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Opportunistic Resource Allocation for URLLC and eMBB in 5G Networks with Time Varying Channels: a Genetic Algorithm Approach

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ABSTRACT

The fifth-generation (5G) New Radio (NR) introduces stringent delay and reliability requirements to support diverse services, including enhanced mobile broadband (eMBB) and ultra-reliable low-latency communication (URLLC). A major challenge is the efficient coexistence of these heterogeneous services, as eMBB demands high throughput while URLLC requires extreme reliability and minimal latency. This study investigates the coexistence of eMBB and URLLC under time-varying channel conditions and formulates a many-to-many URLLC resource allocation problem. To address this, we propose an opportunistic resource allocation scheme based on a genetic algorithm (GA) that dynamically optimizes resource block (RB) allocation for both services. The GA employs a heuristic fitness function designed to maximize eMBB fairness and throughput while ensuring URLLC reliability. Simulation results demonstrate that the proposed approach significantly improves overall system performance: eMBB fairness exceeds 95%, and the average eMBB data rate increases by approximately 500 Kbps compared to random allocation. Moreover, URLLC users maintain a consistent data rate of 600 Kbps, outperforming benchmark methods while satisfying the 99.999% reliability requirement. The results confirm that the proposed GA-based approach effectively balances throughput, fairness, and reliability, making it a promising solution for future 5G networks with mixed traffic demands.

1. INTRODUCTION

5G networks introduce a range of services to meet diverse application needs, including Ultra-Reliable Low-Latency Communication (URLLC) for mission-critical tasks such as telemedicine and intelligent transport systems, Enhanced Mobile Broadband (eMBB) for high-data-rate applications such as 4K/8K real-time video delivery, and massive Machine-Type Communications (mMTC) for IoT [1-3]. A key challenge in 5G is the coexistence of URLLC and eMBB, as they have conflicting requirements. URLLC demands low latency and high reliability, while eMBB requires maximizing throughput [2]. Figure 1 shows the classification of 5G use cases. In 5G networks, timeslots are structured units of time during which data transmissions take place [4]. Typically lasting 1 millisecond, timeslots serve as the basic building blocks for organizing and scheduling communications between users and the network [5]. To meet more precise transmission needs, especially for services requiring low latency, timeslots are further divided into smaller segments known as minislots. Minislots, or shortened Transmission Time Intervals (sTTIs), last for only a fraction of a full timeslot, enabling faster data transfers and allowing services like URLLC to meet their strict latency requirements by transmitting data more frequently and with less delay [6-8].

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Within each timeslot or minislot, data is transmitted using Resource Blocks (RBs), which represent the smallest unit of time-frequency resources allocated to users [9, 10]. Each Resource Block spans a specific duration of time and a particular frequency bandwidth, allowing the network to distribute its available spectrum efficiently. The allocation of RBs to users is dynamic, adapting to real-time channel conditions to optimize data rates while maintaining quality of service for applications with varying demands [10].

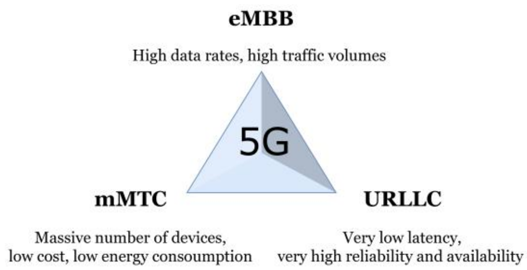

Figure 1. Classification of services in 5G.

The standard considers scheduling to be application specific with the overall goal of taking advantage of the channel variations between devices and schedule transmission to a device on a resource block that has advantageous channel conditions both in frequency and time domains [11]. By employing Channel State Information (CSI), this information can be known at the BS in order to opportunistically assigning RBs to users.

Due to extreme latency requirements (0.25-0.3 msec/packet), upon arrival of short and sporadic URLLC [4] packets, they are scheduled in the immediate minislot by puncturing the RBs that are already assigned to eMBB traffic. In the superposition mode, the URLLC transmissions are overlapped on the ongoing eMBB transmissions. In this approach, the gNB allocates power to both transmissions simultaneously, which leads to a reduction in the data rates for both eMBB and URLLC transmissions [6]. In order to mitigate this and reach reliability constraint of URLLC (99.999%), the puncturing framework is proposed. Puncturing occurs when URLLC traffic interrupts ongoing eMBB transmissions by the gNB, which sets the power of eMBB to zero for a brief period during URLLC transmissions [10, 12]. This process results in a lowered data rate for the affected eMBB users. However, at the end of the TTI, the eMBB users are notified about where puncturing occurred. With this information, the eMBB users can still decode their data, although the rate is reduced based on the number of punctured sTTIs. Figure 2 illustrates this framework.

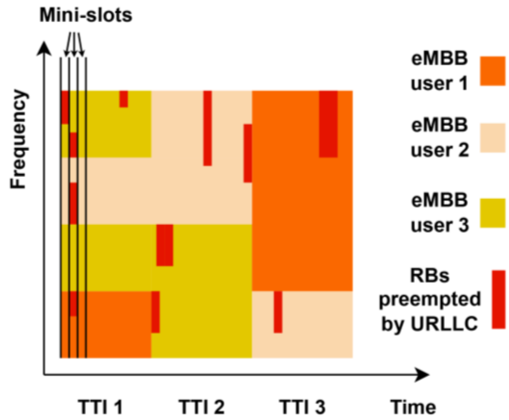

Figure 2. Puncturing framework overview.

