Optimizing Satellite-HAP-User Communication System for Maximum Sum Rate

Mentored by

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Problem Statement

Title: *Optimizing Satellite-HAP-User Communication System for Maximum Sum Rate*
Objective: Maximize the sum rate of a multi-user communication system involving a Geostationary Orbit satellite, a High-Altitude Platform (HAP), and multiple users.
System Used:

- **Satellite-HAP Link**: Ultra-Reliable Low-Latency Communication (URLLC).
- **HAP-User Link**: Enhanced Mobile Broadband (eMBB).

Goal: Achieve optimal resource allocation and power control for maximum data sum rate, especially in regions with limited terrestrial connectivity.

Motivation

Need for Enhanced Connectivity: Remote and underserved areas lack adequate terrestrial infrastructure, limiting broadband access.
Emerging Communication Technologies:

- 5G and 6G demand efficient resource utilization.
- URLLC and eMBB facilitate high data rate, low latency communication in heterogeneous networks.

Optimizing Communication Systems: Effective allocation of resources like power and bandwidth can maximize system efficiency, making high-speed communication accessible to more users.

Specifications

Components

- **Geostationary Earth Orbit Satellite** Provides URLLC link to HAP, maintaining connectivity.
- **High Altitude Platform (HAP)**: Relays data to multiple users via eMBB.
- **User Equipment (UE)**: End-user devices that access broadband via HAP.

Key Technologies

- **Resource Allocation**: Bandwidth, power, and time slot optimization.
- **Channel Modeling**: Path loss, fading, and interference considerations.
- **Optimization Techniques**: Convex and non-convex algorithms for maximizing sum rate.

Applications

1. **Rural and Remote Connectivity**: Bringing high-speed internet to underserved regions where traditional infrastructure is lacking.
2. **Disaster Recovery**: Rapid deployment of communication systems to support recovery efforts in areas where infrastructure is damaged.
3. **Maritime and Aviation Communication**: Providing consistent, high-throughput communication to vessels and aircraft through satellite and HAP networks.
4. **Military and Surveillance Operations**: Secure, reliable communication in remote or hostile environments.

Merits

- **Improved Connectivity**: High-speed data access for users in challenging environments.
- **Optimized Resource Usage**: Enhanced spectral efficiency through optimal power and bandwidth allocation.
- **Scalability**: System architecture can adapt to add more users and resources as needed.
- **Low Latency**: URLLC and eMBB ensure that critical data reaches users with minimal delay.

Demerits

- **High Initial Cost**: Infrastructure deployment for satellite and HAP systems can be expensive.
- **Complexity in Optimization**: Non-convex problems require sophisticated algorithms, which may not always yield global optimal solutions.
- **Environmental Concerns**: Continuous operation of HAPs can contribute to energy consumption and environmental impact.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
1	**eMBB-URLLC Resource Slicing: A Risk-Sensitive Approach**	Madyam Alsenwi, Nguyen H. Tran, Mehdi Bennis, Anupam Kumar Bairagi, Choong Seon Hong 2019	5G networks support three core services with distinct needs: Enhanced Mobile Broadband (eMBB) for high data rates, Ultra-Reliable Low-Latency Communication (URLLC) for mission-critical low-latency applications, and massive Machine-Type Communication (mMTC). Balancing eMBB and URLLC in real-time is challenging, as prioritizing URLLC can limit eMBB resources.. A risk-sensitive metric is used for eMBB risk measure(CVar). Chance constraint is used and relaxed based on Makov's inequality.
2	**A RAN Resource Slicing Mechanism for Multiplexing of eMBB and URLLC Services in OFDMA Based 5G Wireless Networks**	Praveen Kumar Korrai, Eva Lagunas, Shree Krishna Sharma, Symeon Chatzinotas, Ashok Bandi 2023	Managing the diverse requirements of eMBB and URLLC services in 5G is challenging. Network slicing creates independent units for tailored resource allocation, while the Radio Access Network (RAN) dynamically manages resource blocks to ensure high data rates for eMBB and low latency for URLLC. This paper formulates the RAN resource allocation problem as a sum-rate maximization problem to optimize performance under these constraints.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
3	**Joint HAP Access and LEO Satellite Backhaul in 6G: Matching Game-Based Approaches**	Ziye Jia, Min Sheng, Jiandong Li, Di Zhou, Zhu Han 2021	Space-air-ground networks utilize Low Earth Orbit (LEO) satellites and High Altitude Platforms (HAPs) to enhance connectivity in remote areas lacking terrestrial coverage. This paper seeks to maximize LEO satellite revenue in a 6G framework by addressing resource allocation and connectivity challenges using a matching game-based approach called Restricted Three-Sided Matching (R-TMSC) to efficiently manage connections and update matches. The single matching is converted into a two-tier matching problem to improve efficiency.
4	**Integrating LEO Satellite and UAV Relaying via Reinforcement Learning for Non-Terrestrial Networks**	Ju-Hyung Lee, Jihong Park, Mehdi Bennis, Young-Chai Ko 2020	This article investigates integrating LEO satellite mega-constellations and UAVs to enhance non-terrestrial networks for beyond 5G, focusing on optimizing packet forwarding to maximize end-to-end data rates through a deep reinforcement learning approach with action dimension reduction, leading to significant data rate improvements.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
5	**Integrated Access and Backhaul via Satellites**	Zaid Abdullah, Steven Kisseleff 2023	This paper explores the concept of Integrated Access and Backhaul (IAB) using satellite networks, particularly in the context of Non-Terrestrial Networks (NTNs) as an extension of 5G networks. Traditional IAB systems are designed for terrestrial networks, but this paper investigates the adaptation of IAB to satellite-based systems, especially with Low Earth Orbit (LEO) satellites. The goal is to create a more flexible, cost-effective solution for providing connectivity in remote or hard-to-reach areas, where terrestrial infrastructure is difficult to establish.
6	**Network Slicing for URLLC and eMBB with Max-Matching Diversity Channel Allocation**	A. Ortiz, H. Al-Shatri 2017	This paper addresses the challenge of resource sharing in 5G networks between enhanced Mobile Broadband (eMBB), which requires high data rates, and Ultra-Reliable Low-Latency Communications (URLLC), which demands quick and reliable transmission. The study proposes a Deep Reinforcement Learning (DRL)-based framework to allocate resources effectively between these two services, aiming to maximize data rates for eMBB while maintaining reliability standards for URLLC.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
7	**Intelligent Resource Slicing for eMBB and URLLC Coexistence in 5G and Beyond: A Deep Reinforcement Learning Based Approach**	Z. Ali, G. A. & S. Sidhu 2021	This paper addresses the problem of radio resource sharing between enhanced Mobile Broadband (eMBB) and Ultra-Reliable Low-Latency Communications (URLLC), which have different requirements in 5G networks. While eMBB aims to maximize data throughput, URLLC needs low latency and high reliability. The authors propose a Max-Matching Diversity (MMD) algorithm to allocate radio channels for eMBB users, analyzing both Orthogonal Multiple Access (OMA) and Non-Orthogonal Multiple Access (NOMA) methods in a heterogeneous slicing scenario.
8	**UAV-LEO Integrated Backbone: A Ubiquitous Data Collection Approach for B5G IORT Networks**	K. Kim and J. P. Choi 2024	This research investigates the integration of Unmanned Aerial Vehicles (UAVs) and Low Earth Orbit (LEO) satellites to support data collection in Beyond 5G (B5G) networks, specifically for the Internet of Remote Things (IoRT). Given the challenges of high mobility in both UAVs and LEO satellites and the lack of ground infrastructure in remote areas, the study develops a two-layer system where UAVs gather data from IoT devices and transmit it to LEO satellites.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
7	**Deep Learning Based Power Optimizing for NOMA Based Relay Aided D2D Transmissions**	Z. Ali, G. A. & S. Sidhu 2021	This paper addresses the problem of radio resource sharing between enhanced Mobile Broadband (eMBB) and Ultra-Reliable Low-Latency Communications (URLLC), which have different requirements in 5G networks. While eMBB aims to maximize data throughput, URLLC needs low latency and high reliability. The authors propose a Max-Matching Diversity (MMD) algorithm to allocate radio channels for eMBB users, analyzing both Orthogonal Multiple Access (OMA) and Non-Orthogonal Multiple Access (NOMA) methods in a heterogeneous slicing scenario.
8	**3D Network Design for Multi-UAV RAN with THz-Empowered Backhaul**	K. Kim and J. P. Choi 2024	This research investigates the integration of Unmanned Aerial Vehicles (UAVs) and Low Earth Orbit (LEO) satellites to support data collection in Beyond 5G (B5G) networks, specifically for the Internet of Remote Things (IoRT). Given the challenges of high mobility in both UAVs and LEO satellites and the lack of ground infrastructure in remote areas, the study develops a two-layer system where UAVs gather data from IoT devices and transmit it to LEO satellites.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
9	**Secure 3D Mobile UAV Relaying for Hybrid Satellite-Terrestrial Networks**	Pankaj K. Sharma, Dong In Kim 2020	This paper discusses about the eavesdropping problem in a Hybrid satellite - terrestrial networks (HSTNs). they consider two case scenarios (a) the eavesdropper is located at certain fixed distance around a serving UAV relay (b) the eavesdropper is located uniformly random around the relay. By considering the opportunistic closest (CURS), uniform (UURS) and maximum signal to noise ratio (maximum-SNR) (MURS) UAV relay selection (URS) strategies, the secrecy performance of the considered HSTN in terms of probability of non-zero secrecy capacity (PNZSC) and secrecy outage probability (SOP) is analysed.
10	**Network Resource Allocation for eMMB Payload and URLLC Control Information Communication Multiplexing in a Multi-UAV Relay Network**	Xing Xi, Xianbin Cao 2021	This paper investigates resource allocation for the eMMB payload and URLLC control information communication multiplexing in a multi-UAV relay network as both the eMMB and URLLC have their own advantages and disadvantages using both the communication protocols will be useful in UAV relay network. The author proposes various optimization algorithms considering path loss, small-scale fading and different quality of service requirements of eMMB and URLLC communications to improve total transmission data rate and reduce power consumption. Finally, the author decomposes the optimization problem into two optimization problem for eMMB and URLLC, derives closed-form expressions of the optimal bandwidth and transmit power for URLLC and an iterative solution framework of alternatively optimizing user association bandwidth and transmit power for eMMB.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
11	**Resource Slicing for eMMB and URLLC Service in Radio Access Network Using Hierarchical Deep Learning**	Mehdi Setayesh, Shahab Bahrami, Vincent W. S. Wong 2022	This paper investigates Network slicing technique to support eMMB and URLLC services in a shared radio access network infrastructure. Author applies numerology, mini-slot based transmission, and punctured scheduling techniques to support eMMB and URLLC network slicing. Author uses a deep reinforcement learning (DRL) in long time slot and deep neural network (DNN) for short time slots to schedule the eMMB and URLLC communication. The proposed framework achieves higher aggregate throughput and a higher service level agreement (SLA) satisfaction ratio compared to some other RAN slicing approaches.
12	**Coexistence Mechanism Between eMMB and uRLLC in 5G Wireless Network**	Anupam Kumar Bairagi, Shirajum Munir, Madyan Alsenwi 2021	This paper investigates about co-scheduling problem of eMMB and URLLC traffic based upon the puncturing technique. Author formulated an optimization problem aiming to maximize the minimum expected achieved rate (MEAR) of eMMB UE while fulfilling the provisions of the URLLC traffic using penalty successive upper bound minimization (PSUM) based algorithm for eMMB, whereas the optimal transportation model (TM) for URLLC. The proposed approach is evaluated in terms of the MEAR and fairness scores of the eMMB UEs.

