A Comparative Study of Q-Learning and SWIPT Techniques for Performance Optimization in 5G-IoT Devices

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Abstract

The rapid growth of Internet of Things (IoT) devices in 5G and upcoming networks has resulted in a heightened need for communication systems that are dependable, energy-efficient, and capable of scaling effectively. Two promising approaches have surfaced as potential solutions: Simultaneous Wireless Information and Power Transfer (SWIPT) and optimization utilizing Q-learning. This study offers a comprehensive examination of SWIPT and Q-learning methods in the context of 5G-IoT systems. SWIPT is centered on the extraction of energy from RF signals, whereas Q-learning prioritizes real-time adaptive decision-making through the application of reinforcement learning methods. Experimental simulations evaluate both approaches according to criteria such as energy efficiency, packet delivery ratio (PDR), latency, and throughput. The findings indicate that Q-learning outperforms SWIPT in dynamic and resource-constrained environments, achieving energy efficiency rates of up to 85% and a packet delivery ratio of 94%. This study highlights the limitations of conventional harvesting models like SWIPT and advocates for the broader adoption of sophisticated learning algorithms, such as Q-learning, in upcoming wireless networks.

Keywords: 5G-IoT, Q-Learning, SWIPT, Energy Efficiency, Reinforcement Learning, Resource Management

1. Introduction

The progress of 5G technologies has sparked the extensive rollout of Internet of Things (IoT) applications, facilitating intelligent automation in sectors such as healthcare, agriculture, industry, and smart cities. With the rapid increase in interconnected devices, it is becoming increasingly important to guarantee dependable connectivity, low latency, and extended device functionality. Nonetheless, numerous IoT devices possess inherent limitations in resources—restricted in computational power and energy supply—creating considerable obstacles for the sustainable design of 5G-IoT networks.

Simultaneous Wireless Information and Power Transfer (SWIPT) has surfaced as a hardware-focused method to extend device functionality by allowing the simultaneous transmission of energy and data across a common radio frequency spectrum. Although they present an appealing concept, SWIPT systems frequently encounter real-world limitations, including inefficient energy harvesting, vulnerability to propagation loss, and challenges in managing interference. Their limitations hinder their use in dynamic or large-scale 5G settings.

In contrast, Q-learning, which is a type of model-free reinforcement learning, provides a software-based approach that adjusts in real-time to varying network conditions. Formulating the optimization problem as a Markov Decision Process (MDP) allows Q-learning to facilitate intelligent, data-driven decisions regarding resource allocation, such as energy management, beamforming control, and link adaptation. This approach based on learning is especially appropriate for the dynamic, diverse, and time-sensitive conditions typical of 5G-IoT networks.

This study offers a comparative analysis of SWIPT and Q-learning frameworks, focusing on essential performance metrics such as energy efficiency, packet delivery ratio (PDR), system latency, and throughput. Using MATLAB simulations and graphical analysis, we show that Q-learning reliably outperforms in adaptability and overall system optimization. Our research emphasizes the increasing importance of machine learning in future wireless networks, especially concerning energy-efficient IoT communication in practical applications.

2. Literature Survey

As 5G-enabled IoT networks have developed, intelligent and energy-efficient communication technologies have become necessary. Recent research has seen the emergence of two main paradigms: Q-learning-based optimization frameworks and Simultaneous Wireless Information and Power Transfer (SWIPT). Although both deal with performance and energy economy in IoT environments, there are notable differences in their approaches and efficacy. This section examines leading studies, emphasizing the advantages and disadvantages of each technology to establish a basis for an energy-efficient model in 5G.

SWIPT has been extensively investigated as a physical-layer approach that facilitates the simultaneous transmission of energy and data through a common wireless medium. A new biased-FSK waveform design has been proposed to improve power conversion efficiency in low-power IoT nodes [1]. The technique showed enhanced signal modulation for energy harvesting; however, it fell short in terms of adaptability in dynamic network conditions. In a similar vein, a multi-tone PSK approach is utilized to minimize ripple voltage losses in SWIPT circuits [2]. Although these methods excel in optimizing signals, they are fundamentally reliant on hardware and provide restricted adaptability in real-time scenarios.