The key problem here is assigning RBs to eMBB users at each timeslot, possibly based on channel conditions (opportunistic) and scheduling the sporadic URLLC packets at each minislot by puncturing some RBs that have been allocated to eMBB traffic, aiming to maintain reliability, throughput and fairness in the long term [8, 13].

An alternative coexistence mechanism outlined in the standard is orthogonal scheduling [14], in which certain resource blocks (RBs) are reserved for URLLC. However, a disadvantage of this method is that if URLLC traffic is absent, the allocated resources remain underutilized. In this study, we focus on the puncturing method to address the coexistence challenges between eMBB and URLLC, aiming to meet URLLC requirements while minimizing the impact on eMBB users [15]. A genetic algorithm (GA) is proposed for scheduling both eMBB and URLLC, with performance evaluated based on metrics such as fairness, data rate, and packet drop rate.

The remainder of this paper is structured as follows: this section provides a literature review and contributions. Sections 2 and 3 focus on the system model and problem definition, respectively. The proposed solution is introduced and discussed in Section 4, followed by simulation results and evaluations in Section 5. Finally, the paper concludes with the conclusion presented in the last section.

1.1 Contributions

In this paper, we address the challenges of resource allocation and scheduling for the coexistence of eMBB and URLLC services in 5G networks. We propose a novel approach that leverages genetic algorithms and time-varying channel conditions to optimize resource allocation, ensuring high performance for both services. The key contributions of this work are outlined below, highlighting the innovations in many-to-many resource allocation, minimizing the impact of URLLC traffic on eMBB, and providing a comprehensive performance analysis. The summary of the contribution is as follows:

- **Many-to-Many Opportunistic Allocation:** A novel many-to-many resource allocation model is formulated to enable efficient eMBB–URLLC coexistence under time-varying channels using opportunistic scheduling.
- **Genetic Algorithm Optimization:** A GA-based framework is proposed to jointly schedule eMBB and URLLC traffic, optimizing throughput, fairness, and reliability through a heuristic fitness function.

1.2 literature review

As the standard had not specified any coexisting mechanism [15], several approaches have been proposed to tackle the challenge of resource allocation and scheduling of the URLLC and eMBB in 5G networks. The authors of [16] propose using a Max-Matching Diversity (MMD) algorithm to allocate channels in both orthogonal (H-OMA) and non-orthogonal (H-NOMA) network slicing strategies. Their results demonstrate that MMD improves performance by increasing frequency diversity, hereby enhancing both eMBB data rates and URLLC reliability. This approach allows for better resource utilization by minimizing interference, particularly in scenarios where URLLC traffic is light and improves overall system reliability; however, the method introduces increased computational complexity, which scales with the number of channels, potentially limiting its practicality in large-scale networks. Additionally, while the MMD approach generally benefits both services, it leads to a slight increase in control traffic, and its performance advantages decrease when URLLC loads are high, particularly in H-NOMA configurations where interference is more significant.
The authors of [17] propose a two-stage resource allocation scheme for eMBB, coupled with preference-based resource preemption strategies for both bandwidth-sensitive and time-sensitive URLLC traffic. This approach aims to enhance eMBB reliability and improve user satisfaction by protecting eMBB users with poor channel conditions during URLLC resource preemption. This paper uses minislot scheduling for finer granularity, ensuring that eMBB users maintain a high level of reliability even under high URLLC loads. However, although the scheme offers improved reliability and protection for eMBB users, it increases the complexity of resource management, as it requires dynamically prioritizing users based on preference values that consider both channel gains and service requirements. Additionally, the approach may face challenges in scaling efficiently with high traffic loads due to its resource-intensive allocation process.

Almekhlafi *et al.* [18] propose a downlink puncturing scheme aimed at optimizing the simultaneous transmission of URLLC and eMBB traffic in 5G and 6G systems. The technique exploits the symbol similarity between URLLC and eMBB to reduce the impact of puncturing on eMBB transmissions. By identifying and puncturing eMBB symbols that closely resemble URLLC symbols, the scheme improves eMBB spectral efficiency and reliability while meeting the stringent latency and reliability requirements of URLLC. This results in reduced retransmission requirements and enhanced eMBB bit error rate (BER) performance, especially at high signal-to-noise ratios (SNRs). Additionally, the algorithm demonstrates a linear time complexity, making it practical for real-world application. However, the scheme’s reliance on symbol similarity may limit its efficiency when there is less similarity between URLLC and eMBB traffic and puncturing still negatively affects eMBB performance under low SNR conditions or high URLLC loads.
Prathyusha *et al.* [19] tackle the key challenge of resource allocation, using a joint optimization framework to maximize the minimum expected achieved rate (MEAR) of eMBB users while ensuring URLLC users meet stringent Quality of Service (QoS) constraints. The solution leverages non-orthogonal multiple access (NOMA) for superposition of eMBB and URLLC traffic, which helps in improving resource utilization without dedicating exclusive resources to URLLC. The advantages of this approach include enhanced fairness among eMBB users and efficient resource usage due to NOMA's power domain pairing and puncturing fallback in cases where superposition is infeasible. However, the proposed method might face complexity and practicality challenges in large-scale implementations due to the need for matching theory and power optimization for every time slot. Additionally, under heavy URLLC traffic, the method may still incur some eMBB throughput loss.
Zhang et al. [20] present a stochastic optimization model for joint scheduling of URLLC and eMBB traffic with a queuing mechanism aiming to improve the coexistence of both services. By incorporating queuing, the method reduces URLLC packet drop rates while maintaining latency requirements, optimizing overall system performance. The optimization process balances URLLC and eMBB demands dynamically, using techniques like successive convex approximation to simplify complex non-convex problems. However, the queuing mechanism introduces some delays that,

