

AI-Enabled Radio Resource Allocation in 5G for URLLC and eMBB Users

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Abstract—The fifth generation (5G) network is expected to accommodate heterogeneous traffic with diverse QoS demands. In this paper, we address the coexistence of Ultra-Reliable Low-Latency communications (URLLC) and enhanced Mobile Broad-Band (eMBB) users in 5G networks. We propose an AI-enabled approach that uses a reinforcement learning-based algorithm to balance the Key Performance Indicators (KPIs) of both URLLC and eMBB users. The proposed algorithm aims to jointly optimize both latency and reliability of URLLC users as well as the throughput of eMBB users. To achieve this, the algorithm utilizes the flexibility of the time-frequency grid of 5G standard to jointly perform power and resource block allocations to users. We compare our results with two baseline algorithms; a priority-based proportional fairness algorithm with fixed power allocation (PPF) that gives priority to URLLC users and a Q-learning algorithm (LR-Q) that performs joint power and resource allocation with the objective of improving reliability and latency performance of URLLC users only. Our results show that the proposed algorithm outperforms LR-Q by 29% increase and PPF by 21 times increase in throughput. Meanwhile, less than 0.5 ms degradation in URLLC's latency at the 10^{-4} percentile is observed, compared to both LR-Q and PPF.

I. INTRODUCTION

The advent of next-generation wireless networks is mainly driven by the densification and diversification of network services. The recent fifth-Generation New Radio (5G-NR) standard introduced three service categories: Ultra-Reliable Low-Latency Communications (URLLC), enhanced Mobile Broad Band (eMBB), and massive Machine-Type Communication (mMTC) [1]. Each service category is unique in its Quality-of-Service (QoS) demands which implies several trade-offs when multiplexed on a shared channel. For instance, traffic of URLLC users is sparse with short packet size which requires rapid scheduling decisions for achieving close to 1 ms latency. In addition, latency of URLLC traffic is impacted by the desired level of reliability, which is related to packet drop rate, and therefore, related to probability of successful decoding a packet. In particular, an erroneous transmission triggers a re-transmission attempt using Hybrid Automatic Repeat Request (HARQ). HARQ mechanism consequently increases latency. For this reason, latency and reliability of URLLC needs to be jointly considered to address their trade off. Meanwhile, the coexistence of URLLC and eMBB traffic escalates the spectrum utilization

problem. For instance, giving more priority to URLLC users, during resource allocation, in order to satisfy their latency demand, causes puncturing of the resources of eMBB traffic and leads to throughput degradation for eMBB users. This calls for an efficient resource allocation algorithm that jointly optimizes latency-reliability-throughput. The research in [2] provides several insights on the trade-offs among reliability, latency and throughput in cellular networks.

The above mentioned challenges call for innovative solutions to the resource management problem. Scheduling of URLLC and eMBB traffic has been studied in several works. In [3], the authors propose a framework, based on reinforcement learning and neural network, to learn the best scheduling rule, such as fairness, at every iteration. The objective is to improve latency and packet drop rate of URLLC users. Authors in [4] propose a priority-based proportional fairness algorithm to improve latency of URLLC traffic with some degradation in throughput of eMBB traffic. Different than the previous papers in the literature, in this paper, we jointly consider power and resource block allocation to address the balance between QoS of both URLLC and eMBB users (latency, reliability and throughput).

In this paper, we address the coexistence of URLLC and eMBB traffic over 5G-NR network, where we seek to simultaneously balance QoS demands of both types of traffic. In particular, besides improving latency and reliability of URLLC users, we aim to maintain throughput performance of eMBB users. To achieve this, we propose a multi-agent Q-learning algorithm, namely Latency-Reliability-Throughput Improvement in 5G NR using Q-Learning (LRT-Q), to perform joint power and resource block allocation for each general Node-B (gNodeB) at every scheduling interval. The reward and state functions of LRT-Q is designed carefully to satisfy three key performance indicators (KPIs); i.e. reliability, queuing and transmission delays of URLLC users, and throughput of eMBB users. We evaluate the performance of LRT-Q in the presence of Constant Bit Rate (CBR) traffic, in addition to Poisson traffic. Furthermore, we compare the performance of LRT-Q to two baseline algorithms: A priority-based proportional fairness algorithm (with addition of equal power allocation), proposed in [4], and a Q-learning-

