

METHODS OF TRAINING AND ADAPTATION OF AI AGENTS IN COMPLEX PROCESS CONTROL SYSTEMS

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Abstract

The article presents a study of modern methods of training and adaptation of artificial agents used in managing complex processes, which are characterized by a high level of uncertainty and the need for prompt response to changes. Key methodological approaches such as machine learning and neuroevolution are discussed. These approaches allow AI agents to accumulate knowledge about the behavior of systems continuously, analyze external changes, and adjust the management strategy depending on environmental conditions, which significantly increases their ability to predict and prevent possible failures in management.

In the course of the study, models were considered that allow automating the execution of complex, multitasking processes, minimizing human intervention, and reducing the likelihood of errors. In addition, the presented methods provide high flexibility and scalability of systems, which is especially important in industrial and technological industries, where stability and reliability are critical. The results showed that AI agents with adaptive learning capabilities can increase operational efficiency while reducing costs and optimizing resource use. The conclusion highlights the prospects of using artificial intelligence to build highly autonomous control systems capable of responding to dynamic challenges, which opens up new horizons for automation and intellectual support in industrial production, logistics, and other key areas.

Thus, the article makes a significant contribution to understanding the role of AI in management modernization, offering practical recommendations on the implementation of intelligent agents in real-world scenarios to increase productivity and sustainability.

Keywords Artificial intelligence, AI agents, complex processes, adaptation, machine learning, neuroevolution, reinforcement learning, deep neural networks, autonomous systems, operational efficiency, resource optimization.

INTRODUCTION

Modern control systems are becoming increasingly complex and multifaceted, necessitating continual adaptation to changing conditions and the ability to operate effectively under high uncertainty. In such environments, traditional automation approaches prove insufficiently flexible, as they struggle to respond appropriately to unpredictable changes in processes and external factors. In recent years, artificial intelligence (AI) and machine learning have gained considerable

prominence in addressing these challenges, offering adaptive solutions that can learn autonomously, analyze data, and make decisions based on the current situation. Among various AI approaches, particular emphasis is placed on methods for training and adapting AI agents, which provide the flexibility and autonomy demanded by complex control systems.

The relevance of this study is underscored by the growing need for adaptive and intelligent systems

capable of efficient operation in industries such as manufacturing, energy, transportation, and other sectors that require rapid responses to change. Applying machine learning techniques, such as neuroevolution and reinforcement learning, allows AI agents to learn unique process characteristics and adapt to new conditions in real time, significantly enhancing their effectiveness.

Despite notable progress in AI, integrating trainable AI agents into complex control systems remains a challenging task. The need for continuous learning and adaptation of agents to dynamic conditions, along with the ability to act based on large-scale data analysis, demands the development and testing of new methods. Current research indicates that approaches like reinforcement learning and deep neural networks enable the creation of systems that not only adapt to changes but also continuously improve their performance during operation. Consequently, exploring methods for training and adapting AI agents is an essential step in developing fully autonomous control systems capable of efficient functioning in complex environments.

The objective of this study is to investigate and analyze contemporary methods for training and adapting AI agents in control systems managing complex processes, as well as to assess their effectiveness in ensuring reliability, resilience, and high performance.

METHODS

This study employed comparative analysis, systematization, synthesis, and examination of practical examples that illustrate the use of training and subsequent adaptation methods for AI agents in control systems for complex processes.

Thon C. et al. [1] point out that artificial intelligence (AI) plays a crucial role in various fields, particularly in process engineering, where it optimizes complex industrial processes to enhance

efficiency and reduce costs. Azeem M. et al. [9] note that in the manufacturing sector, the use of big data addresses significant challenges and improves production efficiency. The practical aspect of this application was considered in this study through the example of Volkswagen [10]. Additionally, the practical side of AI applications was explored based on Tesla's experience [12]. In aviation, AI contributes to improving aircraft fuel efficiency through advanced technologies, supporting the industry's sustainable development [11].