while minimized, could still affect URLLC's ultra-low latency requirements under high traffic loads.

Bairagi *et al.* [21], formulated the problem as an optimization problem, decomposed into two sub-problems for eMBB and uRLLC traffic, solved using a heuristic algorithm and a one-sided matching game, respectively. The advantages of the proposed method include higher fairness and improved minimum expected rate for eMBB users compared to baseline methods like random and preemptive scheduling.

Anand *et al.* [22] introduce both linear and convex models for rate loss in eMBB traffic due to URLLC superposition or puncturing, with the linear model offering an optimal scheduler that separates the decisions for URLLC and eMBB traffic. In more complex convex and threshold models, joint optimization of scheduling is required. It further develops stochastic approximation algorithms that maximize eMBB utility while meeting URLLC demands. Alsenwi *et al.* [14] formulate this problem as an optimization task, aiming to maximize eMBB data rates while ensuring the stringent latency and reliability requirements of URLLC. The authors propose a two-phase resource allocation framework: an optimization-based approach for eMBB resource allocation and a deep reinforcement learning (DRL)-based algorithm for URLLC scheduling. The optimization phase decomposes the problem into sub problems to allocate resources for eMBB users efficiently. The DRL phase dynamically schedules URLLC traffic, using a policy gradient-based actor-critic algorithm to handle the uncertainty of traffic and channel conditions. Bairagi *et al.* [2] propose an optimization model that seeks to maximize MEAR for eMBB users while ensuring the performance of uRLLC traffic. The problem is decomposed into two sub-problems: resource scheduling for eMBB and uRLLC users. A penalty successive upper bound minimization (PSUM) algorithm is used for scheduling eMBB users, while a transportation model (TM) approach is applied for uRLLC scheduling. Additionally, a heuristic algorithm is provided to address complexity in solving the first sub-problem.

Huang *et al.* [23] propose DELUXE, a deep learning-based link adaptation mechanism that dynamically selects the modulation and coding scheme (MCS) for eMBB transmissions. This ensures that the link reliability is maintained while optimizing throughput. DELUXE incorporates a deep learning approach to accurately predict the block error rate (BLER) for different MCS configurations, effectively handling the complex interference caused by URLLC traffic. The method compresses high-dimensional data on channel conditions and URLLC behaviour into a low-dimensional representation, ensuring that the essential information is preserved while reducing computational complexity. DELUXE outperforms traditional link adaptation techniques, such as exponential effective SNR mapping (EESM), especially in URLLC puncturing scenarios. Moreover, the deep learning framework enables real-time decision-making, with the entire process completed within the stringent 5G time requirements.

Daneshvar *et al.* [24] propose a solution that employs Graph Neural Networks (GNNs) to optimize resource allocation, ensuring that eMBB data rates and fairness are maximized while minimizing URLLC outage probability. The problem is divided into two phases: resource allocation for eMBB and a puncturing-based method for URLLC. The eMBB allocation is handled with a heuristic algorithm with an O(n) runtime complexity, ensuring optimal resource allocation under a min-max fairness paradigm. For URLLC, the authors propose a GNN-based approach that models resource blocks as nodes in a graph, capturing complex interactions between resource blocks and users. The GNN is trained using a custom loss function that balances eMBB throughput and URLLC reliability. Additionally, the GNN-based method is shown to be robust to changes in network topology and traffic volumes, making it a practical solution for real-time resource allocation in 5G networks.

1.3 Genetic Algorithm

The Genetic Algorithms (GA) are versatile methods based on principles of natural selection [25]. The solutions to a problem are modelled as chromosomes or individuals containing genes. A chromosome can be thought of as a linear array of numbers. A fitness function assigns a fitness value to each individual. They can also mutate and give birth to offspring [26]. The GA uses natural selection to combine the most suitable solutions found so far while the mutation ensures exploring the unknown regions of the search space. By controlling various aspects of GA such as the fitness function, the crossover and mutation functions and parent selection method, it can be used to solve many problems. Genetic algorithms have been demonstrated to reliably converge on global optima for a wide range of computationally difficult NP-hard problems [25]. They are highly effective in solving problems with large solution spaces. [27]. A review of application of GA in wireless networks is presented in [28]. The use of GA in 5G networks specifically has also been investigated as in [29-32].