based algorithm designed to improve KPIs of URLLC solely. Simulation results show 29% and 21 times increase in eMBB users' throughput compared to LR-Q and PPF, respectively, at high traffic load of URLLC, i.e. 2 Mbps. This causes less than 0.5 ms degradation in URLLC users' latency at the 10^{-4} percentile compared to both LR-Q and PPF.

The paper is organized as follows. In section II, related work is presented. Section III present the system model followed by the proposed algorithm as well as the baseline algorithms. Performance results are presented in section IV. Finally, section V concludes the paper.

II. RELATED WORK

Multiplexing the traffic from URLLC and eMBB users constitutes a significant challenge in 5G, hence it has been tackled several times in the literature very recently. Diverse QoS demands, in addition to the spectrum scarcity problem call for innovative approaches in addressing the resource management problem. In [4], authors study multiplexing URLLC and eMBB traffic on a shared channel for 5G networks. The authors propose a joint link adaptation and spectrum allocation for improving latency of URLLC at the expense of degradation in throughput of eMBB traffic. As such, they develop a modified proportional fairness algorithm that gives priority to URLLC over eMBB traffic. In this work, we compare our proposed algorithm, LRT-Q, with the modified proportional fairness in [4]. Authors in [5] study multiplexing of URLLC and eMBB traffic with the objective to optimize utility of eMBB while satisfying URLLC requirements. They characterize feasible throughput regions and online scheduling algorithms of placement of URLLC traffic under various eMBB rate loss models, e.g. linear, convex, and threshold models. In [6], authors formulate an optimization problem with the objective of maximizing throughput of eMBB users while maintaining strict latency and reliability requirements of URLLC users. To achieve this, the authors propose a priority selection strategy for resource allocation to eMBB users based on a simplified k-arm bandit process. However, unlike our proposed scheme, they do not consider power allocation. We show that joint allocation of power and spectrum achieves significant improvements.

Considering that URLLC traffic requires immediate resource allocation, which takes some resources from eMBB users and eMBB users with lower data rate than other eMBB users are impacted more, the authors in [7], formulate a problem using a conditional value at risk metric to perform puncturing over the resources of high rate eMBB users. The authors propose a risk-sensitive resource allocation technique to schedule URLLC traffic while minimizing the risk of degraded performance of eMBB users due to puncturing. In [3], the authors propose a scheduling framework based on neural network and reinforcement learning that targets reducing packet drop rates and packet delays. However, their implementation does not schedule URLLC according to

5G-NR standard. Hence, the achievable delay is limited by the longer TTI (7 OFDM symbols) of LTE implementations.

Authors in [8] proposed a multi-user scheduling that aims to jointly improve network spectral efficiency and latency of URLLC users. Puncturing of eMBB resources is performed to immediately allocate URLLC traffic as it arrives. The choice of resources to puncture depends on the channel quality reported by URLLC users. In [9], authors consider power and resource allocation of vehicular URLLC users with the objective to minimize network-wide power consumption while ensuring high reliability in terms of probabilistic queuing delays. Extreme value theory and federated learning are used to characterize extreme events that happen when queue length exceeds a predefined threshold. Authors in [10] propose a joint cell selection and packet scheduling method that aims to maximize the served average traffic load while ensuring strict reliability and latency of all payloads. Authors use sequential process, in which cell association is performed first, then users assigned to different cells, are allocated resources.

Unlike previous works, in this paper, we perform joint power and resource allocation to multiplex URLLC and eMBB traffic on a 5G-NR time-frequency grid. The proposed algorithm is based on a multi-agent Q-learning approach, which learns to improve the KPIs of URLLC and eMBB users jointly.

III. PROPOSED SCHEME

In this Section, we first present our system model followed by the proposed algorithm and the baseline algorithms.

