertwined and influence each other, forming industry barriers for its widespread implementation [8]. At the cost input level, Hardware investment for reinforcement learning-based automation control systems is 30%-50% higher than that of traditional systems. The hardware upgrade mainly involves the replacement and addition of high-precision sensors and edge computing modules. The average increase in software research and development costs is 600,000 yuan. For small and medium-sized enterprises with limited financial strength, the high pressure on software and hardware investment makes it difficult to bear, which also directly leads to the application penetration rate of relevant technologies of small and medium-sized enterprises being less than 10%, becoming an important obstacle to large-scale promotion. In terms of talent supply, there is a significant gap in the supply of professional talents in the intersection of automation control and reinforcement learning. According to statistics released by the Ministry of Education in 2023, there is a talent shortage of 120,000 in this field in China, of which 40% are high-caliber talents with practical industrial engineering capabilities. The insufficient talent supply directly restricts the efficiency and application quality of technology landing.

The lack of sound industry standards is another key constraint factor. Currently, there is no unified technical standard and performance evaluation system for reinforcement learning in the field of automation control. The compatibility between algorithms and control systems developed by different enterprises is poor. In the field of industrial robots alone, the compatibility of RL algorithms across different manufacturers is less than 30%, which seriously hinders the promotion and application across enterprises and scenarios, and increases the difficulty and cost of system integration. In addition, data security risks are relatively severe, and the training of reinforcement learning models relies on a large amount of industrial production core data, which includes confidential information such as production processes and equipment parameters. The "2024 Industrial Data Security Report" shows that 35.7% of enterprises are afraid of core production data leakage and production security risks, and are reluctant to adopt reinforcement learning control technology, which further delays the process of its large-scale application [9].

6. The Future Application Prospects and Development Trends of Reinforcement Learning in the Field of Automation Control

With the continuous upgrading of algorithm optimization, cross-domain technological integration, and the increasing demand in the industrial control industry, the application prospects of reinforcement learning in the field of automation control are becoming increasingly broad, presenting a clear development trend that combines technology orientation and market drive. In terms of algorithm optimization, the core breakthrough direction in the future will be sample efficiency, strong robustness, and high real-time performance. With the support of lightweight algorithms, edge deployment, and other technological means, combined with the current industry technology iteration rhythm prediction, by 2026, the sample efficiency of reinforcement learning will be improved by more than 60%, and the response delay can be reduced to less than 20ms [10], which can fully adapt to the requirements of high-end manufacturing, intelligent energy, and other refined and high demand automation control scenarios. At the level of technological integration, reinforcement learning will be deeply coupled with emerging technologies such as digital twins, the Internet of Things, and big data to achieve efficient interaction and collaborative decision-making of industrial-grade multi-source data, build a full process closed-loop system of "perception-simulation-decision-control", further improve the intelligence level and operational reliability of automated control, and reduce the cost of human intervention in industrial control.

From the perspective of industry market evolution, the market size of the reinforcement learning industry will continue to maintain a steady growth trend. According to Global Information, Inc.'s forecast, the global reinforcement learning market size will reach $36.27 billion by 2029, with a compound annual growth rate of 28.2% from 2025 to 2029. Europe, America, and the Asia Pacific region will be the core engines of global market growth, and the automation control field will still be the core application scenario. Its market share will continue to increase with the popularization of technology. At the level of industry standards, the first RL benchmark for industrial control will be officially released in 2025. In the next 3-5 years, China will gradually improve the technical standards and performance evaluation system of reinforcement learning in the field of automation control based on the industry-academia-research-application collaborative mechanism, laying a solid institutional foundation for the standardization and development of the industry. In addition, with the decrease in software and hardware costs brought about by technological maturity, the continuous growth of professional talent teams, and the support and guidance of industrial policies for the intelligent upgrading of small and medium-sized enterprises, it is expected that by 2028, the application proportion of reinforcement learning automation control systems for small and medium-sized enterprises will increase from 8.3% to 35% [11], truly realizing the large-scale popularization of this technology in industrial enterprises of different scales.

7. Conclusion

This article relies on authoritative industry data and practical industrial application cases to comprehensively review the current application status of reinforcement learning in the field of automation control, deeply analyze its core adaptability logic with automation control, mainstream application scenarios, key technological breakthroughs, and existing technological bottlenecks. At the same time, it explores the core factors that restrict the large-scale implementation of this technology, and provides a reasonable outlook on its future development path and application prospects. From a practical perspective, the core characteristics of reinforcement learning, such as model-free adaptation, online adaptation, and autonomous strategy optimization, have been effectively implemented in automation control scenarios such as industrial processes, robots, and intelligent energy, effectively addresses the nonlinear and multi-constraint challenges that traditional control methods struggle to handle. They have played an irreplaceable role in improving control accuracy, reducing production energy consumption, and optimizing production efficiency. In 2024, the market size of China's reinforcement learning industry has reached 26 billion yuan, with automation control applications accounting for over 40%. This data fully confirms its extremely high application value and industrial potential in the field of industrial control.

At the same time, it is necessary to be aware that the application of reinforcement learning in the field of automation control still faces multiple challenges, such as low sample efficiency, insufficient robustness and other technical bottlenecks, coupled with the reality of high implementation costs and a shortage of cross-disciplinary professionals, which jointly constrain its large-scale promotion and deep application. In the future, with the continuous optimization of reinforcement learning algorithms, the deepening integration with emerging technologies such as digital twins, and the gradual improvement of industry standards and the steady growth of professional talent teams, reinforcement learning will gradually break through existing development bottlenecks, achieve deeper integration with the field of automation control, promote the transformation and upgrading of the automation control industry towards intelligence, adaptiveness, and collaboration, further broaden its application boundaries in industrial manufacturing, robot research and development, intelligent energy regulation and other fields, inject new momentum into industrial intelligent transformation, and thus provide a clear research framework and practical implementation guidelines for subsequent related research.

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