2. SYSTEM MODEL

The model considers a scenario where a base station serves multiple eMBB and URLLC users. We denote the set of URLLC users, eMBB users, and RBs K, U, and B. We denote the number of TTIs as T, where each TTI if further divided into $M=8$ minislots. We also consider time-varying channels in which the maximum data rate for each user can be obtained using CSI. We assume eMBB requests are scheduled on TTIs (1ms) and URLLC requests are scheduled on minislots of length 0.125ms. A URLLC user may have up to one packet of length L in each minislot. The linear rate loss model applies to eMBB users as a result of puncturing. the data rate of eMBB user k on the RB b at time t, according to the Shannon's capacity theory, is given by (1) [2].

$$r_k^b(\mathrm{t}) = f_b log_2(1 + \frac{p_k^b(t)h_k^b(t)}{N}) \quad (1)$$

Where f_b is the bandwidth of the RB b, $h_k^b(t)$ is the time-varying Rayleigh fading channel gain of the transmission, $p_k^b(t)$ is the transmission power and N is the noise power. An eMBB user may be assigned multiple RBs, therefore, the total rate of eMBB user k at time t is defined by (2).

$$r_k(t) = \sum_{b \in B} r_k^b(t)x_k^b(t) \quad (2)$$

Where $r_k^b(t)$ is the data rate of eMBB user k on RB b at and $x_k^b(t)$ is the binary variable indicating if RB b is assigned to eMBB user k at time t.

To meet the stringent delay requirements of URLLC, the block length must be kept short [33], meaning that the data rate no longer adheres to Shannon's capacity theory. In such cases, finite block length coding should be employed. The data rate for a URLLC user u on resource block b is described by equation (3).

$$r_u^b(t') = f_b \log(1 + \frac{p_u^b(t\prime)h_u^b(t\prime)}{\sigma^2}) - \sqrt{\frac{D_u^b(t\prime)}{c_u^b(t\prime)}} Q^{-1}(\vartheta) \quad (3)$$

Where Q^{-1} is the inverse of Gaussian Q-function, ϑ is the transmission error probability, $D_u^b(t')$ is the channel dispersion rate and $c_u^b(t')$ is the number of symbols in a minislot. A URLLC user may use more than one RB in a minislot, the total rate of URLLC user u is given by (4):

$$r_u(t') = \sum_{b \in B} r_u^b(t')y_u^b(t') \quad (4)$$

Where $y_u^b(t)$ is binary variable representing URRLC to RB allocation.

3. PROBLEM DEFINITION

At the beginning of each timeslot, the available RBs will be allocated to the eMBB users to maximize high-level goals such as total throughput and fairness. The resource allocation algorithm should consider the time-varying channel characteristics to opportunistically find the most suitable RB for a given user. Additionally, it is important to also take the impact of URLLC puncturing on the data rate of eMBB users into account. The linear rate loss model is assumed here. In this model, if RB b is punctured in N out of M minislots, the actual rate of eMBB user k on RB b will be $\frac{(M-N)* r_k^b(\mathrm{t})}{M}$, and the total actual rate of eMBB user k over all assigned RBs at timeslot t under the influence of URLLC traffic is given by (5):

$$r_k^{actual}(t) = \sum_{b \in B} \left[r_k^b(t)x_k^b(t) \frac{M - \sum_{t' \in C(t)} \sum_{u \in U} v_u(t')y_u^b(t')}{M} \right] \quad (5)$$

Where $C(t)$ is the set of minislots of the timeslot t, U is the set of URLLC users, $v_u(t')$ is a binary variable that is 1 if user u has a packet at minislot t' and 0 if not. In each minislot, upon arriving of URLLC traffic and in order to satisfy the delay requirements of URLLC, the URLLC packets are scheduled on the current minislot immediately, via puncturing RBs already assigned to eMBB users. URLLC has also an extreme reliability requirement. In order to formulate the outage probability constraint of URLLC we first define the set of served URLLC users at minislot t'. A user is considered served if the allocated data rate allows for transmission of a URLLC packet in brief time window of a minislot [24].

The set of served URLLC users at minislot t' is defined as follows.

$$S(t') := \left\{ u \mid u \in U \text{ and } r_u(t') \geq \frac{L}{\delta} v_u(t') \right\} \quad (6)$$

Where L is payload length of a URLLC request, and δ is the length of one minislot (0.125ms). The outage probability is then defined as (7).

$$\Omega = \frac{\sum_{t=1}^{T} \sum_{t' \in C(t)} |S(t')|}{\sum_{t=1}^{T} \sum_{t' \in C(t)} \sum_{u \in U} v_u(t')} \quad (7)$$

That is the ratio of total number of served URLLC packets to the total number URLLC packets over all timeslots and minislots in question.