A. System Model

In this paper we implement the 5G-NR Rel.15 standard to verify our proposed algorithm on a set of gNodeBs that serve URLLC and eMBB users. 5G-NR standard provides a flexible resource allocation through variable length Transmit Time Interval (TTI). In particular, resolution in the time-direction is based on slots of 2, 4, 7, or 14 OFDM symbols. The finest resolution, i.e. TTI of 2 OFDM symbols, is implemented in the standard to facilitate rapid transfer of messages which best fit URLLC communication. On the other hand, larger resolutions, such as TTI of 14 OFDM symbols, is implemented to satisfy the high throughput demands of eMBB users. On the spectrum allocation side, the total downlink bandwidth, B MHz, is divided into N_{RB} resource blocks, where a resource block is a set of 12 contiguous subcarriers. In addition, consecutive resource blocks are grouped to form Resource Block Group (RBG) as defined in [11]. Let \mathfrak{K} be a set of K RBGs, where the size of a RBG is $\lceil N_{RB}/K \rceil$ resource blocks. To limit the set of states in our Q-learning approach, we consider RBG as our unit of allocation in the frequency direction. Furthermore, each k^{th} RBG is allocated a transmission power, $p_{k,j}$, by j^{th} gNodeB. The Q-learning algorithm that is described in the following section, aims to improve the allocation of RBGs and their transmission power

assignments.

According to our system model, each gNodeB holds a number of transmission buffers corresponding to the number of its attached users. Every TTI, downlink scheduler allocates resources to the active users, i.e. users with pending data transmissions. In particular, the scheduler performs joint power and RBG allocation while taking into account QoS demands of URLLC and eMBB users. Traffic model of URLLC users is composed of a mixture of constant bit rate (CBR) and Poisson arrivals; whereas the traffic of eMBB users follows Poisson arrivals.

Capacity of a link between the UE i and gNodeB j can be formulated as:

$$C_{i,j} = \sum_{k=1}^K \omega_k \log_2 \left(1 + \frac{p_{k,j} x_{k,i,j} g_{k,i,j}}{\omega_k N_0 + \sum_{\substack{m \in \mathcal{J} \\ m \neq j}} p_{k,m} x_{k,i,m} g_{k,i,m}} \right), \quad (1)$$

where ω_k is the bandwidth of k^{th} RBG and N_0 is additive white Gaussian noise single-sided power spectral density. $p_{k,j}$ is transmit power of j^{th} gNodeB on k^{th} RBG, $g_{k,i,j}$ is channel coefficient, and $x_{k,i,j}$ is RBG's allocation indicator of link (k, i, j) . $p_{k,m}$ is transmit power of m^{th} interfering gNodeB, $g_{k,i,m}$ is the channel coefficient, and $x_{k,i,m}$ is allocation indicator of link (k, i, m) . Eq. (1) shows that interference mitigation plays a key role in enhancing throughput. As it is well-known, inefficient power allocation might impact edge-users significantly, which reduces the overall achieved throughput.

Latency of packets can be decomposed into three components as follows:

$$T = T^q + T^{tx} + T^{harq}, \quad (2)$$

where T^q is queuing delay, T^{tx} is transmission delay, and T^{harq} is round-trip delay of a HARQ re-transmission. In line with [12], we assume $T^{harq} = 4.TTI$. During HARQ, a re-transmitted packet has higher priority than a new packet.

Transmission delay of user i associated to gNodeB j can be calculated by dividing the packet length $L_{i,j}$ to the capacity of the link, as below:

$$T_{i,j}^{tx} = \frac{L_{i,j}}{C_{i,j}}, \quad (3)$$

As observed from eq. (3), interference mitigation, hence optimal power allocation, plays a key role in transmission delay - besides throughput. On the other hand, transmission rate has an implication on the Radio Link Control (RLC) layer. As the rate increases less segmentation is observed. This consequently reduces the transmission delay. Furthermore, allocation of more RBGs to a user increases the size of the allocated transport block, which further decreases the

transmission delay.