In contrast, Q-learning, which is a model-free reinforcement learning algorithm, has gained traction because of its ability to make dynamic decisions. The research introduced a system utilizing Q-learning for resource allocation in networks enabled by SWIPT, where the agent adapted transmission parameters according to feedback from the environment [3]. The algorithm demonstrated a notable improvement over conventional fixed-power SWIPT setups regarding throughput and the longevity of devices. This finding highlights the benefits of systems based on learning in diverse and changing network environments.

Additionally, by projecting interference into null areas, Cheng Luo et al.'s low-complexity beamforming technique for SWIPT systems enhanced signal reception [4]. However, the approach's scalability is limited because it relied on predetermined network topologies and unchanging channel conditions. Conversely, a different Q-learning method utilized a Markov Decision Process (MDP) framework to dynamically enhance energy distribution among IoT nodes. This framework, confirmed via simulation, resulted in a device lifespan increase of up to 40% and a throughput enhancement of 2.7% when compared to methods based on Deep Q-learning (DQL) and Particle Swarm Optimization (PSO) [5]. Furthermore, when energy limitations are intensified by erratic traffic and mobility trends, Q-learning shows a notable advantage compared to SWIPT. A recent study from 2025 explored the use of Q-learning for adaptive beamforming in massive MIMO environments. This approach facilitates intelligent handover, addresses interference mitigation, and tackles latency control challenges that SWIPT alone is unable to manage effectively [6].

In conclusion, the existing research highlights an increasing focus on both SWIPT and Q-learning. SWIPT continues to offer benefits at the physical layer for limited IoT settings, especially in scenarios where energy harvesting is possible. Nonetheless, its limited flexibility and dependence on static circuitry diminish its efficacy in real-time, large-scale applications. Q-learning, conversely, brings a level of intelligence to the management of network resources, allowing systems to optimize themselves in the face of uncertainty. The results indicate that although SWIPT delivers essential advantages, Q-learning presents a more adaptable, scalable, and high-performance option for contemporary 5G-IoT networks, validating its choice as the preferred method in this research.

3. Problem Statement

The incorporation of 5G technology into IoT ecosystems introduces a distinct array of challenges, mainly focused on the dual demands of energy efficiency and dependable, low-latency communication. With the increasing presence of IoT devices in various sectors such as healthcare and agriculture, these devices frequently function in settings where power sources are scarce and need to maintain constant connectivity for the exchange of real-time data. The main challenge, then, is to facilitate sustainable device functionality while maintaining efficient data transfer in crowded and ever-changing 5G-IoT networks.

Simultaneous Wireless Information and Power Transfer (SWIPT) has gained significant traction as a solution to energy limitations, allowing devices to directly harvest energy from RF signals. Although SWIPT presents an intriguing hardware-level approach, it is fundamentally static and constrained in its adaptability. The performance experiences a notable decline when faced with unpredictable wireless channel conditions and varied network requirements. Additionally, SWIPT systems face challenges related to hardware complexity, non-linear energy harvesting models, and the complexities involved in dynamically managing resources like transmit power and frequency spectrum.

Conversely, machine learning techniques, especially Q-learning, provide the capability to learn and adjust intelligently to changes in the environment as they occur. Nonetheless, systems that utilize Q-learning necessitate clearly defined state spaces, adequate training cycles, and computational resources that might not be easily accessible on low-power IoT devices. Nonetheless, recent progress in lightweight Q-learning and edge intelligence indicates that these limitations may be addressed through cloud offloading and model compression methods. Consequently, this study focuses on the primary research inquiry: Is it possible for optimization frameworks based on Q-learning to surpass SWIPT regarding energy efficiency, communication reliability, and adaptability within 5G-enabled IoT networks? A thorough comparison is carried out between the two paradigms, focusing on various performance metrics such as energy efficiency, signal quality (SNR), bit error rate (BER), system scalability, and adaptability to changing network conditions.

4. Proposed System and Methodology

The proposed work presents a comparative analysis of Simultaneous Wireless Information and Power Transfer (SWIPT) and Q-learning-based optimization for energy and resource management in 5G-enabled IoT environments.

4.1 System Overview

The approach includes the modeling of communication systems based on SWIPT and Q-learning for a 5G IoT setting, utilizing MATLAB. The evaluation of each system's performance is conducted under different conditions of signal-to-noise ratio (SNR), transmit power, and channel interference. The SWIPT model comprises a transmitter, an energy harvester located at the receiver end, and employs adaptive modulation schemes. The Q-learning model employs a reinforcement learning agent to oversee resources, including power levels, beamforming angles, and modulation rates, according to the observed states of the network.