Our goal is to maximize the data rate of eMBB users while satisfying the stringent requirements of URLLC. The min-max fairness is adopted in order to enhance spectral efficiency and overall user experience of eMBB users. Based on min-max fairness the problem is formulated as an optimization problem defined below.

$$Maximize \quad \min\left(\left\{ \sum_{t=1}^{T} r_k^{actual}(t) \mid k \in K \right\}\right) \quad (8)$$

Subject to:

$$\frac{\sum_{t=1}^{T} \sum_{t' \in C(t)} |S(t')|}{\sum_{t=1}^{T} \sum_{t' \in C(t)} \sum_{u \in U} v_u(t')} \leq \varepsilon \quad (9)$$

$$\sum_{k \in \mathbb{K}} x_k^b(t) \leq 1, \forall\, b \in B\,, t \quad (10)$$

$$\sum_{u \in U} y_u^b(t') \leq 1, \forall\, b \in B\,, t' \quad (11)$$

$$x_k^b(t) \in \{0,1\}, \forall\, k, b, t \quad (12)$$

$$y_u^b(t') \in \{0,1\}, \forall\, u, b, t' \quad (13)$$

4. PROPOSED SOLUTION

The problem formulation (8) assumes the values of all input variables are known. This formal definition cannot be directly used to solve the problem in a timeslot-by-timeslot manner [24, 34]. In practice two separate problems of URLLC and eMBB RB assignment are solved at each sTTI and TTI respectively. Therefore, we decompose the problem and restate it as two separate problems: eMBB RB assignment and URLLC RB assignment. When allocating RBs to eMBB users, URLLC requests are absent, as a result constraint (9) in problem (8) is removed. Also, we use the expected value notation to reflect the fact that the problem is re-stated for a single timeslot. The eMBB resource allocation is defined as (14).

$$Maximize\ \min\left(\left\{\mathbb{E}_h\left[\sum_{t=1}^{T} r_k^{actual}(t)\right] \mid k \in K\right\}\right) \quad (14)$$

Subject to:

$$\sum_{k \in \mathbb{K}} x_k^b(t) \leq 1, \forall\, b \in B\,, t \quad (15)$$

$$x_k^b(t) \in \{0,1\}, \forall\, k, b, t \quad (16)$$

We proposed a GA based solution with a heuristic fitness function so to find an optimal solution for problem (14). The GA based approach examines different assignment of eMBB users to RBs and chooses the most suitable solution according to a fitness function.

To apply GA, the problem needs to be defined in a genetic friendly way. That is, a mapping between all feasible solutions to a vector space that is called the gene space. We consider the number of genes as the number of RBs where each gene consists of an eMBB user id. This way all, the possible assignments of RBs to eMBB users can be represented. For example, if there are 5 RBs and 3 users, a chromosome can be <0,1,1,2,2> where the first RB is assigned to user 0 the next two RBs are assigned to user 1 and the last two RBs are assigned to user 2. At the start of GA, an initial population of N_p random chromosomes is generated. This population undergoes a predefined number of generations. In each generation the steady state parent selection is used. In this mode, only a few of the chromosomes in the population are replaced in each generation with the offspring of the fittest parents. The crossover operation is used to get an offspring from a number of parents. We used the single point random crossover formulated in (17).

$$g_i^{offpsring} = \begin{cases} g_i^{parent1} & rand \geq 0.5 \\ g_i^{parent2} & otherwise \end{cases} \quad (17)$$

Where g_i^c is the *i*-th gene of the chromosome *c*. The crossover operation is used to exploit the best-found solutions but exploring the unknown is also desirable. To add exploration, a mutation operation is introduced. The mutation will randomly change the value of genes with a predefined probability. Finally in order to rank solutions, a fitness function should be designed. We define our fitness function as (18).

$$fitness(x,t) = \min\left(\left\{\frac{r_k^{actual}(t)}{\sum_{i=1}^{t-1} r_k^{actual}(i)}\right\} \mid k \in K\right) \quad (18)$$

According to this fitness function the best solution is the solution that can add proportionally more total rate to eMBB users by giving more rate to users with low total throughput, this is adopted form the widely used min-max fairness paradigm. Algorithm 1 lists the pseudo code of the GA based algorithm.

At the start of each timeslot the BS uses the genetic algorithm to allocate RBs to eMBB users. In order to evaluate an individual, the current data rate of time *t* and total data rate until *t-1* are required. As mentioned before, by employing CSI such that the data rate for each RB-user pair is known [14]. The genetic algorithm finds an optimal solution and the BS applies the solution onto the network.

Algorithm 1: Pseudo code of the GA based algorithm.

```
Cparent := number of parent per generation
Coffspring := number of offspring per generation
POP := initial population
best := null
gen := 0
while gen < Gmax do
  POP := POP sorted by fitness given by (18)
  TOP := TOP Cparent individuals in POP
  for i := 0 to Coffspring:
    p1,p2 := distinct random members of TOP
    offspring := crossover of p1 and p2 by (17).
    remove a random member of POP
    add offspring to POP
  end for
  apply mutation to all members of POP
  best := best member so far
  gen := gen + 1
end while
return best
```

The second sub-problem that is solved on the minislot timescale is the URLLC allocation. At each minislot, a subset of all URLLC users, each having one packet may arrive. We call this subset the active URLLC users. The BS must allocate a number of RBs to each active URLLC user such that all of them are satisfied with minimal effect on eMBB users. Note that unlike many similar works here we consider the many-to-many RB to URLLC allocation problem. Other works either assume one RB is enough for each URLLC like in [2], [14] or assume only one URLLC user that may use multiple RBs as in [22], [21], [34]. The many-to-many case is important when the channel state on different RBs are varying individually for each URLLC user and we cannot assume all URLLC users as one. Also, some RBs might be in poor condition and unable to satisfy one URLLC packet singlehandedly. This many-to-many allocation should be done with minimal impact one eMBB users. There is no reason to define a different fitness function here. If the fitness function (18) really captures our goal for the eMBB users it must be also used here. I.e. our goal regarding eMBB users which is higher data rates and better fairness is the same in both TTI and minislot time. However, we have to make sure that all the URLLC request are satisfied.