LITERATURE SURVEY

S. NO.	TITLE	AUTHOR & YEAR	SUMMARY & KEY POINTS
13	**Deep learning-based optimal placement of a mobile HAP for common throughput maximization in wireless powered communication networks**	Hong-Sik Kim and Inwhee Joe, Vincent W. S. Wong 2022	This research paper discusses the problem in which the location of the High Altitude Platform (HAP) can be varied to maximise the throughput to the devices. The suggested methods for this to be achieved by using Deep Learning algorithms where the location of the HAP can be varied and the sum rate is calculated for various locations and the location to obtain the maximum sum rate can be determined
14	**Integrated Satellite-HAP-Terrestrial Networks for Dual-Band Connectivity**	Wenwei Zhang, Ruoqi Deng, Boya Di, and Lingyang Song 2021	The Paper proposes the usage of HAP (High Altitude Platforms) to assist the satellite - terrestrial Network. Author uses the HAP to communicate with the terrestrial users and the terrestrial terminals. The Paper focuses on the bandwidth and the power distribution optimization by the HAP to the users.

WorkFlow

Comprehensive Literature Review

a. A comprehensive review of the URLLC and eMBB communication standards is performed, focusing on existing optimization frameworks in satellite-HAP networks.

b. Apart from communication standards, an examination is done on ML methods/approaches being used to solve the complex optimization problems within these systems.

System Model Development

a. A system model is created based around the satellite, HAP and the user nodes.

b. The key objectives and also the key constraints such as channel capacity, bandwidth and power limitations are defined.

c. The key steps are as follows

- Channel Modelling
- Resource Allocation
- Performance Metrics

Formulation of Optimization Problem

Using the model/channel information, we create an optimization problem in accordance to our problem statement

Generation of Dataset

a. Using the optimization equation derived from above step, a dataset is generated with realistic parameter configurations.

b. This dataset provides the basis for model training and testing.

Reinforcement Learning and model development

a. Based on the requirements, a suitable Reinforcement learning model is selected for solving the optimization problem.
b. Agent and Environment for the problem statement are to be created.

Work Done

- Literature Review
- Background
- System Development
- Channel Modelling

Literature Review

We conducted a thorough literature review covering various topics relevant to GEO-HAP-user communication networks and optimization strategies. Our exploration included the application of machine learning techniques to enhance the performance of communication systems, focusing on resource allocation and sum rate maximization. We examined advancements in Ultra-Reliable Low-Latency Communication (URLLC) and enhanced Mobile Broadband (eMBB) standards, assessing their roles in supporting mission-critical and high-throughput applications within GEO-HAP architectures.

Background

GEO (Geostationary Earth Orbit) Satellites: GEO satellites orbit at altitudes greater than 30000 kilometers, allowing them to provide low-latency communications due to their proximity to the Earth's surface.

High Altitude Platforms(HAP): HAPs, typically deployed in the stratosphere at altitudes between 17 to 22 kilometres, serve as intermediaries between satellites and end users.

Ultra-Reliable Low-Latency Communication (URLLC): URLLC is a core component of next-generation communication standards, including 6G, designed to meet the stringent requirements of mission-critical applications.

