Chapter 11
Reinforcement Learning for Autonomous Optimization in Intelligent Engineering

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ABSTRACT

Reinforcement learning (RL) is emerging as a transformative approach for autonomous optimization in intelligent engineering systems, facilitating adaptive decision-making and continuous self-improvement. This chapter examines the applications of reinforcement learning in critical engineering fields such as manufacturing, robotics, energy management, and industrial automation, where optimization is essential for system efficiency and scalability. Through iterative learning and reward-based feedback mechanisms, reinforcement learning agents actively interact with complex environments, thereby enhancing their strategies. Engineers can make systems work better in real-time, use fewer resources, and respond faster by using advanced reinforcement learning techniques like Actor-Critic methods, Proximal Policy Optimization (PPO), and Deep Q-Networks (DQN).

INTRODUCTION

Reinforcement learning (RL) has emerged as a transformational instrument for autonomous optimization within the expansive field of intelligent engineering, which is constantly expanding. In contrast to more conventional methods of optimization,

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reinforcement learning enables systems to acquire knowledge in a dynamic manner by means of interactions with their surroundings. This, in turn, improves decision-making through the process of learning through trial and error. In situations when pre-programmed heuristics are unsuccessful, this method is extremely useful since it is particularly advantageous in complicated, high-dimensional systems. Within the context of Markov Decision Processes (MDPs), which delineate decision-making problems via states, actions, reward functions, and transition probabilities, reinforcement learning (RL) Reinforcement Learning (RL) use the Bellman equation to iteratively refine optimal strategies, facilitating efficient policy development for autonomous agents. Within the realm of reinforcement learning algorithms, there are three primary classifications that may be distinguished: value-based, policy-based, and actor-critic techniques. In Q-learning, a fundamental value-based strategy, values are updated in an iterative manner through the use of the Bellman equation. Additionally, a Q-function is utilized in order to compute the anticipated reward for every state-action combination. The breakthroughs that have been made in deep learning have resulted in the creation of Deep Q-Networks (DQN), which are neural networks that are used to estimate Q-values in multiple-dimensional spaces. It is possible to directly optimize decision-making processes through the use of gradient-based approaches such as REINFORCE and Proximal Policy Optimization (PPO). These strategies work by altering policy parameters. The combination of value-based and policy optimization paradigms, in conjunction with actor-critic frameworks like Deep Deterministic Policy Gradient (DDPG) and Advantage Actor-Critic (A2C), results in an increase in both the stability and efficiency of autonomous systems that are driven by reinforcement learning. Learning through reinforcement is applied in a number of different areas within the field of intelligent engineering. Some of these fields include energy efficiency, sophisticated control systems, and autonomous robots. When it comes to industrial automation, adaptive control is made easier by optimizing dynamic control techniques with RL-driven controllers. Reinforcement learning is a technique used in robotics that improves decision-making for grasping mechanics, trajectory planning, and autonomous navigation. This enables self-learning robots to undertake complicated maneuvers. Furthermore, reinforcement learning (RL) approaches offer real-time adaptation in smart grids by means of multi-agent reinforcement learning (MARL). This results in improved load balancing and power distribution, which in turn leads to an increase in energy efficiency.

Despite the fact that it has a great deal of benefits, reinforcement learning also presents a significant number of difficulties and constraints for study. When it comes to reinforcement learning models, sample inefficiencies require huge volumes of interaction data, which typically leads to simulations that are computationally costly. The issue of exploration vs exploitation makes it more difficult to strike a balance between the development of new tactics and the improvement of existing programs.