# Multi-Agent Reinforcement Learning and its practical applications in games: a review of the literature

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## Abstract

Multi-agent reinforcement learning (MARL) has achieved tremendous success in various artificial intelligence domains such as the gaming industry. This literature review explores the theoretical foundations, principles, algorithms, applications, challenges, and recent advancements in MARL.

Algorithms such as Q-Learning, Policy-based algorithms, SARSA, and more algorithms have laid the groundwork for MARL by providing approaches to agent decision-making and learning. Q-decomposition methods have also further enhanced MARL by decomposing the global value function into local components, allowing for efficient coordination, and learning among agents (Russel & Zimdars, 2003).

The architectures employed in MARL range from centralised to decentralised, with each influencing the coordination and decision-making processes of agents in the environment. Centralised architectures, in which all agents share a single state representation and make collaborative decisions, provide benefits in terms of global coordination and information exchange. Decentralised architectures, on the other hand, encourage agent autonomy by allowing each agent to have its own state representations and decision-making procedures. These designs, when combined with communication and coordination mechanisms, enables MARL systems to model complex interactions and achieve emergent behaviours.

Beyond the gaming industry, MARL is extensively used in a variety of domains, including multi-robot systems, autonomous vehicles, and social dilemmas. Obstacles such as credit assignment, scalability, and ethical considerations persist, emphasising the importance of continued research and innovation in the field.

It is hoped that this paper will provide valuable insights for game developers and researchers regarding MARL and its challenges and advancements.

## Review of Literature

### Overview of MARL

Multi-agent reinforcement learning (MARL) is a subfield of reinforcement learning that focuses on the behaviour of multiple learning agents interacting in a shared environment. MARL algorithms are designed to address various scenarios, including fully cooperative, fully competitive, and mixed cooperative-competitive environments. These algorithms enable agents to learn optimal strategies through interactions with the environment and other agents.

MARL presents unique challenges and applications across different domains. Challenges include nonstationary, varying learning speeds, scalability issues in deep reinforcement learning, and handling partial observability through centralised learning of decentralised policies. To address these challenges, researchers have developed diverse algorithms and methodologies to enhance the performance of MARL systems (Canese, et al., Multi-Agent Reinforcement Learning: A Review of Challenges and Applications, 2021).

The framework of MARL involves models such as Markov Decision Processes (MDPs), Markov Games, Partially-Observable Markov Decision Processes (POMDPs), and Decentralised Partially-Observable Markov Decision Processes (Dec-POMDPs). Single-agent reinforcement learning algorithms like Q-Learning and REINFORCE serve as foundational components in developing MARL algorithms. These algorithms consist of critics for estimating value functions and actors for updating policy parameters based on feedback from the environment. (Canese, et al., Multi-Agent Reinforcement Learning: A Review of Challenges and Applications., 2021).

MARL has been applied in various domains such as robotics, distributed control, telecommunications, and economics due to its ability to address complex tasks that are challenging to solve with preprogrammed behaviours. The field of MARL continues to evolve with advancements in algorithm design, benchmark environments for multi-agent systems, and practical applications across industries (L. Bus¸oniu & Schutter, 2010).

### Frameworks of MARL expanded

#### Markov Decision Processes (MDPs)

Markov Decision Processes (MDPs) serve as a foundational concept in the realm of Multi-Agent Reinforcement Leaning (MARL), providing a mathematical framework for modelling decision-making processes where outcomes are influenced by both random factors and agent actions. In the context of MARL, MDPs extend to game models, enabling the representation of interactions among multiple agents within a shared environment (Albrecht, Christianos, & Schäfer, 2024).

An MDP is defined by a tuple (S, A ,P ,R ,γ), where:

* S represents the set of states,
* A represents the set of actions available to agents,
* P represents the state transitions probabilities,
* R represents the reward function,
* Γ represents the discount factor.

In MARL, MDPs serve as a foundational concept that guides agents in navigating complex decision spaces, learning optimal strategies through interactions with the environment and other agents, and adapting policies to maximise cumulative rewards over time. By leveraging MDPs, researchers can design algorithms that address challenges such as nonstationary, varying learning speeds scalability issues, and partial observability inherent in multi-agent systems.

The formal description of an MDP includes essential components like states, actions, rewards, and policies that shape agent decision-making processes. Reinforcement learning algorithms within MARL aim to find optimal solutions to MDPs by maximising long-term rewards through iterative policy updates and value function estimations.

Through the utilisation of MDPs in MARL, researchers can unlock new avenues for algorithmic advancements, applications in real-world scenarios, and a deeper understanding of multi-agent interactions with complex environments.

### Key Challenges in Multi-Agent Reinforcement Learning

Multi-agent reinforcement learning (MARL) presents several key challenges that must be addressed for the successful development and deployment of efficient algorithms. One of the primary challenges is nonstationary, which refers to the dynamic nature of the environment due to interactions among multiple agents. As highlighted by (Canese, et al, 2021), in MARL, each agent perceives other agents as part of the environment, leading to constant changes influenced by all agents’ actions. This introduces a significant hurdle in achieving convergence and maintaining acceptable performance, especially when a large number of agents are involved. Additionally, scalability is another crucial challenge as developing algorithms capable of accomodating real-world problems involving numerous agents requires careful consideration. Futhermore, observaility poses a challenge in terms of acquiring complete information about the state and actions of other agents within the environment, thereby impacting decision-making processes. The scalability to a high number of agents is an essential feature that must be taken into account when developing algorithms that can be applied to real-world problems. MARL has shown potential applications in various real-world scenarios. One such application is in robotics, where MARL enables multiple agents to collaborate and learn from each other to accomplish complex tasks efficiently and effectively (Canese, et al., Multi-Agent Reinforcement Learning: A Review of Challenges and Applications, 2021). The versatality of MARL makes it well-suited for addressing diverse challenges across different domains by harnessing the collective intelligence and coordination capabilities of multiple autonomous entities.

# References

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