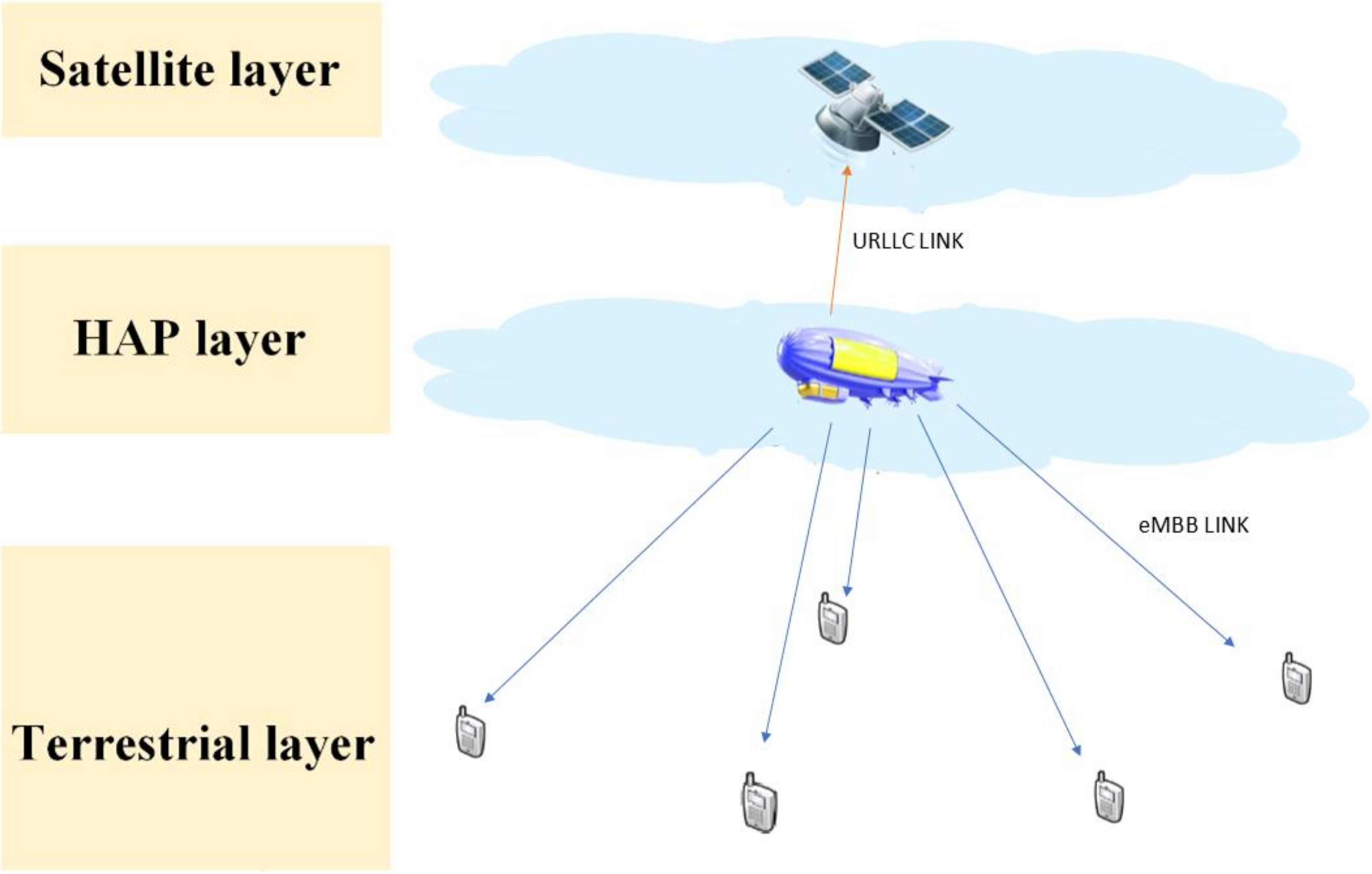
Enhanced Mobile Broadband (eMBB): eMBB is focused on delivering high data rates and capacity, essential for applications like video streaming, virtual reality, and massive IoT.

System Modelling

1) The HAP directly transmits data from the core network to terrestrial users over C-band.

2) The HAP first transmits data from the core network to the UT via the HAP-based backhaul link over Ka-band. The UT then forwards the received data to terrestrial users over C-band.

3) The satellite first transmits data from the core network to the UT via the satellite-based backhaul link over Ka-band. The UT then forwards the received data to terrestrial users over C-band.


Satellite layer
URLLC LINK
HAP layer
eMBB LINK
Terrestrial layer

Channel Modeling for HAP-User link

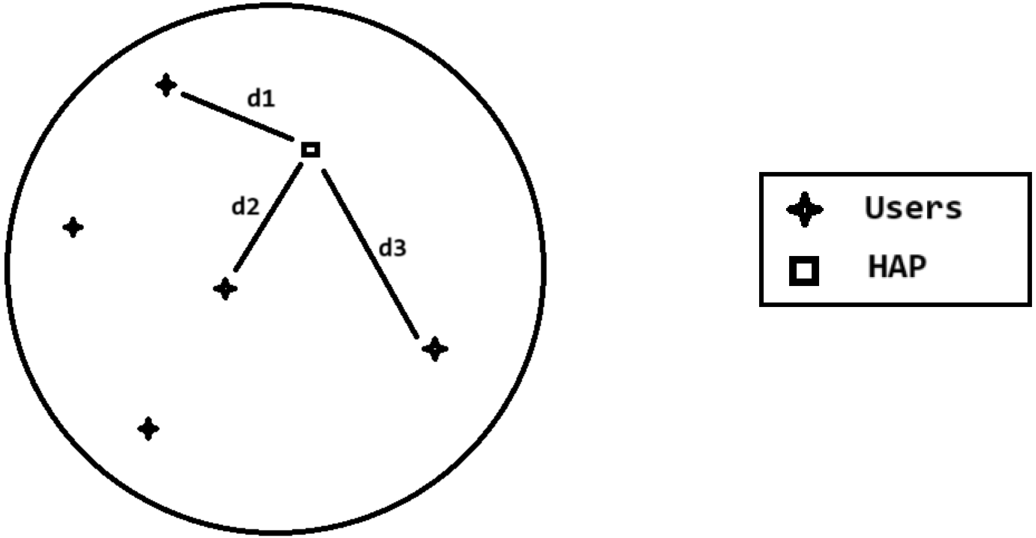
To model the channel between HAP and users, we make use of large-scale fading (or distance-dependent path loss modelling). If h_{kb} represents the channel coefficient between HAP and user k for a Resource Block b, it can be defined as follows:

$$|h_{kb}|^2 = (d_{kb})^{-\epsilon}$$

where ϵ refers to the path loss exponent (generally in the range [2,4]) and d_{kb} is the distance between HAP and user k.

Channel Modeling for HAP-User link

```
power[user] = distance[user] ^ epsilon
epsilon = -3
```



User Distribution in the Region

Channel Modeling for HAP-satellite link

The channel modelling of HAP-satellite link is done by assuming Line of Sight (LoS) between the Satellite and HAP. Free Space Path Loss (PL) model is used in order to model this channel. For this link, the corresponding channel gain is as follows:

$$\beta_i = \left(\frac{G_{sat}G_{HAP}}{PL_i}\right)\psi(\theta_{HAP})$$

where G_{sat} and G_{HAP} refer to satellite and HAP antenna gains respectively.

Channel Modeling for HAP-satellite link

Here PL_i is defined as follows:

$$PL_i = (4\pi f_c \, d_{S2H}/c)^2$$

refers to the Path Loss in free space between HAP and the satellite with f_c being the carrier frequency and d_{S2H} being the distance between satellite and HAP and c is the speed of light.

Channel Modeling for HAP-satellite communication

$\psi(\theta_{HAP})$ is the normalized antenna gain pattern at the satellite with respect to HAP, such that $\psi(\theta_{HAP})$ is 1 if (θ_{HAP}) is zero. Otherwise, it is defined as follows:

$$\left|\frac{J_1\left(k.a.sin(\theta_{HAP})\right)}{k.a.sin(\theta_{HAP})}\right|$$

where (θ_{HAP}) refers to boresight angle from satellite's node to HAP. The parameter k is defined as $k = \frac{2\pi f_c}{c}$. The parameter a in above equation refers to radius of satellite's circular antenna apreture. $J_1(\quad)$ is the Bessel function of the first kind and first order.

eMBB data rate calculation (HAP-User Link)

The Modified eMBB data rate considering puncturing can be written as follows:

$$r_{kb}^{e}(t) = f_b\left(1 - \frac{z_{kb}(t)}{M}\right)\log_2\left(1 + \frac{p_{kb}(t)h_{kb}(t)}{\sigma^2}\right)$$

where,

f_b refers to the bandwidth of RB,

$h_{kb}(t)$ is channel coefficient

$p_{kb}(t)$ refers to the power allocated by HAP to transmit message to user k over RB b in a time slot t.

eMBB data rate calculation (HAP-User Link)

