Reinforcement Learning (RL) is one of the machine learning (ML) techniques to learn sequential decision-making in complex problems [49]. RL is a learning approach in which an RL agent interacts with its surrounding environment by trial and error method and tries to learn an optimal behavioral strategy based on the reward signals received from previous interactions.

One of the most fruitful aspects of RL is its adaptability to other scientific and engineering fields. RL offers a great opportunity to open new frontiers where system models are unavailable or too difficult and expensive to build. The learning process of the RL agent is quite similar to the human learning approach. In recent years, RL has appeared as an efficient technique for solving complicated sequential decision-making tasks. RL is producing significant results in fields such as game playing [51],[52] [53], robotics [54], vehicle navigation [55], intelligent transportation system [56], healthcare [57], recommender systems [58], and business management problems.

The modern RL research is mainly based on the function approximation by deep neural network (DNN). Google DeepMind’s success with the function approximation by DNN for problems like Atari Games [88], [89], and AlphaGo [90], [91] has revolutionized the field of Deep Reinforcement Learning (DRL). After the IBM chess-playing program Deep Blue's success in 1997 [92] against the chess world champion Garry Kasparov, DeepMind's success in game playing was a remarkable achievement in the field of artificial intelligence (AI). In ML, generalization refers to the ability of an algorithm to be effective across a range of new inputs and applications. DRL is a powerful technique for model-free learning, which also addresses the problem of generality. So without the knowledge of complete system dynamics, DRL can learn directly from experience samples in offline or online modes. Thus DRL is an efficient technique to find a suboptimal policy for stochastic nonlinear systems having continuous state and action spaces. DRL can lead us to the construction of an autonomous AI agent with a high level of critical thinking and understanding [93]. Currently, DRL algorithms are being applied in the field of robotics to learn optimal control policies directly from visual inputs for different real-world problems [94], [95].

Control systems have a deep, broad, and strong base of foundational knowledge developed over the last 60 years with a major emphasis on decision-making under uncertainty. Dynamic systems modeling, structural properties, model reduction, identification, stability, feedback, optimality, robustness, adaptation, fault tolerance, and architecture have been among the central concerns on the theoretical side. These issues have been explored in a wide variety of settings: linear, nonlinear, stochastic, hybrid, distributed, supervisory, and others. Applications have been wide-ranging: aerospace, automotive, manufacturing, chemical process, energy, power, transportation, etc. Despite all the progress in various subfields of systems and control, much remains to be done to satisfactorily address control of large, complex, distributed dynamical systems under rapid changes in the environment and high levels of uncertainty.

On the one hand, a major goal of AI is to build machines that can learn and think for themselves, including having imagination, reasoning, planning, etc. On the other hand, we have a rich body of knowledge in control systems. The field of control can both benefit from and influence the ongoing revolutionary advances in ML and AI. By leveraging these ongoing trends and advances in ML/AI, we can aim to have significantly more powerful and versatile control systems. For this, we would need to define specific goals that are currently unachievable with existing control techniques but could potentially be achieved by leveraging ML/AI advances. Such goals would likely be driven by major application areas for control. On the other side, we can identify ideas, tools, and techniques from control systems that have the potential to advance AI in its quest of building machines that learn and think for themselves. There are historical connections between learning, AI, and control systems going back to the 60’s. Research fields such as intelligent control and neural networks for control arose from these long-standing connections.

Traditionally, control systems analysis and design have been based on detailed mathematical models of the system and the environment and with fairly well-understood sources of uncertainty. These models are typically described using differential equations, discrete-event formalisms, Markov processes, etc. Construction of such models requires highly specific scientific and engineering knowledge, data, and domain expertise.

By contrast, RL methods aim to learn models and control actions directly from data and experiments. Clearly, in areas where detailed traditional control-oriented models are feasible and have already been developed, there is modest scope for RL. However, a much larger opportunity arises in areas where (a) such detailed, mechanistic mathematical models do not exist, and/or (b) where performance goals are described at a high level, and/or (c) where the amount of uncertainty is significantly greater with unknown sources, and/or (d) where the control goals and tasks have high diversity.

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