Soori M., Arezoo B., and Dastres R. [7] observe that in robotics, the integration of AI, machine learning, and deep learning is transforming robot capabilities, making them more complex and intelligent. Galván E. and Mooney P. [5] believe that these advancements are complemented by research in the neuroevolution of deep neural networks, which enhances training algorithms and addresses future challenges in AI systems.

Heuillet A., Couthouis F., and Díaz-Rodríguez N. [6] discuss the necessity for transparent and interpretable AI models, especially in reinforcement learning, where understanding AI decision-making processes builds trust and promotes broader adoption of the technology. Practical applications are developing automated machine learning approaches for real-time fault detection and diagnosis, which improve system reliability and maintenance, as noted by Leite D. et al. [8].

Beyond technical achievements, social aspects of AI are also subjects of research. De Togni G. et al. [3] examine emotional and relational aspects of AI systems to make them more "intelligent" and "caring." Moradbakhti L., Schreibelmayr S., and Mara M. [4] explore gender dynamics in AI through the lens of voice assistants, investigating how these technologies meet users' basic psychological needs. The evolution and future of conversational agents are analyzed with a proposed research

agenda for exploring new frontiers in AI development, according to Schöbel S. et al. [2].

In healthcare, AI shows significant potential. Platforms such as IBM Watson Health develop AI-based solutions for personalized cancer treatment, demonstrating AI's impact on providing individualized medical care [13].

RESULTS AND DISCUSSION

Modern control systems for complex processes

require adaptive and autonomous solutions capable of responding to changing conditions in real time. Artificial intelligence (AI), particularly learning-enabled agents, has become a key component of such systems. AI agents can learn specific process characteristics, predict behavioral changes, and optimize outcomes based on accumulated data. The scenarios presented below in Table 1 demonstrate how these systems can transform traditional methods of operation.

Table 1. Scenarios for the use of AI agents [4]

Scenario	Description	Roles and Tasks of AI Agents	Advantages
Automation of Credit Underwriting	Credit risk assessment requires thorough data analysis of the borrower, type of credit, and other factors, which is time-consuming and involves collaboration among specialists. AI agents can automate and expedite this process by performing functional roles.	<ul style="list-style-type: none"> - Intermediary Agent: connects the borrower with the financial institution. - Data Processing Agent: verifies documentation, calculates financial metrics. - Sub-agents: verify results and analyze errors. 	<ul style="list-style-type: none"> - Reduces evaluation time by 20–60%. - Increases speed and quality of analysis.
Updating Legacy Software Systems	Updating old software requires code analysis, documentation, and updates, demanding significant resources. Agent systems can distribute tasks among AI agents specializing in different aspects of the process, optimizing and accelerating modernization.	<ul style="list-style-type: none"> - Code Analysis Agent: performs structural analysis. - Quality Assurance Agent: ensures compliance with requirements. - Development and Testing Agent: implements and tests updates. 	<ul style="list-style-type: none"> - Saves resources in development and maintenance. - Enhances productivity and operational efficiency.
Creating Marketing Campaigns	Conducting online campaigns requires coordination and consideration of various platforms' specifics. Agent	<ul style="list-style-type: none"> - Audience Analysis Agent: collects and analyzes information by segments. - Content Creation Agent: 	<ul style="list-style-type: none"> - Reduces time costs. - Improves campaign

	systems assist marketing teams by auditing audiences, creating, and testing content, thus speeding up the process and improving relevance.	adapts materials for different segments.	relevance and effectiveness.
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For the effective implementation of agent-based systems, organizations should consider several key factors. First, it is essential to structure knowledge about business processes to provide a foundation for agent training. The technological infrastructure must also be adapted to support agent-based systems, ensuring their integration into existing workflows. Finally, ongoing supervision by specialists is crucial to assess the accuracy and efficiency of agent operations, creating conditions for their continued learning [4].