Using this, total data rate from one single user can be written as follows:

$$r_k^e(t) = \sum_{b \in \mathcal{B}} x_{kb}(t) r_{kb}^e(t)$$

Where $x_{kb}(t)$ tells us which resource block is allocated to which user at a time slot t. . $x_{kb}(t)$ is defined as follows:

$$x_{kb}(t) = \begin{cases} 1, & \text{if the RB } b \text{ is allocated to user } k \text{ at time } t \\ 0, & \text{otherwise.} \end{cases}$$

URLLC data rate

The URLLC data packets are very small. Hence we cannot use Shannon's capacity theorem directly. The data rate is calculated as follows:

$$r_n^u(t) = \sum_{k\in\mathcal{K}} \sum_{b\in\mathcal{B}} f_b \frac{x_k^b(t) z_{kb}(t)}{M \times N} \log\left(1 + \frac{p_{nb}^u(t) h_{nb}^u(t)}{\sigma^2}\right) - \sqrt{\frac{D_{nb}^u(t)}{c_{nb}^u(t)}} Q^{-1}(\vartheta)$$

where, $Q^{-1}()$ refers to inverse of Gaussian Q-function, is the transmission error probability, and $D_{nb}^u(t)$ represents channel dispersion and is defined as follows:

$$D_{nb}^u(t) = 1 - \left(\frac{1}{1 + \frac{p_n^u(t) h_n^u(t)}{\sigma^2}}\right)^2 .$$

Optimization Problem Main Goals

At the start of each time slot, all the RBs are allocated to eMBB users. During the time slot, if URLLC traffic request arrives, some of the mini-slots of RBs are punctured and are given to deal with the URLLC traffic. Puncturing should be done such that

1. Maximization of eMBB throughput
2. Making sure eMBB transmission is reliable
3. Satisfying URLLC constraints

Optimization Problem Main Goals

To ensure eMBB Fairness, we need to make sure variance between data rates is as less as possible. The following function can take care of both constraints:

$$\mathcal{F}(x, p, z) = \sum_{k=1}^{K} \mathbb{E}_{\mathbf{h}} \left[\frac{1}{T} \sum_{t=0}^{T} r_k^e(t) \right] - \beta \, \mathrm{Var}_{\mathbf{h}} \left[r_k^e(t) \right]$$

In the above equation, beta refers to variance weight, Var is the variance.

Optimization Problem Main Goals

To satisfy URLLC constraints, we have to make sure that the outage probability is less than a threshold. If we consider $L_m(t)$ as URLLC traffic at a mini-slot m, then the total URLLC packets that arrive during a given time slot is defined as

$$L(t) = \sum_{m \in \mathcal{M}} L_m(t)$$

Using this, URLLC reliability is defined as follows (zeta is the length of each packet):

$$\Pr\left[\sum_{n \in \mathcal{N}} r_n^u(t) \le \zeta L(t)\right] \le \Theta^{max}$$

Optimization Problem

The eMBB/URLLC joint resource allocation problem is defined as follows:

$$
\begin{aligned}
\text{maximize}_{x,p,z} \quad & \sum_{k=1}^{K} \mathbb{E}_{\mathbf{h}}\left[\frac{1}{T}\sum_{t=0}^{T} r_k^e(t)\right] - \beta \,\mathrm{Var}_{\mathbf{h}}\left[r_k^e(t)\right] \\
\text{subject to} \quad & \Pr\left[\sum_{n=1}^{N} r_n^u(t) \le \zeta L(t)\right] \le \Theta^{\max}, \\
& \sum_{k=1}^{K}\sum_{b=1}^{B} p_{kb}(t) \le P_{\max}, \\
& \sum_{k=1}^{K} x_{kb}(t) \le 1, \quad \forall b \in \mathcal{B}, \\
& p_{kb}(t) \ge 0, \quad \forall k \in \mathcal{K},\ b \in \mathcal{B}, \\
& x_{kb}(t) \in \{0,1\}, \quad \forall k \in \mathcal{K},\ b \in \mathcal{B}, \\
& z_{kb}(t) \in \{0,1,\ldots,M\}, \quad \forall k \in \mathcal{K},\ b \in \mathcal{B}
\end{aligned}
$$

Modification of the problem

The optimization problem defined in (8a) is a mixed-integer nonlinear programming (MINLP) type problem which is difficult to solve. Firstly, we convert the simplify the main optimization function (utility function) into a simple exponential function that deals with both mean and variance as follows:

$$\mathcal{G}(x, p, z) = \frac{1}{\mu} \log E_h \left[\exp \left(\mu \sum_{k=1}^{K} r_k^e(t) \right) \right]$$

Here the parameter μ is used to manage the risk-sensitivity. As the value of μ becomes more negative, the function becomes more risk-averse.

Redfined Optimization Problem

- The Redefined optimization problem is as follows

$$
\begin{aligned}
\mathbf{P:} \quad & \underset{\mathbf{x},\mathbf{p},\mathbf{z}}{\text{maximize}} \quad \frac{1}{\mu} \log \mathbb{E}_h \left[\exp\left(\mu \sum_{k=1}^{K} r_k^e(t) \right) \right] \\
\text{subject to} \quad & \Pr\left[\sum_{n=1}^{N} r_n^u(t) \leq \zeta L(t) \right] \leq \Theta^{\max}, \\
& \sum_{k=1}^{K} \sum_{b=1}^{B} p_{kb}(t) \leq P_{\max}, \\
& \sum_{k=1}^{K} x_{kb}(t) \leq 1, \quad \forall b \in \mathcal{B}, \\
& p_{kb}(t) \geq 0, \quad \forall k \in \mathcal{K},\ b \in \mathcal{B}, \\
& x_{kb}(t) \in \{0, 1\}, \quad \forall k \in \mathcal{K},\ b \in \mathcal{B}, \\
& z_{kb}(t) \in \{0, 1, \ldots, M\}, \quad \forall k \in \mathcal{K},\ b \in \mathcal{B}.
\end{aligned}
$$

Redfined Optimization Problem

- To solve this redefined problem, we make use of an algorithm called as DDRA (Decomposition and Relaxation based Resource Allocation). In this algorithm, first the main problem P is split into 3 smaller problems.
- The first problem deals with eMBB RB allocation,
- The second problem deals with eMBB power allocation.
- The third problem deals with the URLLC scheduling
- These 3 problems are iteratively solved until convergence is reached.

eMBB RB allocation

For a fixed power allocation “p” and URLLC scheduling “z”, the problem can be written as follows:

$$\begin{aligned}
\textbf{P1:} \quad & \underset{\mathbf{x}}{\text{maximize}} \quad \frac{1}{\mu} \log \mathbb{E}_h \left[\exp\left(\mu \sum_{k=1}^{K} r_k^e(t) \right) \right] \\
\text{subject to} \quad & \sum_{k=1}^{K} x_{kb}(t) \leq 1, \quad \forall b \in \mathcal{B}, \\
& x_{kb}(t) \in \{0, 1\}, \quad \forall k \in \mathcal{K} \text{ and } b \in \mathcal{B}.
\end{aligned}$$

eMBB RB allocation

$$\tilde{\mathbf{P1}}: \quad \underset{\tilde{\mathbf{x}}}{\text{maximize}} \quad \frac{1}{\mu} \log \mathbb{E}_h \left[\exp \left(\mu \sum_{k=1}^{K} r_k^e(t) \right) \right]$$

$$\text{subject to} \quad \sum_{k=1}^{K} \tilde{x}_{kb}(t) \leq 1, \quad \forall b \in \mathcal{B},$$

$$0 \leq \tilde{x}_{kb}(t) \leq 1, \quad \forall k \in \mathcal{K},\ b \in \mathcal{B}.$$

where,

$$x_{kb}^* = \begin{cases} 1, & \text{if } \tilde{x}_{kb}^* \geq \eta, \\ 0, & \text{otherwise.} \end{cases}$$

eMBB RB allocation

$$\textbf{P2:} \quad \text{maximize}_{\mathbf{p}} \quad \frac{1}{\mu} \log \mathbb{E}_{\mathbf{h}} \left[\exp \left(\mu \sum_{k=1}^{K} r_k^e(t) \right) \right]$$

$$\text{subject to} \quad \sum_{k=1}^{K} \sum_{b=1}^{B} p_{kb}(t) \leq P_{\max},$$

$$p_{kb}(t) \geq 0, \quad \forall\, k \in \mathcal{K},\ b \in \mathcal{B}.$$

URLLC Scheduling problem

$$\begin{aligned}
\mathbf{P3:} \quad & \text{maximize}_{\mathbf{z}} \quad \frac{1}{\mu} \log \mathbb{E}_{\mathbf{h}} \left[\exp\left(\mu \sum_{k=1}^{K} r_k^e(t) \right) \right] \\
& \text{subject to} \quad \Pr\left(\sum_{n=1}^{N} r_n^u(t) \leq \zeta L(t) \right) \leq \Theta^*, \\
& z_{kb}(t) \in \{0, 1, \ldots, M\}, \quad \forall\, k \in \mathcal{K},\ b \in \mathcal{B}.
\end{aligned}$$