The queuing delay in eq. (2) is identical to the scheduling delay of the MAC scheduler. As such, to achieve close to 1-ms for URLLC users, the scheduler has to immediately schedule URLLC traffic once it arrives and limit the number of HARQ re-transmissions. In particular, we assume only 1 HARQ re-transmission is allowed to achieve the lowest possible latency. However, limiting the number of re-transmissions can lead to higher Packet Drop Rate (PDR), i.e. lower reliability. Such low reliability can be more severe for edge-users. Thus, in order to achieve high reliability while meeting the latency budget, RBG-based transmission power control is employed in our proposed algorithm.

It is worth noting that improving latency and reliability of URLLC users is expected to impact the throughput performance of eMBB users (eq. (1)). This calls for efficient resource allocation algorithm that balances the trade-off between KPIs of URLLC and eMBB. In the following section, we present our proposed algorithm, based on Q-learning, for joint power and resource block allocation in order to jointly optimize latency and reliability of URLLC users as well as throughput of eMBB users.

B. Latency-Reliability-Throughput Improvement in 5G NR using Q-learning (LRT-Q)

The proposed algorithm is based on decentralized reinforcement learning, where each gNodeB acts an agent running a Q-learning algorithm to perform resource allocation. The mathematical formulation of Q-learning relies on Markov Decision Processes (MDP) which is defined by agents, states, actions, reward function and a policy. The operation of Q-learning relies on interaction with the environment and learning from trial and error based rewards being given to accepted or favored actions. More specifically, an agent selects an action, executes it, and receives a reward that reflects the quality of the selected action. This process is repeated until the agent reaches a policy of action selection that maximizes its total discounted reward. Q-learning estimates the quality of the visited state-action pair using an iterative update as follows:

$$Q^{new}(s^{(t)}, a^{(t)}) \leftarrow (1 - \alpha) \cdot Q(s^{(t)}, a^{(t)}) + \alpha \cdot [r^{(t)} + \gamma \cdot \max_a Q^{old}(s^{(t+1)}, a)], \quad (4)$$

where $Q^{new}(s^{(t)}, a^{(t)})$ is the quality value, i.e. Q-value of state-action pair $(s^{(t)}, a^{(t)})$ at t^{th} iteration, α is learning rate, γ is discount factor, and $r^{(t)}$ is instantaneous reward. Q-values are stored in a Q-table indexed by the states and actions, hence the size of the Q-table relies on the state-action space.

The proposed algorithm, LRT-Q, is a Q-learning algorithm with a reward function designed to improve latency and reliability of URLLC users as well as throughput of eMBB users. In LRT-Q, actions are the joint power and resource

block allocations performed by agents, i.e. gNodeBs. To keep the Q-table size manageable we group 8 consecutive resource block into a RBG and the agent allocates RBGs [11].

In LRT-Q, states are driven by observations from the environment which reflect the impact of actions of other agents. In particular, interference among users represent the major bottleneck against achieving better latency, reliability and throughput. As such, states are defined to capture the average SINR achieved by users attached to each gNodeB as follows:

$$S_{k,j} = \begin{cases} S_0 & \bar{\gamma}_{k,j} \geq \gamma_{th}, \\ S_1 & \text{Otherwise}, \end{cases} \quad (5)$$

where $\bar{\gamma}_{k,j}$ represents the average estimate of the SINR value of k^{th} RBG and defined as $\bar{\gamma}_{k,j} = \beta \bar{\gamma}_{k,j}^U + (1-\beta) \bar{\gamma}_{k,j}^E$, where $\bar{\gamma}_{k,j}^U$ is the average SINR of URLLC users, $\bar{\gamma}_{k,j}^E$ is the average SINR of eMBB users, and β is a factor controlling the priority given to URLLC and eMBB users. γ_{th} is a threshold SINR value. The value γ_{th} is chosen to maintain high probability of decoding. Finally, the reward function is formulated to reward actions that achieve the objectives of the proposed scheme:

$$\rho_{k,j}^U = \begin{cases} 1 - \max_{i \in \mathcal{U}} (T_{i,j}^q)^2 & \bar{\gamma}_{k,j}^U \geq \gamma_{th}, \\ -1 & \text{otherwise}, \end{cases} \quad (6)$$