To solve the URLLC scheduling problem at the start of a minislot another genetic-based algorithm is suggested. The fitness function remains largely the same. But now, the effect of URLLC on the eMBB is also taken into account implicitly as $r_k^{actual}(t)$ captures the linear rate loss due to some number of minislots being punctured. In eMBB scheduling phase, this rate loss is zero because no URLLC packet is arrived and no puncturing is occurred yet. In order to satisfy the reliability requirements of URLLC a term is added to the fitness function to prevent the algorithm to choose solutions with lower number of served URLLC users. The fitness function used for the URLLC resource allocation is formulated in (19):

$$fitness(y,t,t') = \alpha\min\left(\left\{\frac{r_k^{actual}(t)}{\sum_{i=1}^{t-1} r_k^{actual}(i)}\right\} \mid k \in K\right) + \beta|S(t')| \qquad (19)$$

The number of served URLLC users is added to the fitness function, weighted by a factor of β. Also, unlike the eMBB allocation where all eMBB users are considered to always have traffic in their buffers, here we want to allocate all RBs to a subset of URLLC users and the chromosome presentation similar to eMBB allocation phase cannot be used. To tackle this, we considered the gene vector to be a priority list of RBs to be punctured. In other words, a gene represents an RB like before, but the value of each gene is the priority of the RB to become punctured, higher values move the RB to the top the priority list. This way the genetic solver can potentially examine all the possible sequence of RB to be punctured. In order to evaluate the fitness function, the URLLC to RB allocation must be extracted from the RB priority list represented by the gene vector at hand. To do this we start from the top of the priority list, and consider active URLLC users one by one and assign as many RBs as it needs from the priority list in a greedy manner. This is possible because the required data rate of a URLLC user and the data for each RB-user are known. Algorithm 2 lists the algorithm for URLLC resource allocation. Here we also assumed a natural ordering between active URLLC users in a minislot. In practice it might be adopted from first-in-first-out or randomly.

Algorithm 2: Pseudo code of URLLC to RB assignment.

```
RBS := prioratized array of RBS based on GA solution
AU := active URLLC users
rb_ind := 0
for u in AU do
  rate_total := 0
  for i :=rb_ind to | RBS | do
    r_tot := r_tot+r_u^{RBS[i]}(t')
    y_u^{RBS[i]}(t') :=1
    if r_tot > L/δ:
      rb_ind := rb_ind+i+1
      break
    end if
  end for
end for
reurn y
```

In the following section, the simulation environment description and results are presented.

5. EXPERIMENTAL RESULTS AND DISCUSSION

Simulation is used to assess the performance of the solution. The algorithm is compared to a number of baselines for both eMBB and URLLC scheduling sub-problems as follows.

- **Random (eMBB):** Randomly assigns RBs to eMBB users.
- **Sum-Rate (eMBB):** Maximizes the sum of data rates among eMBB users using the same GA as the proposed algorithm but different fitness function in order for comparisons to be fair.
- **Min-Rate (eMBB):** Maximizes the minimum rate of eMBB users. Uses the same GA as the proposed method but different fitness function in

order for comparisons to be fair.

- **Random (URLLC):** Punctures RBs randomly and assigns RBs to URLLC users also randomly.
- **Greedy (URLLC):** A fixed priority for RB puncturing is used and each URLLC user in turn takes as many RBs from top of list as it needs.
- **LMCS:** URLLC traffic is scheduled on the eMBB users with low modulation coding scheme [14].

The simulated environment consists of a BS and a fixed number of URLLC and eMBB users. The fully buffered model is applied for eMBB traffic, where it is assumed that users constantly have an unlimited amount of data in their input buffers. This approach is commonly employed in network simulations [24]. In contrast, the URLLC request only arrive at some minislots. The inter arrival time of URLLC requests for different users follow an i.i.d Poisson distribution [35]. The data rate of users on different channels is modelled as a normal distribution. For URLLC users, the mean of data rate is μ_{URLLC} and standard deviation of the normal distribution is σ_{URLLC}. These parameters for eMBB are μ_{eMBB} and σ_{eMBB} respectively. Table 1 lists the parameters of the simulation. The simulations are programmed using python and each experiment is repeated 10 times for better convergence.