URLLC Scheduling problem

$$r_{kb}^{e}(t) = f_b\left(1 - \frac{w_{kb}(t)}{1}\right)\log_2\left(1 + \frac{p_{kb}(t)\,h_{kb}(t)}{\sigma^2}\right)$$

Then we can calculate the URLLC data rate as follows

$$r_n^u(t) = \sum_{k\in\mathcal{K}}\sum_{b\in\mathcal{B}} \frac{f_b x_k^b(t) w_{kb}(t)}{M \times N} \log\left(1 + \frac{p_{nb}^u(t) h_{nb}^u(t)}{\sigma^2}\right) - \sqrt{\frac{D_{nb}^u(t)}{c_{nb}^u(t)}} Q^{-1}(\vartheta),$$

URLLC Scheduling problem

We make use of Markov's inequality to represent chance constraint to linear constraint

$$\Pr\left[\sum_{n\in\mathcal{N}} r_n^u(t) \le \zeta L(t)\right] \le \frac{\zeta\mathbb{E}[L]}{\sum_{n\in\mathcal{N}} r_n^u(t)}.$$

URLLC Scheduling problem

The URLLC problem can be reformulated as

$$\tilde{\mathbf{P}}\mathbf{3}: \quad \text{maximize}_{\mathbf{w}} \quad \frac{1}{\mu} \log \mathbb{E}_{\mathbf{h}} \left[\exp \left(\mu \sum_{k=1}^{K} \tilde{r}_k^e(t) \right) \right]$$

$$\text{subject to} \quad \sum_{n \in \mathcal{N}} \tilde{r}_n^u(\mathbf{w}) \geq \frac{\zeta \mathbb{E}[L]}{\Theta^*}, .$$

$$0 \leq w_{kb} \leq 1, \quad \forall k \in \mathcal{K}, \ b \in \mathcal{B}.$$

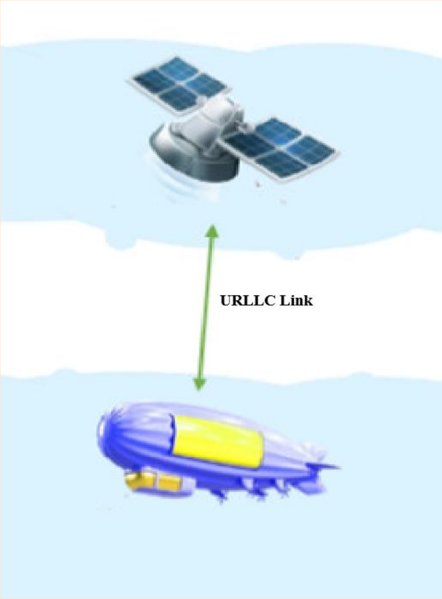
Deep Reinforcement Learning (DRL) for URLLC Scheduling

Properties of URLLC Traffic

- URLLC traffic is often characterized by sporadic and unpredictable bursts of small data packets.

- Meeting the stringent and often conflicting demands of URLLC (high reliability AND low latency) requires sophisticated and often complex resource management techniques.

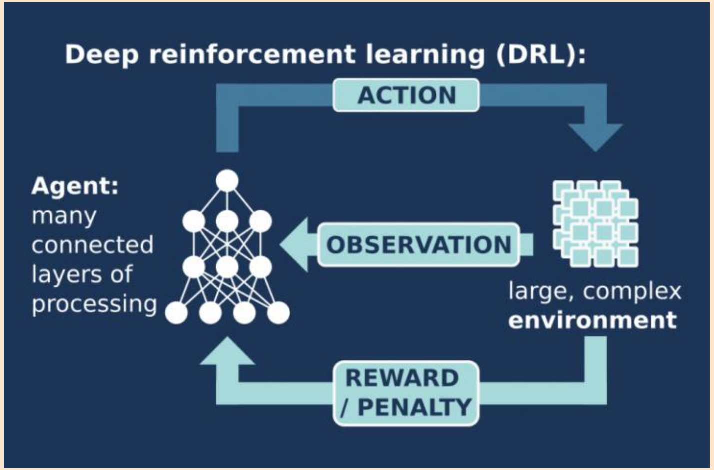
- The iterative nature of the DRRA algorithm often leads to long convergence times, and it may not always satisfy all constraints.



URLLC Link

Why DRL?

- DRL can handle complex state and action spaces.
- Sequential decision can be made by DRL Algorithm.
- Neural Network can be used in DRL to achieve autonomous and adaptive learning
- Dynamic and Uncertain environments are well handled by DRL Algorithms.



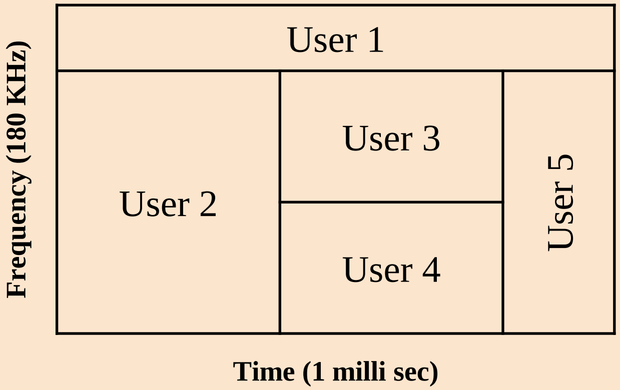
DRL Algorithm

Environment

- Environment is the simulated setting in which the DRL agent operates and learns.

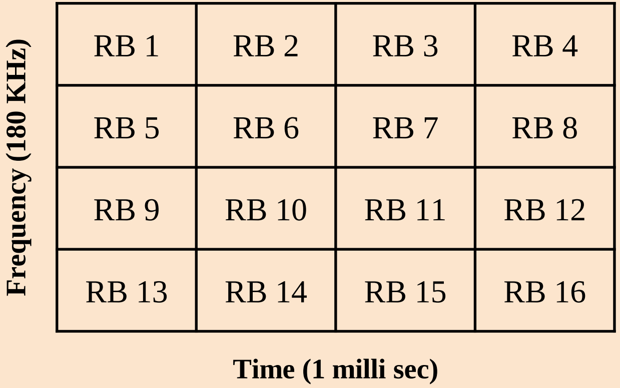
Environment contains

- Action Space
- Observation State
- Transition Function
- Reward Function

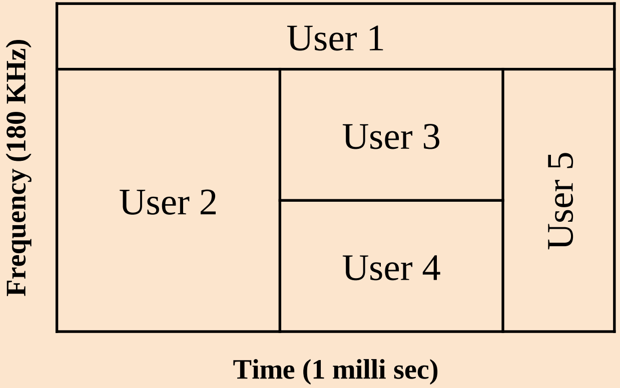


Resource Block is the Environment for DRL Agent

Environment



Resource Block is the Environment for DRL Agent



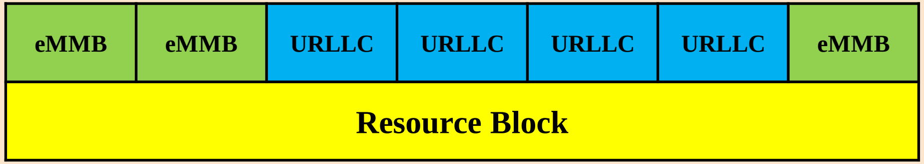
Resource Block is the Environment for DRL Agent

Environment

Resource Block

- Resource Block is defined for a specific spectrum at a specific time period.