$$\rho_{k,j}^E = \frac{2}{\pi} \tan^{-1}(\bar{C}_{k,j}^E), \quad (7)$$

$$\rho_{k,j} = \beta \rho_{k,j}^U + (1-\beta) \rho_{k,j}^E, \quad (8)$$

where $\rho_{k,j}^U$ is the reward of URLLC users on k^{th} RBG, $\rho_{k,j}^E$ is the reward of eMBB users, and $\rho_{k,j}$ is the total reward of j^{th} gNodeB. $T_{i,j}^q$ represents the last packet queuing delay of i^{th} URLLC user ($i \in \mathcal{U}$), and $\bar{C}_{k,j}^E$ is the average throughput of eMBB users. Eq. (8) serves in addressing the KPIs of both URLLC and eMBB users through adjustment of parameter β . In particular, eq. (6) aims at improving latency and reliability of URLLC users where the agent is rewarded a value relative to the queuing delay as long as its reliability is meeting certain threshold, i.e. SINR threshold. Indeed, the reward value relies on the maximum queuing delay experienced by URLLC users. This means that the algorithm will aim to improve the worst queuing delay. In addition, achieving better average SINR significantly contributes to the overall latency since better SINR leads to less packet segmentation and reduced transmission delay. Overall, eq. (6) motivates the MAC scheduler to immediately allocate URLLC users to better RBGs, i.e. hence achieving low-latency and high reliability at the same time.

Eq. (7) serves in improving the throughput of eMBB users, where increased throughput leads to a reward value close to one. Using the parameter β in eq. (8), we obtain the balance between the conflicting KPIs. The LRT-Q technique is compared with two baseline algorithms that are described below.

Algorithm 1 presents steps of LRT-Q algorithm performed by each agent, i.e. gNodeB.

Algorithm 1 LRT-Q

- 1: **Initialization:** Q-table $\leftarrow 0$, α , γ , and ϵ .
 - 2: **for** TTI $t = 1$ to T **do**
 - 3: **Step 1:** Agent (i.e. gNodeB) receives uplink report (i.e. SINR) from its attached users.
 - 4: **Step 2:** Compute the reward as in Eq. 6, 7, and 8.
 - 5: **Step 3:** Update the Q-value of the current state-action pair as in Eq. (4).
 - 6: **Step 4:** Observe and transit to next state as in Eq. 5.
 - 7: **Step 5:** Select the next action based on ϵ -greedy policy.
 - 8: **Step 5:** Repeat at **Step 1**.
 - 9: **end for**
-

C. Baseline Algorithms: PPF and LR-Q

PPF is a proportional fairness technique based scheme with priority given to URLLC users. Priority-based Proportional Fairness (PPF) is proposed in [4] and implemented here with addition of equal power allocation. Simply, PPF allocates RBGs to URLLC users with pending data transmission, then, it allocates the remaining RBGs to eMBB users.

The second baseline algorithm, namely Latency-Reliability Enhancement using Q-learning (LR-Q), is based on Q-learning, similar to the proposed scheme, however it only considers the KPI for URLLC users.

IV. PERFORMANCE EVALUATION

Simulations are performed using our discrete-level simulator based on Matlab 5G toolbox. In our simulations, we consider 5 gNodeBs, each covering 10 URLLC and 5 eMBB users. The traffic of URLLC users is a mixture of 20% CBR and 80% Poisson arrivals, whereas traffic of eMBB follows Poisson arrivals only. Payload size is fixed to 32 bytes for all users. In addition, URLLC traffic loads per cell is varied between 0.5 and 2 Mbps whereas eMBB traffic load is fixed to 0.5 Mbps. Simulation results are collected for 5000 TTIs and averaged over 10 simulation runs and presented with 95% confidence interval. In this paper, we select the finest time resolution, i.e. TTI of 2 OFDM symbol, as our scheduling interval. The action space of Q-learning-based algorithms consists of the combination of power and RBG allocations. For a system bandwidth of 20 MHz, 13 RBGs are used where the first 12 RBGs contains 8 consecutive resource blocks while the last RBG contains 4 consecutive resource blocks. Maximum gNodeB's transmission power is set to 40 dBm [13] and power allocation, $p_{k,j}$, is drawn from the set $\{0, 1, 2, 3\}$ dBm. Finally, SINR threshold of $\gamma_{th} = 20$ dB is used to maintain high probability of successful reception. Table I lists all the network and Q-learning settings considered for our simulations.