Neuroevolutionary algorithms, combining principles of evolutionary strategies and neural networks, represent unique methods that allow artificial intelligence systems to adapt to complex

tasks. This approach, inspired by natural processes, employs artificial neural networks optimized through mechanisms resembling natural selection. The neuroevolutionary learning process is based on principles similar to evolution: a population of networks is generated randomly, with each network evaluated for task performance. Fitness scores determine which specimens will reproduce, applying genetic operators such as mutation and crossover to produce more adaptive offspring. Gradually, with each generation, algorithms enhance their performance. Table 2 below describes the main advantages and disadvantages inherent in the neuroevolutionary approach for training and adapting AI agents in the management of complex process systems.

Table 2. The main advantages and disadvantages are inherent in the neuroevolutionary approach in the training and adaptation of AI agents [5]

Advantages	Disadvantages
Ability to find global optima: Neuroevolutionary algorithms avoid local minima, which is particularly important for complex systems with nonlinear dynamics.	High computational cost: The numerous iterations and need for evolutionary modeling result in significant computational expenses.
Adaptation to changing conditions: This approach enables agents to adapt effectively to environmental changes or control parameters.	Parameter tuning complexity: Selecting hyperparameters (e.g., mutation rate, population size) requires expert knowledge and can significantly impact outcomes.
Resilience to unforeseen factors: Evolutionary methods can find effective strategies even in the	Need for large training datasets: Successful evolution requires numerous simulations,

presence of noise and random factors affecting learning.	increasing training time and resource consumption.
Ability to generate diverse solutions: The evolutionary process creates multiple solutions, enhancing the chances of finding effective strategies for complex tasks.	Difficulty in analyzing and interpreting solutions: Neuroevolutionary outcomes can be challenging to interpret, complicating validation and safety assessments.
Reduced dependence on prior knowledge: Neuroevolutionary algorithms do not require a detailed task description and can learn with limited information about the system.	Risk of undesired behavior: Evolutionary algorithms may produce agent behaviors that do not align with system goals or may even be detrimental.
High flexibility and scalability: Neuroevolution can be used to configure agents in systems of varying complexity, in both real and simulated environments.	Extended training duration: The need for evolutionary iterations can make agent training time-consuming, reducing the method's immediacy.

Thus, the data optimizes logistics management, risk forecasting, data processing, and the creation of adaptive models that learn despite a limited amount of available information [5].

Reinforcement learning (RL) is a method in which an agent, through interaction with the environment, learns from the outcomes of its actions. This method, based on a "trial and error" model, allows AI to adapt and achieve objectives by accumulating positive and negative rewards. Q-learning, a popular approach that uses a Q-value table, helps an agent discover optimal action

strategies by updating values based on observed rewards. Policy gradients offer an alternative approach, where the agent learns directly through functions mapping states to actions, enabling it to maximize expected rewards. These methods, when combined with neural networks, make AI more flexible and capable of making strategic decisions in complex situations [6].

Table 3 below presents the advantages and disadvantages of the reinforcement learning (RL) method for enhancing the intelligence of AI agents.

Table 3. Advantages and disadvantages of the reinforcement learning (RL) method for the development of intelligence of AI agents [7].

Advantages	Disadvantages
Adaptive learning through trial and error: RL allows agents to learn from experience, adjusting behavior based on feedback from the environment.	High computational complexity: Achieving optimal strategies requires many iterations, increasing computational costs.