- Each Resource Block is divided into 7 Sub-slots which can be with allocated to URLLC Traffic or eMMB Traffic



RBs’ Sub-slot Allocation

- **Action Space** – [1, 6] – Number of URLLC Sub-slots Utilized
- **State** – Present Allocation Matrix

Environment

	RB 1	RB 2	RB 3	RB 4
User 1	1			
User 2			1	
User 3				1
User 4		1		

RB Allocation Matrix

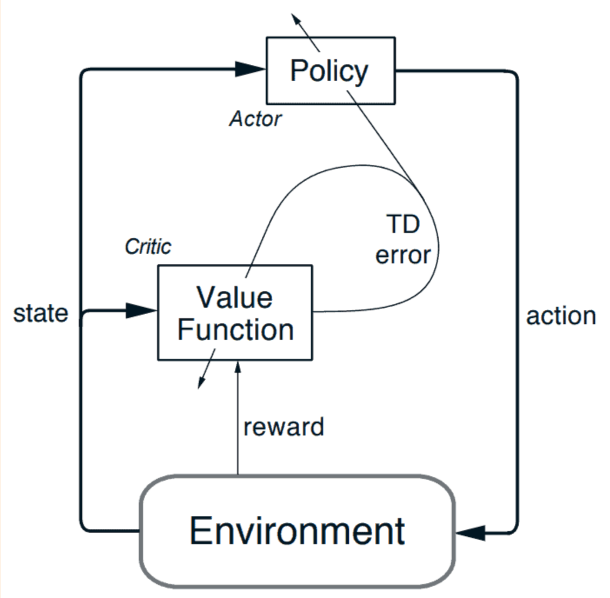
	RB 1	RB 2	RB 3	RB 4
User 1	6			
User 2			5	
User 3				3
User 4		2		

URLLC Allocation Matrix

PGACL – DRL Algorithm

PGACL Algorithm

- **PGACL** stand for Policy based Gradient Actor Critic Learning Algorithm
- Components of PGACL – Policy Network, Critic Network, Environment
- Policy Network is the Actor which decides next action based on present state and env
- Critic Network observes the state and rewards and criticizes the policy network decision making



PGACL Architecture

Reward Function

- The reward function for our system can be written as follows:

$$R\big(a(t), s(t)\big) = g(t) + \phi(t)E\left[\sum_{n=1}^{N} r_n^u(t) - \zeta L(t)\right]$$

- Here,
- g(t) refers to the utility function value
- $r_n^u(t)$ is the data rate of URLLC user of user n
- Zeta is the length of packet
- L(t) defines the number of packets that have arrived in a time slot ‘t’

Reward Function

- The reward function for our system can be written as follows:

$$R\big(a(t), s(t)\big) = g(t) + \phi(t)E\left[\sum_{n=1}^{N} r_n^u(t) - \zeta L(t)\right]$$

- Here, $\phi(t)$ is a time-varying weight that ensures the URLLC reliability over time slots as the network changes dynamically. It is defined as follows:

$$\phi(t+1) = \max\{\phi(t) + \Theta(t) - \Theta^{max}, 0\}$$

- Here, $\Theta(t)$ estimated outage probability at time slot t and Θ^{max} is the threshold outage probability

Reward Function

- In Reinforcement Learning (RL), the reward function is a fundamental component that quantifies the desirability of an agent's actions in a given state.
- It provides numerical feedback (reward or penalty) to the agent based on its behavior, guiding it toward achieving its goal.
- The reward function is a function of action taken, current state and next state

PGACL – DRL Algorithm

Input Layer
(Flatten)
(1 x 20)

Dense Layer
(ReLU)
(20 x 64)

Dense Layer
(ReLU)
(64 x 64)

Output Layer
(Sigmoid)
(64 x 7)

Policy Network

- **Input –** State Matrix
- **Output** - Action

Input Layer
(Flatten)
(1 x 21)

Dense Layer
(ReLU)
(20 x 64)

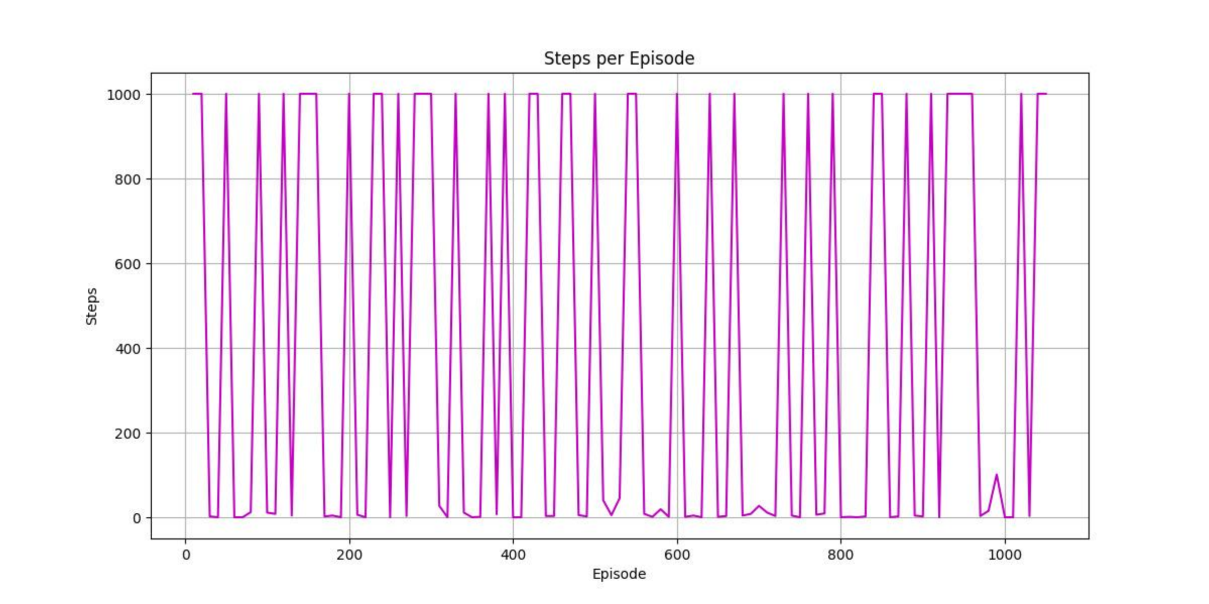
Dense Layer
(ReLU)
(64 x 64)

Output Layer
(Sigmoid)
(64 x 1)