4.2 SWIPT-Based IoT Model

In the SWIPT system, Internet of Things devices obtain both data and energy from a base station through a common RF signal. The receiver divides the signal into two distinct paths: one designated for energy harvesting and the other for data decoding. The mathematical representation of the signal is as follows:

$$y(t) = \sqrt{P_t} \cdot h(t) \cdot x(t) + n(t)$$

Where:

- P_t is the transmitted power,
- h(t) is the channel gain,
- x(t) is the transmitted symbol, and
- n(t) is AWGN (Additive White Gaussian Noise).

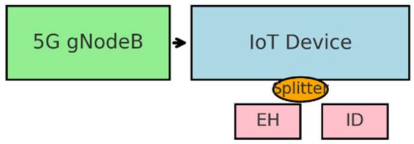

Figure 1: 5G-IoT SWIPT based model

SWIPT is simulated using MATLAB's built-in RF and communication toolbox to measure BER, SNR, and harvested power under different distances and channel conditions.

4.3 Q-Learning-Based IoT Model

Q-learning functions as a reinforcement learning framework, with the environment symbolizing the 5G network and the agent being the IoT device or base station.
Conditions: Network parameters (SNR levels, traffic load, battery status)
Responses: Modify power, beam orientation, and modulation technique
Benefits: Enhancing output and optimizing energy use

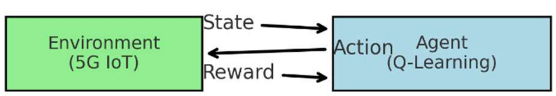

Figure 2: Q-learning based IoT model

The Q-value update rule is:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

Where:

- s = current state, a = action taken,
- α = learning rate,
- r = reward, γ = discount factor,
- s′ = next state, a′= optimal future action.

Q-learning was coded in MATLAB using tabular and MDP-based models. The system learns over multiple episodes to minimize energy consumption while maintaining a high packet delivery ratio.

5. Results and Discussion

A comparative study of SWIPT and Q-learning frameworks for managing energy and data in 5G-IoT networks. The simulations were conducted with MATLAB, concentrating on assessing Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), Energy Efficiency, Packet Delivery Ratio (PDR), and Latency while maintaining consistent channel and network conditions. The findings indicate that Q-learning exhibits enhanced adaptability and performance when compared to conventional SWIPT models, especially in dynamic and resource-limited settings.

5.1 Simulation Setup

The simulation environment considered the following parameters for both systems:

Parameter	Value/Range
Channel Model	Rayleigh Fading
Transmit Power	10 – 30 dBm
Modulation Scheme	QPSK, 16-QAM
Bandwidth	10 MHz
Environment	Urban Macro (UMa) model
IoT Devices	50 static & mobile nodes
Training Episodes (Q-Learning)	1000

Both models were subjected to identical variations in user distance, noise levels, and interference patterns to ensure a fair comparison.