Table 1. Parameters of Simulation

Parameter	Value
Number of RBs	*50*
M	*8*
δ	*0.125ms*
L	*32 bits [4]*
μ_{URLLC}	*150 Kbps*
σ_{URLLC}	*75 Kbps*
μ_{eMBB}	*360 Kbps*
σ_{eMBB}	*180 kbps*
N_p	*100*
G_{max}	*35*
C_{parent}	*4*
$C_{offspring}$	*10*

To evaluate the performance of eMBB resource allocation, a network where no URLLC users are present is considered, then different number of eMBB users ranging from 10 to one hundred users are simulated. This will test the scalability of the algorithms. The measured metrics are Jain's fairness index and average data rate per user. Jain's fairness is defined by (20).

$$fariness(flows) = \frac{\left(\sum_{f \in flows} f\right)^2}{|flows| \sum_{f \in flows} f^2} \quad (20)$$

Where *flows* is a set of data flow values, here it is considered to be average data rate per user. Figure 3 shows the chart for average data rate per user for the simulated methods. The results of 10 to 100 eMBB user are shown, which is more than what suggested in 3GPP standards body for dense urban scenario [34].

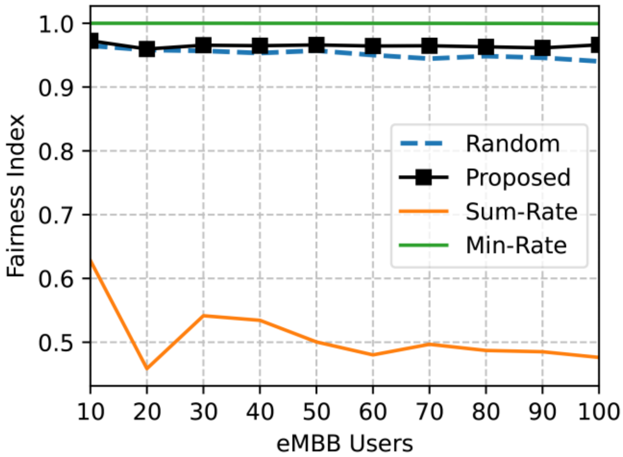

Figure 3. Fairness index per eMBB user count plots.

It is evident that the sum-rate method is the best in this regard. It is expected because the sum-rate chooses the solution that maximizes the total data rate among users. This method however has no regard for fairness among users. The fairness index plot is shown in Figure 4.

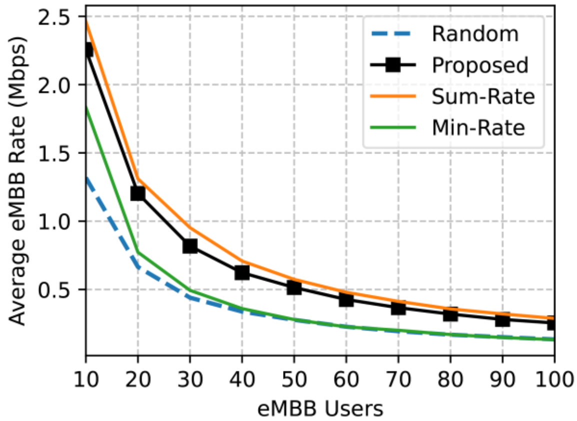

Figure 4. Average eMBB data rate per user count plot.

The proposed algorithm managed to closely match the data rate of the sum-rate protocol while maintaining the fairness almost as good as the random method. While the random method yields good fairness and poor throughout and sum-rate has good throughout and bad fairness, the proposed algorithm manages to consolidate the best of both worlds. The performance of min-rate method which is direct min-max is also plotted as a baseline. The success of the proposed algorithm is due to considering long term goals in the fitness function by taking into account the throughput of users so far and scoring better those solutions that compensate the poorly serviced users while also yield better total throughput. The convergence curve of the GA for a sample run is plotted in Figure 5.

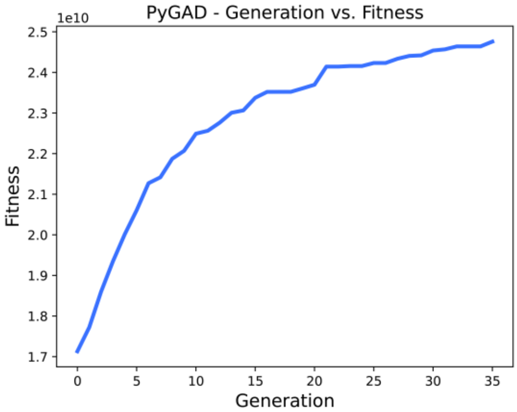

Figure 5. The Convergence curve of the GA based algorithm for eMBB.

In addition, the CCDF of the eMBB data rate for the first experiment in presented in Figure 6.

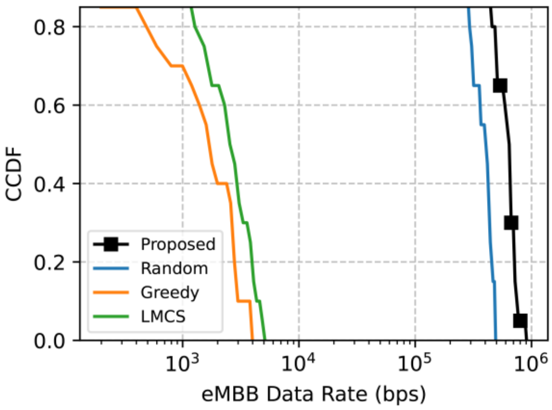

Figure 6. CCDF of eMBB data rate for different algorithms.