Critic Network

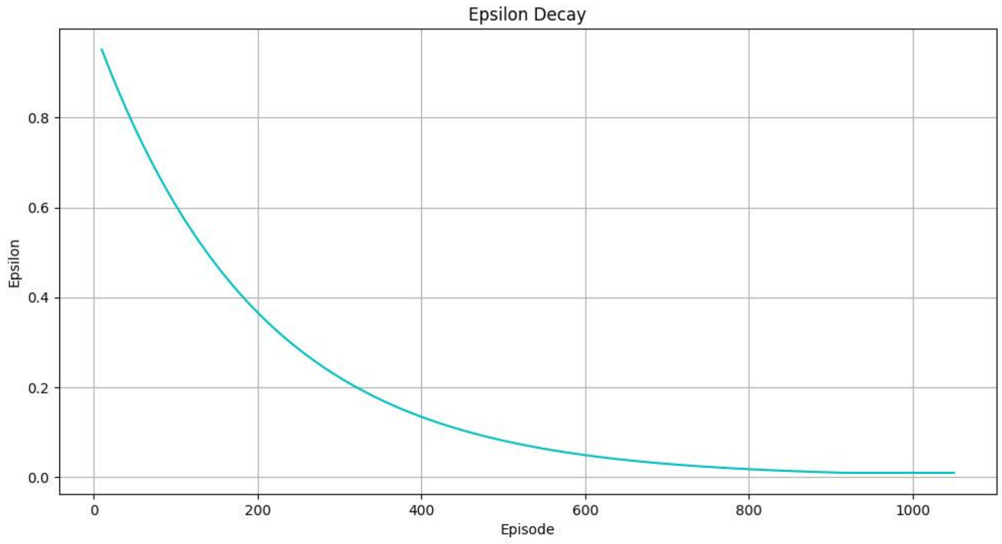
- **Input –** State Matrix, Reward
- **Output –** State Value