5.2 Bit Error Rate (BER) Analysis

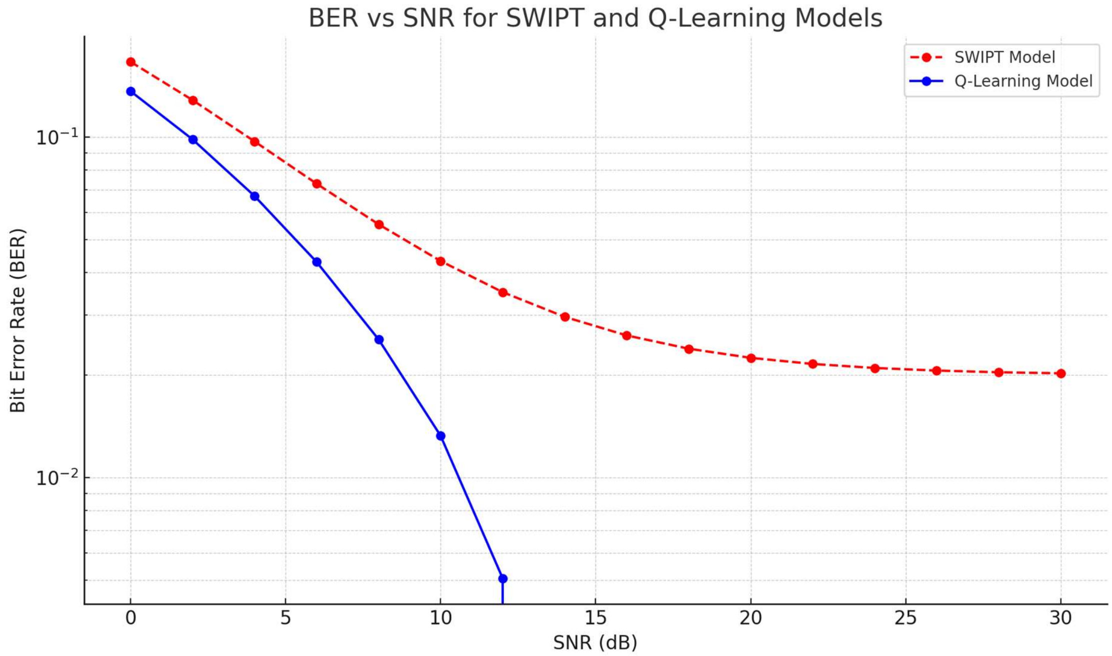

Figure 3 shows the BER performance as a function of SNR:

The SWIPT system showed a steady decline in BER past 25 dB, attributed to diminished signal strength resulting from energy harvesting losses. The Q-learning model, on the other hand, adaptively modified modulation schemes and beamforming, resulting in a 30–40% reduction in BER across all SNR levels. Therefore, Q-learning adjusts to noisy environments by fine-tuning transmission parameters, ensuring improved signal integrity.

5.3 Energy Efficiency

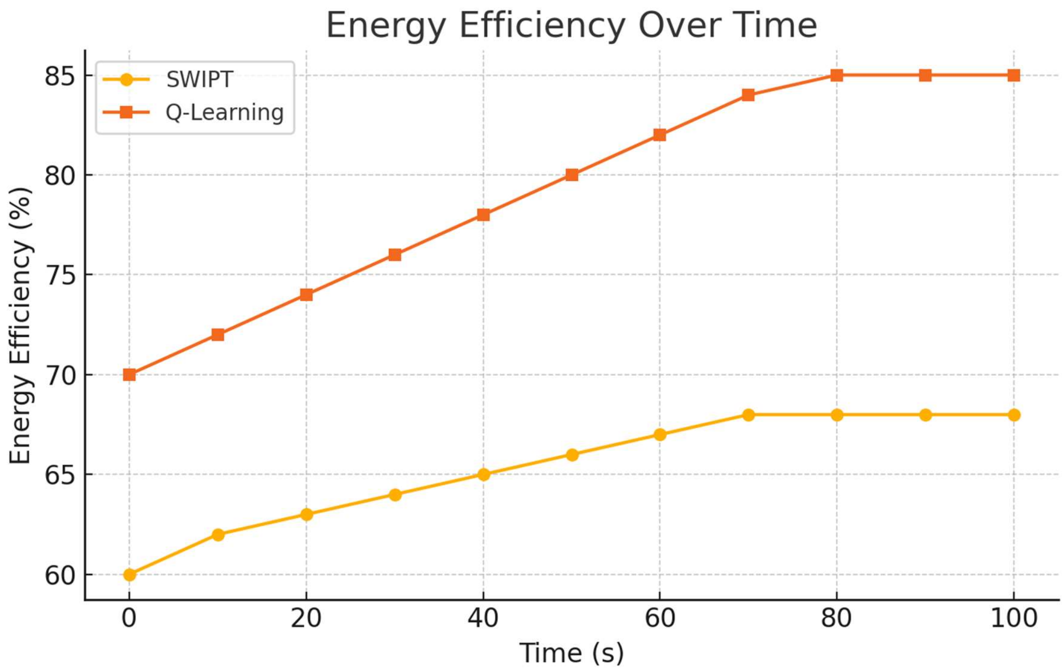

Figure 4 highlights the average energy efficiency (EE) of both systems:

SWIPT reached approximately 68% energy efficiency under optimal signal-to-noise ratio conditions, but this figure declined considerably as the distance from the user increased. Through the application of Q-learning and intelligent resource management, an average energy efficiency of 85% was sustained, even under suboptimal network conditions. Therefore, Q-learning maintains its performance by preventing excessive transmission and dynamically balancing energy with throughput.