The URLLC scheduler is evaluated against three baselines. To make the comparison fair, for all the URLLC schedulers that are tested, the proposed eMBB resource allocator is used with the same parameters. Also, the same genetic algorithm solver is used when maximizing a function. The random baseline simply punctures the eMBB user randomly. The method labelled as greedy starts by the first RB and greedily assigns RBs to user one by one and does not examine different RB priorities. Figure 7 shows the impact of URLLC users on the data rate of eMBB users as the number of URLLC users grow.

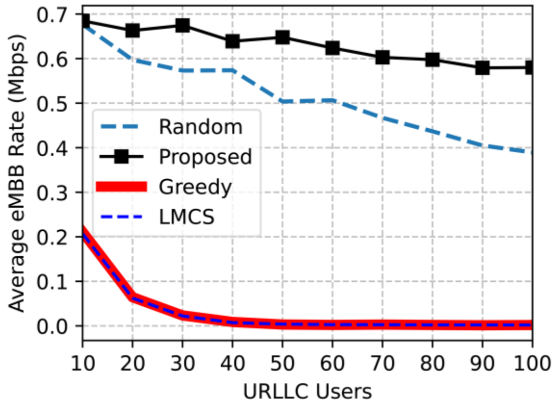

Figure 7. Impact of URLLC users on data rate of eMBB users.

The proposed protocol has outperformed all the other methods. This is due to examining different many-to-many assignments of RBs to URLLC users and finding the one that not only satisfies all URLLC users but also has the least negative effect on the experience of eMBB users. Figure 8 shows the fairness index plot for the same experiment.

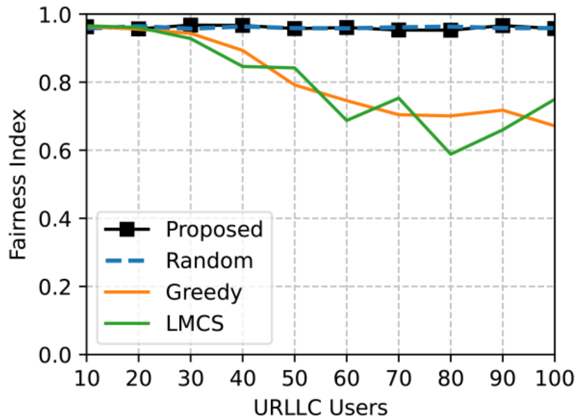

Figure 8. Impact of URLLC users on fairness index of eMBB users.

The fairness among eMBB users achieved by the proposed algorithm is as good as the random allocation while the average data rate is much better. Figure 9 shows the minimum eMBB data rate vs number of URLLC users.

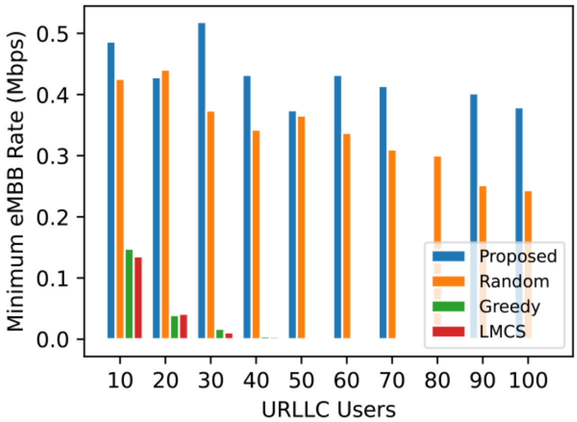

Figure 9. Minimum eMBB data rate per URLLC user count for different algorithms.

Table 2 lists the outage probabilities achieved by different algorithm for 100 URLLC users. The proposed algorithm successfully served all the URLLC requests while random and min-rate methods have non-zero outage probability.

Table 2: Outage Probability of Different Methods

Method	Outage probability
Proposed	0%
Greedy	0%
Random	0.0001%
Min-Rate	0.00015%

6. CONCLUSION

In this paper, we have studied the coexistence of eMBB and URLLC in 5G networks, focusing on optimizing resource allocation using a genetic algorithm-based approach. The proposed solution effectively balances the needs of both services, ensuring high eMBB data rates and fairness while meeting the stringent latency and reliability requirements of URLLC. Our simulation results demonstrate the effectiveness of the proposed method, showing improvements in fairness and data rate compared to baseline methods, particularly in high URLLC load scenarios. The graphical results, including fairness index plots and data rate comparisons, clearly highlight the superior performance of our approach in both eMBB and URLLC resource allocation. For future work, several directions can be explored. First, the integration of advanced machine learning techniques to further enhance the adaptability of the resource allocation scheme could be considered. Additionally, a more comprehensive evaluation involving real-world channel models and varying traffic conditions would provide deeper insights into the practical applicability of the solution. Lastly, investigating the scalability of the proposed approach in large-scale 5G networks and beyond, such as in 6G, could offer valuable contributions to the field.

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