DRL Results

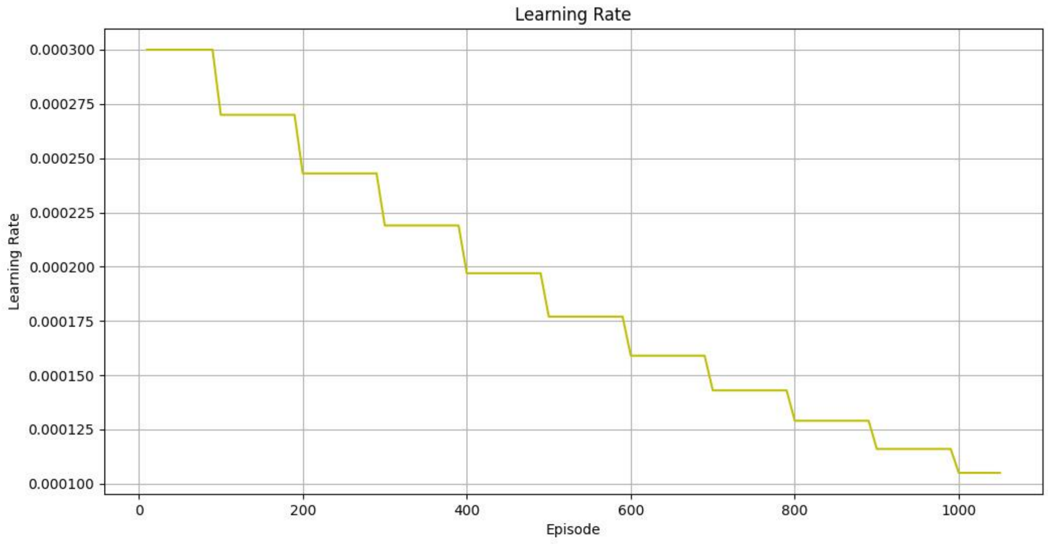


Steps per Episode
1000
800
600
400
200
0
Steps
0
200
400
600
800
1000
Episode

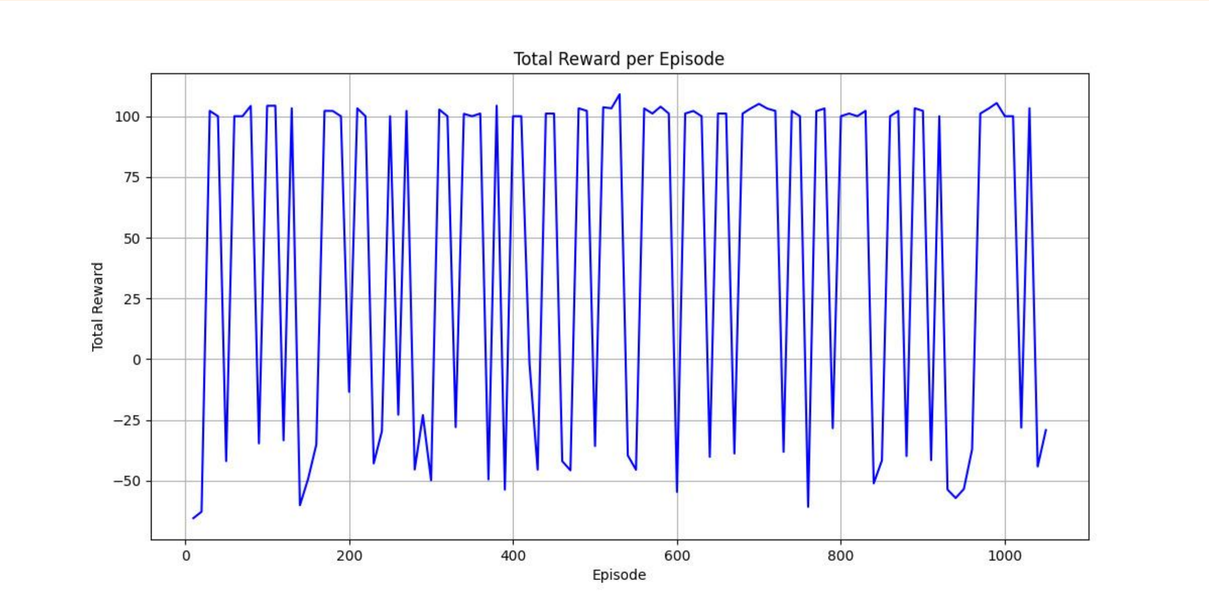
DRL Results – DRL Reward



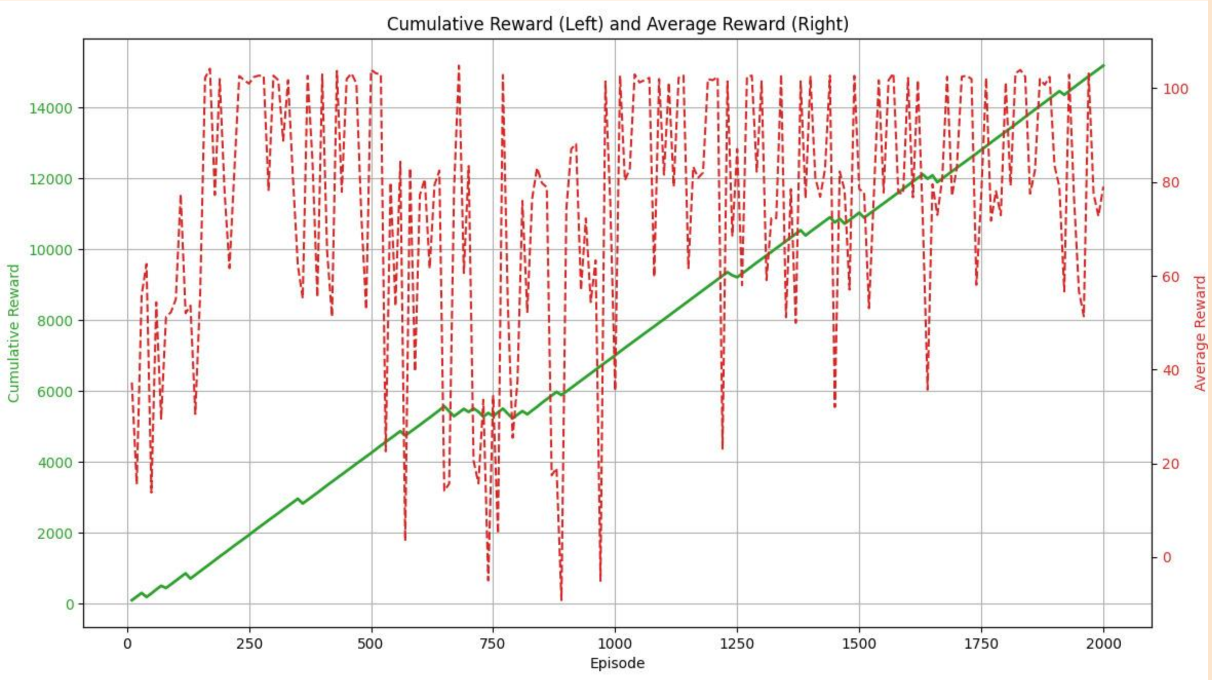
DRL Results – DRL Reward



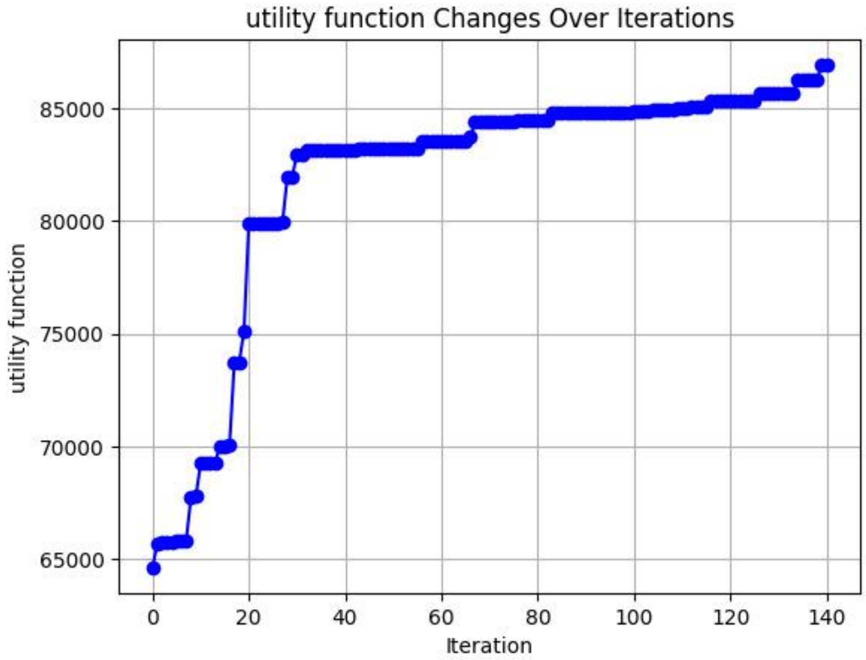
DRL Results – DRL Reward



DRL Results – DRL Reward

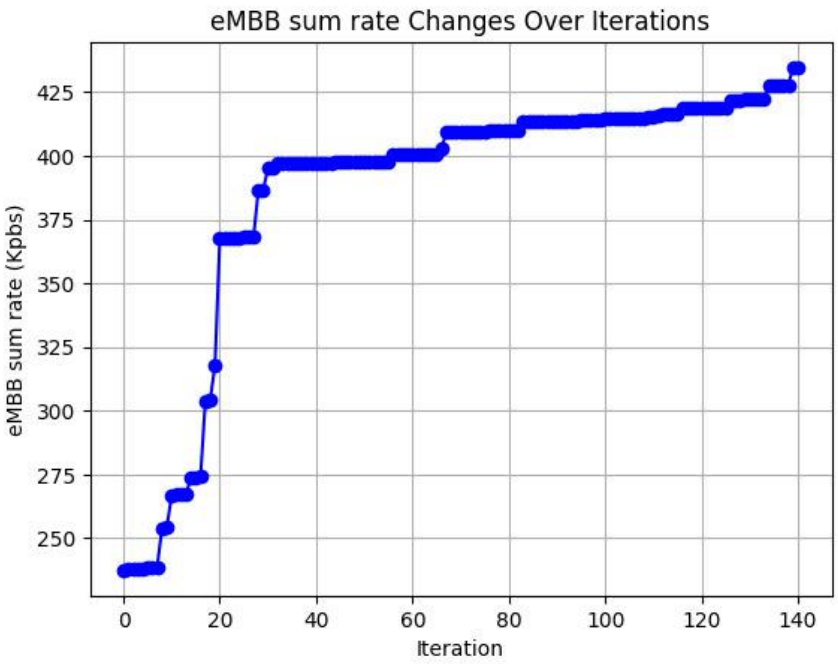


Results



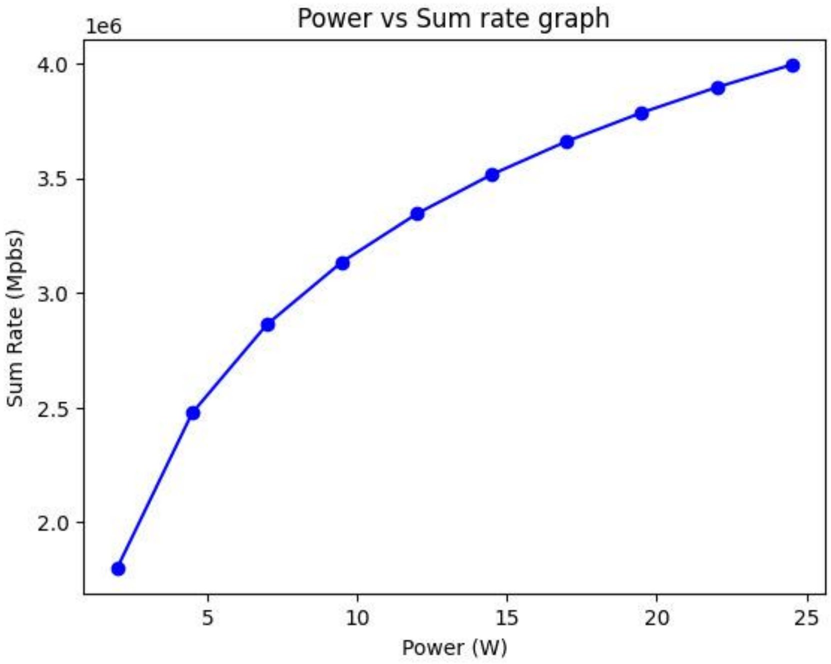
Utility Function for Each Iteration

Results



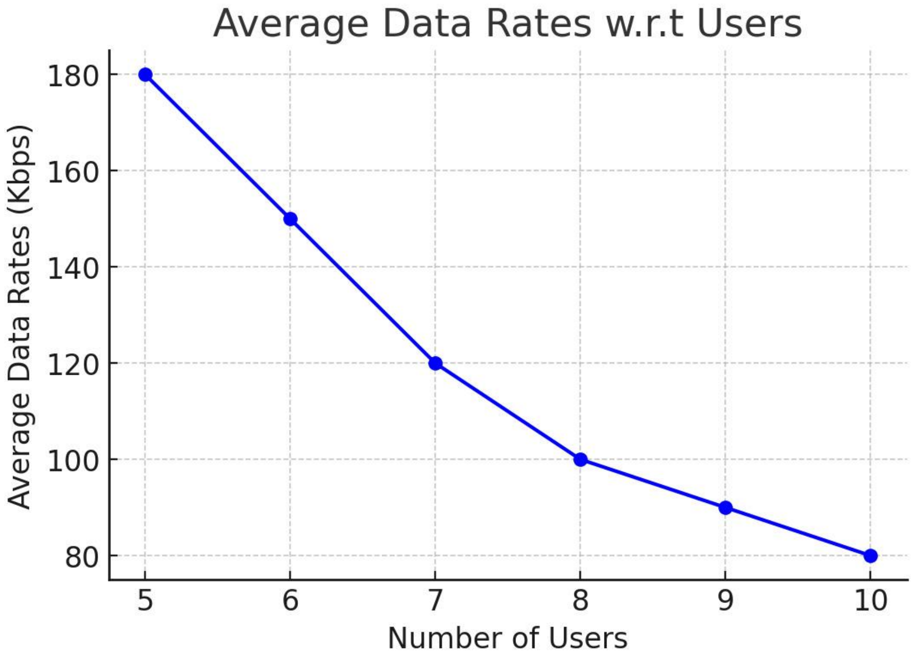
Total eMBB Sum-Rate for Each Iteration

Results



Power vs eMBB Sum-Rate

Results



Average Data-Rate vs Number of Users

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Thank You