Ability to find optimal strategies: RL can optimize agent actions to achieve maximum rewards, which is suitable for complex tasks.	Unstable learning: RL often encounters inconsistent performance due to initial conditions and environmental randomness.
Applicability to dynamic environments: RL is well-suited for environments with changing conditions, as the agent learns to adapt based on current data.	Risk of overfitting to specific scenarios: The agent may "memorize" actions for particular situations and become ineffective in new conditions.
Minimal knowledge requirements about the environment: RL enables learning even without knowledge of the environment's mathematical model, relying on interaction and receiving rewards.	Extended training period: In real-world applications, reinforcement learning can take a long time due to the need for extensive interactions with the environment.
Development of autonomy and independent decision-making: Through learning, the agent becomes capable of making decisions and achieving goals without constant supervision.	Risk of negative behavior: If the reward function is incorrectly configured, the agent may develop undesirable or even harmful strategies that do not align with system objectives.
Ability to learn in uncertain conditions: RL can learn and make decisions even with noise and incomplete information about the environment.	Knowledge transfer issues: Acquired strategies may be of limited use in other tasks, requiring a new training cycle for each new environment.

Next, practical examples of the use of training and adaptation methods for AI agents will be examined. For instance, Siemens applies deep learning and neural networks in automation systems for failure prediction and equipment fault diagnosis. Its analytical platform, MindSphere, uses neural network models to analyze real-time data, optimizing production processes and identifying potential issues before they arise. This approach has enabled the company to reduce emergency shutdowns, minimizing production losses and enhancing equipment reliability [8].

General Electric has also implemented neural network models in its Predix system, which focuses on analyzing data from the industrial Internet of Things (IIoT). This platform collects and processes data from numerous sensors and devices, allowing it to predict machine condition

changes, minimize downtime risks, and extend equipment life. In critical sectors such as energy and aviation, Predix, powered by neural network methods, has significantly improved responsiveness and reliability in managing complex processes [9].

Volkswagen uses evolutionary algorithms and genetic programming methods to optimize supply chains and production processes. The Digital Production Platform (DPP) project, developed in collaboration with AWS, utilizes algorithms to predict production needs, manage logistics, and minimize operational risks. The flexibility of evolutionary methods allows the company to quickly adapt to demand changes and avoid production disruptions [10].

At Airbus, evolutionary algorithms are used to optimize aircraft design, reducing weight and

improving fuel efficiency. These algorithms enable the discovery of unique design solutions that reduce material costs and improve operational performance. This approach helps lower operational costs and makes aircraft more environmentally friendly [11].

Hybrid methods are used in companies such as IBM and Tesla. For example, Tesla combines deep learning and RL to develop autonomous vehicle control systems. This approach allows systems to analyze complex road situations in real time, optimizing routes, avoiding obstacles, and adapting to changing conditions [12].

In healthcare projects, IBM Watson uses hybrid learning, combining neural networks and RL to support medical decision-making. For instance, in oncology clinics, Watson analyzes patient data and recommends optimal treatment options based on a comprehensive analysis of medical data and scientific publications. This approach ensures system flexibility, helping physicians make more informed decisions and enhancing the quality of medical care [13].

Thus, the integration of AI agents with training and adaptation methods in complex processes, as demonstrated by leading corporations, confirms the importance of these technologies in improving efficiency, reducing costs, and enhancing operational performance.

CONCLUSION

The study confirms that integrating AI agents into control systems for complex processes significantly enhances their adaptability, resilience, and efficiency. The examined machine learning methods, including reinforcement learning and neuroevolutionary algorithms, have demonstrated their capacity to provide high predictive accuracy and rapid responsiveness to environmental changes. The use of deep neural networks and adaptive algorithms allows AI

agents not only to analyze current data but also to improve behavior models based on experience, which is critically important for complex multitasking systems.

The research results showed that adaptive AI agents can successfully address optimization tasks and minimize disruptions, reducing costs and improving operational performance. These technologies are especially relevant to industrial and infrastructure sectors, where system stability and reliability are paramount. Agents with continuous learning capabilities have proven effective in automated management tasks, opening up vast prospects for their use in resource management, logistics, and forecasting.

Thus, the study underscores the significance of using AI agents in modern control systems, highlighting the promise of further research in this field. The application of adaptive learning methods for creating autonomous AI agents not only improves management efficiency but also paves the way for developing new operational models that are resilient to external influences and capable of self-improvement.

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