TABLE I
NETWORK SETTINGS

Network environment	3GPP Urban Macro (UMa) network 5 gNodeBs and 500 meter inter-site distance
PHY configuration	15 KHz subcarrier spacing 12 subcarriers per resource block Number of RBG $K = 13$ TTI size of 2 OFDM symbols (0.1429 ms) Max. transmission power of 40 dBm [13] Tx/Rx antenna gain of 15 dB
Carrier configuration	$B = 20$ MHz bandwidth $N_{RB} = 100$ resource blocks Carrier frequency of 4 GHz
HARQ	Asynchronous HARQ round trip delay is 4 TTI 6 HARQ processes Max. 1 HARQ re-transmission
Propagation	$128.1 + 37.6 \log_{10}(D[Km])$ Log-Normal Shadowing (8 dB) Noise Figure of 5 dB Penetration loss of 5 dB
User distribution	Stationary and uniformly distributed 50 URLLC (10 per cell) 25 eMBB (5 per cell)
Traffic model	URLLC: 20% CBR and 80% Poisson eMBB: Poisson Payload size: 32 Byte
URLLC Load/Cell	[0.5 : 0.5 : 2] Mbps
eMBB Load/Cell	0.5 Mbps
Q-Learning	Learning rate (α) of 0.5 Discount factor (γ) of 0.9 Exploration probability (ϵ) of 0.05 β of 0.1

The performance of the proposed algorithm is evaluated in terms of KPIs of URLLC and eMBB traffic, i.e. latency and reliability of URLLC and throughput of eMBB. Fig. 1 presents the aggregate throughput of eMBB users in the presence of varying traffic loads of URLLC users from 0.5 Mbps to 2Mbps offered load per cell. Indeed, increasing URLLC's traffic load should impact the throughput performance of eMBB users. However, the proposed algorithm, LRT-Q, is able to maintain stability of throughput performance of eMBB users, with a slight degradation when the offered load is 2 Mbps. This shows a throughput increase of 29% compared to LR-Q and 21 times increase compared to PPF algorithm even under the highest offered load scenario. Even when the offered load is 0.5 Mbps, the proposed algorithm has twice as much throughput than PPF.

Fig. 2 and Fig. 3 present the Empirical Complementary Cumulative Distribution Function (ECCDF) of latency of URLLC users in ms for URLLC traffic loads [0.5, 1] Mbps and [1.5, 2] Mbps, respectively. The results are plotted in two figures in order to preserve readability. In Fig. 3, it can be observed that LRT-Q algorithm experiences less than 0.5 ms latency degradation at the 10^{-4} percentile compared to both LR-Q and PPF for high traffic load of URLLC, i.e. 2 Mbps. It is worth mentioning that although PPF achieves better latency for URLLC users compared to LRT-Q and LR-Q, its throughput is degrading faster than LRT-Q and LR-Q.

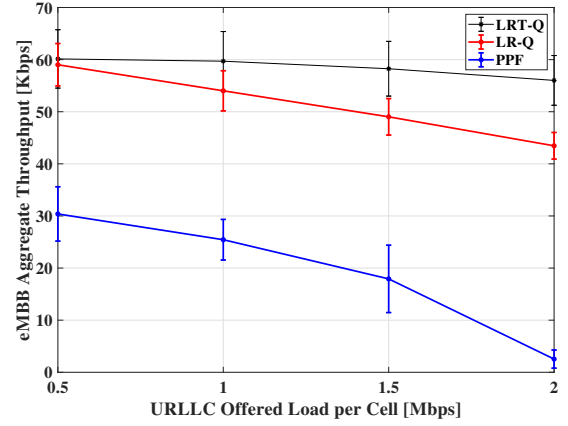


Fig. 1. Aggregate Throughput of eMBB Users [Mbps] against URLLC's Traffic Load.