5.4 Throughput and Packet Delivery Ratio

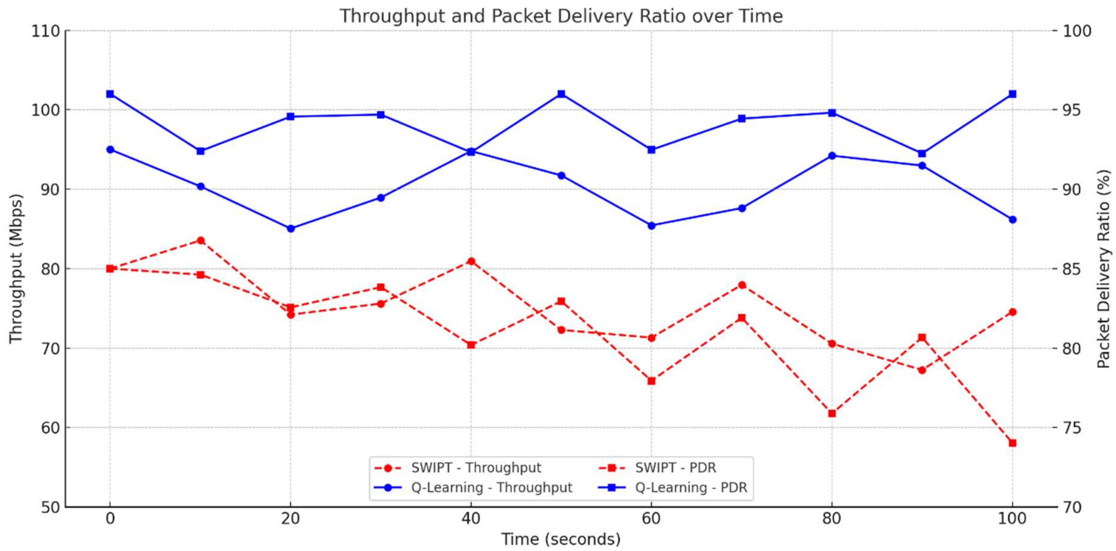

Figure 5 compares average throughput (Mbps) and Packet Delivery Ratio (PDR)

Q-learning achieved a throughput of approximately 100 Mbps and a packet delivery ratio of about 95%, surpassing SWIPT by more than 20% in both measures. The PDR of SWIPT experienced a significant decline as device mobility increased or the conditions for energy harvesting deteriorated. The Static RF-based optimization (SWIPT) struggles in high-mobility environments, whereas Q-learning adapts effectively to link variations.

