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# Deep Reinforcement Learning for Dynamic Beamforming In Millimeter-Wave and Terahertz Bands

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## Abstract

The integration of Deep Reinforcement Learning (DRL) for dynamic beamforming in millimeter-wave (mmWave) and terahertz (THz) communication systems represents a transformative approach to optimizing the performance of next-generation wireless networks. These high-frequency bands offer significant bandwidth advantages but present substantial challenges, including high propagation losses, rapid channel variations, and interference in densely populated environments. DRL, with its capability to learn optimal strategies through interaction with the environment, provides an effective solution to these challenges by adapting beamforming parameters in real time. This chapter delves into the application of DRL for dynamic beamforming, focusing on key aspects such as channel state estimation, interference mitigation, and energy-efficient power control. Through a comprehensive review of current advancements, this chapter highlights case studies, the impact of stochastic channel conditions, and the scalability of DRL models in large-scale wireless networks. Furthermore, the chapter explores the trade-offs between exploration and exploitation within the DRL framework, offering insights into overcoming critical obstacles like computational complexity and real-time decision-making in mmWave and THz systems. The potential of DRL to revolutionize beamforming strategies in these frequency bands is immense, paving the way for more reliable, adaptive, and efficient wireless communication systems.

Keywords: Deep Reinforcement Learning, Dynamic Beamforming, Millimeter-Wave, Terahertz Communication, Interference Mitigation, Energy Efficiency.

## Introduction

The advent of next-generation wireless technologies, particularly with the deployment of 5G and the exploration of 6G, has significantly heightened the demand for higher capacity and lower latency [1]. Millimeter-wave (mmWave) and terahertz (THz) frequency bands have become prime

candidates to meet these evolving requirements due to their ability to support vast bandwidths [2]. These high-frequency bands, ranging from 30 GHz to 3 THz, offer tremendous potential for ultra-high-speed data transmission [3]. Their adoption comes with a unique set of challenges, primarily due to the increased path loss, environmental factors such as weather, and the sensitivity to physical obstructions like buildings and foliage [4]. Overcoming these challenges requires innovative beamforming strategies that can adapt to the rapidly changing conditions within these frequency ranges [5].

Dynamic beamforming is one such strategy that has gained significant attention for its ability to optimize signal transmission in real time [6]. Unlike static beamforming, which relies on pre-configured settings, dynamic beamforming continuously adjusts the direction and power of the antenna beams based on environmental feedback [7]. This real-time adaptability is crucial in mmWave and THz systems [8], where channel conditions fluctuate rapidly due to factors such as user mobility, interference, and signal blockage [9]. In this context, Deep Reinforcement Learning (DRL), a powerful subset of machine learning, offers a promising approach to dynamically optimize beamforming parameters. DRL enables systems to learn optimal strategies through trial and error, making it well-suited for the unpredictable environments encountered in mmWave and THz communication systems [10].

DRL in dynamic beamforming, its application in wireless communication systems faces several challenges [11]. One significant hurdle is the stochastic nature of wireless channels, which are highly variable and subject to frequent disruptions [12]. In mmWave and THz bands, this variability is exacerbated by the physical properties of high-frequency signals, which experience greater attenuation and are more sensitive to environmental conditions [13]. As a result, the channel state can change rapidly, complicating the task of real-time optimization. DRL algorithms must be capable of learning from these unpredictable conditions while continuously updating their strategies to ensure robust performance [14]. The inherent uncertainty in channel conditions necessitates the development of more sophisticated DRL models that can adapt effectively without relying on static or predetermined parameters [15].