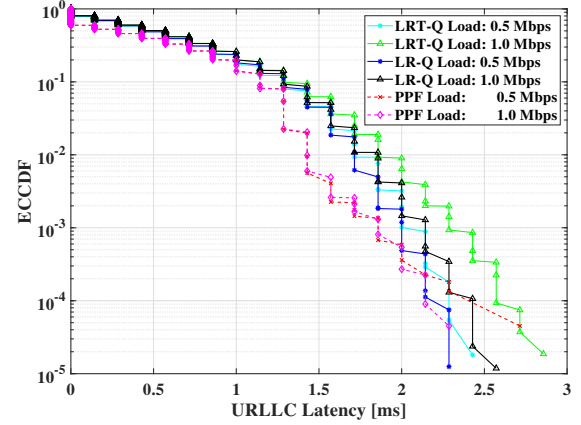


Fig. 2. Average URLLC Latency [ms]; URLLC Loads are 0.5 and 1 Mbps; eMBB Load is 0.5 Mbps.

Fig. 4 shows the PDR under varying traffic load of URLLC users. Both LRT-Q and LR-Q achieve identical and very low PDR (0.06%); Whereas PDR of PPF increases rapidly with load of URLLC. Finally, we observed that both Q-learning algorithms converge after 3000 TTIs, i.e. 428.5 ms.

V. CONCLUSION

In this work, we studied the trade off among the key performance indicators (KPIs) of ultra-reliable and low-latency communications (URLLC) and enhanced Mobile Broadband (eMBB) users. We proposed Q-learning based joint power and resource allocation algorithm which aims at improving both latency and reliability of URLLC users as well as throughput of eMBB users. The proposed algorithm was compared to two algorithms: Priority-based proportional fairness, and Q-learning for improving the KPI of URLLC users solely. Simulation results revealed that the proposed algorithm achieved a significant performance gain in eMBB's throughput when compared to the baseline algorithms, while it has incurred a slight degradation in latency for URLLC users.

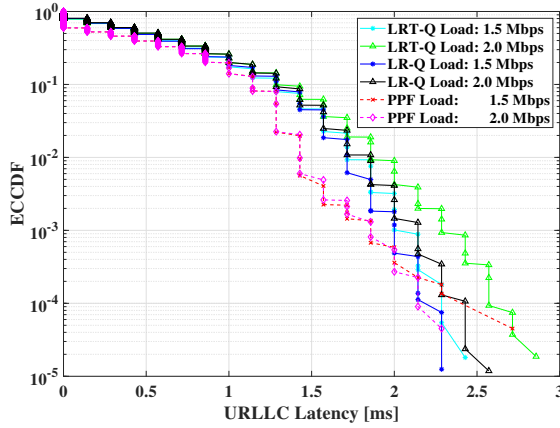


Fig. 3. Average URLLC Latency [ms]; URLLC Loads are 1.5 and 2 Mbps; eMBB Load is 0.5 Mbps.

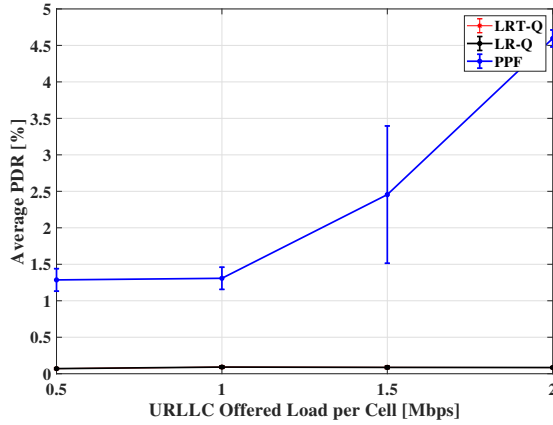


Fig. 4. Average Packet Drop Rate [%]; eMBB Load is 0.5 Mbps.

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