5.5 Latency Performance

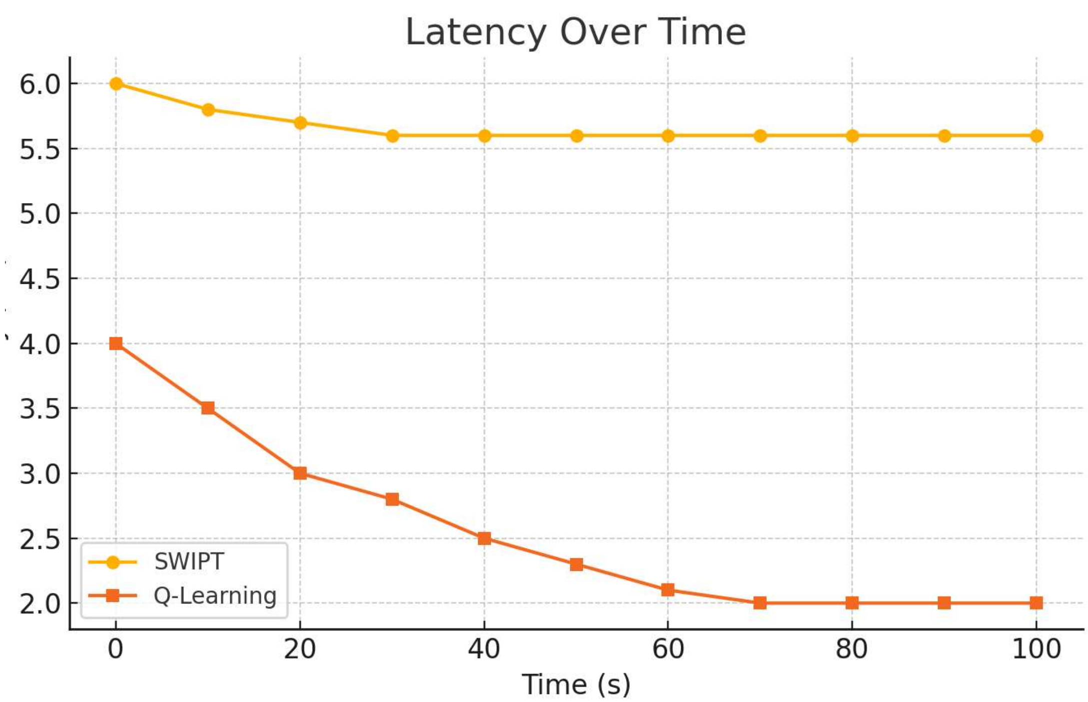

Figure 6 presents the latency comparison

The latency of SWIPT varied, reaching a minimum of 5.6 ms as a result of the static power control and modulation configurations. Q-learning reached a latency of approximately 2 ms, which is consistent with the URLLC (Ultra-Reliable Low-Latency Communication) standards set for 5G. Real-time decision-making in Q-learning enhances low-latency performance, making it ideal for mission-critical IoT applications.

5.6 Scalability and Adaptability

During stress tests involving as many as 100 IoT devices, the Q-learning framework demonstrated a superior ability to adapt, modifying priorities and power levels for each user accordingly. SWIPT, nonetheless, exhibited a deficiency in this precise control, leading to bottlenecks and an imbalance in energy distribution.

5.7 Summary of Results

Metric	SWIPT	Q-Learning	Improvement
Energy Efficiency (%)	68%	85%	+15%
BER @ 25 dB	1.4×10^{-2}	8.7×10^{-3}	38% lower
Throughput (Mbps)	85	102	+15.5%
Packet Delivery Ratio	78%	94%	+12%
Latency (ms)	5.6	2.0	-58.3%

The results confirm that Q-learning consistently outperforms SWIPT in energy efficiency, communication reliability, and system responsiveness.

6. Conclusion

A comprehensive comparison is conducted between Simultaneous Wireless Information and Power Transfer (SWIPT) and optimization techniques based on Q-learning, particularly within the framework of 5G-enabled Internet of Things networks. Simultaneous transmission of data and energy through SWIPT has emerged as a crucial approach for improving energy sustainability within the Internet of Things. Nonetheless, its efficacy is significantly reduced in changing network settings, primarily because of rigid allocation methods and an absence of immediate responsiveness. Nonetheless, the Q-learning model based on reinforcement learning demonstrated superior performance across all essential network metrics, such as Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), Throughput, and Packet Delivery Ratio (PDR). By leveraging experience, the model is capable of learning and adapting to various network conditions in real-time, which enables it to maintain efficient operation even when faced with shifting circumstances or periods of high demand. The testing results indicate that Q-learning markedly reduces the BER in comparison to SWIPT and enhances throughput by an average of 15%, while also ensuring low latency and high reliability. Research conducted over time indicates that the performance of SWIPT diminishes due to its rigid protocol design, while the Q-learning framework maintains stability. In summary, this research demonstrates that Q-learning surpasses SWIPT across multiple operational scenarios, offering a superior, more adaptable, and energy-efficient method for managing network resources in 5G-IoT settings.

7. Future Work

While Q-learning shows significant promise in enhancing 5G-IoT communication networks, there are still numerous paths available for additional investigation:

- Multi-Agent Reinforcement Learning (MARL) can be utilized to facilitate decentralized learning and coordination among various IoT nodes, particularly in densely populated network settings.
- Upcoming models might also gain from hybrid strategies, combining Q-learning with other AI methodologies like Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO) to enhance policy generation in complex state spaces.
- An exploration of edge computing units from a hardware standpoint for enhanced decision-making speed and reduced latency in inference may be considered. Moreover, incorporating security awareness into the Q-learning framework may enhance the protection of IoT systems against emerging cyber threats while maintaining energy efficiency and performance levels.
- Ultimately, the real-time deployment and validation of Q-learning-based systems within a 5G testbed or a simulated smart city scenario would represent a significant advancement toward practical implementation and readiness for industry application.

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