

Summary

To foster the advancement of smart city components and the Internet of Things (IoT) applications, future wireless systems need to offer extensive system capacity, ultra-high data speeds, minimal latency, high dependability, low energy consumption, and large connection densities. These networks are expected to revolutionize various applications in a variety of contexts, including massive machine-type communications (mMTC), ultra-reliable low latency communication (uRLLC), and better mobile broadband services (EMBB).

Due to the widely varying and quickly growing need for mobile wireless networks, meeting the requirements of these applications has become challenging. To provide ubiquitous connections for billions of devices, efficiently manage the surging mobile data traffic, and support algorithm-driven applications, an effective solution is necessary. Machine learning (ML) is seen as a crucial tool to address these challenges. Moreover, the utilization of new frequencies and surge in number of users motivated new technologies such as non-orthogonal multiple access (NOMA) and intelligent reflecting surfaces (IRS).

The goal of this thesis is to establish ML-based methods for 5G and beyond (B5G) wireless communication systems that use NOMA and IRS. The study involves the utilization of deep reinforcement learning (DRL) to enhance IRS operations in downlink NOMA situations, as well as terahertz (THz) networks assisted by multi-hop IRS. The emphasis will be on maximizing the total data transmission rate. Furthermore, DRL is utilized for the secure cross-layer design of the IRS NOMA-SWIPT (Simultaneous Wireless Information and Power Transfer) IoT scenario, focusing on maximizing the secure sum-rate for legitimate IoT devices (IoTds) operating under the IRS NOMA-SWIPT scheme, and meeting packet loss constraints within the system. It was shown that the utilization of the DRL in the aforementioned scenarios enabled significant performance enhancements compared to existing classical solutions, which are typically sub-optimal due to the non-convex nature of the formulated problems. Furthermore, DRL models had better complexity scaling properties with increased system complexity (e.g. number of IRS elements).