How Should I Orchestrate Resources of My Slices for Bursty URLLC Service Provision?

Peng Yang  
Singapore University of Technology and Design  
peng_yang@sutd.edu.sg

Xing Xi  
Beihang University  
xixing@buaa.edu.cn

Jingxuan Chen  
Beihang University  
chenjingxuan@buaa.edu.cn

Xianbin Cao  
Beihang University  
xbcao@buaa.edu.cn

Tony Quek  
Singapore University of Technology and Design  
tonyquek@sutd.edu.sg

Dapeng Oliver Wu  
University of Florida  
dpwu@ufl.edu

ABSTRACT

Future wireless networks are convinced to provide flexible and cost-efficient services via exploiting network slicing techniques. However, it is challenging to configure network slicing systems for bursty ultra-reliable and low latency communications (URLLC) service provision due to its stringent requirements on low packet blocking probability and low codeword error decoding probability. In this paper, we propose to orchestrate network resources for a network slicing system to guarantee a more reliable bursty URLLC service provision. We re-cut physical resource blocks (PRBs) and derive the minimum upper bound of bandwidth for URLLC transmission with a low packet blocking probability. We correlate coordinated multipoint (CoMP) beamforming with channel uses and derive the minimum upper bound of channel uses for URLLC transmission with a low codeword error decoding probability. Considering the agreement on converging diverse services onto shared infrastructures, we further investigate the network slicing for URLLC and enhanced mobile broadband (eMBB) service multiplexing. Particularly, we formulate the service multiplexing as an optimization problem of maximizing the long-term total slice utility. The mitigation of this problem is challenging due to the requirements of future channel information and tackling a two timescale issue. To address the challenges, we develop a joint resource optimization algorithm based on a sample average approximate (SAA) technique and an alternating direction method of multipliers (ADMM) with provable performance guarantees.

CCS CONCEPTS

• Networks → Network management; Network reliability.

KEYWORDS

Network slicing, bursty URLLC, coordinated multipoint, eMBB

1 INTRODUCTION

Future wireless networks are desired to provide diverse service requirements concerning throughput, latency, reliability, availability as well as operational requirements, e.g., energy efficiency and cost efficiency [26, 41]. These service requirements are made by mobile networks and some novel application areas such as Industry 4.0, airborne communication, vehicular communication, and smart grid. The International Telecommunication Union (ITU) has categorized these services into three primary use cases: enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable and low latency communications (URLLC) [45]. In order to provide cost-efficient solutions, it is agreed by some telecommunication organizations including Third Generation Partnership Project (3GPP) and the Next Generation Mobile Network Alliance (NGMA), on the convergence of each use case onto a shared physical infrastructure instead of deploying individual network solutions for each use case [3].

To satisfy the requirement of reducing cost efficiency, the concept of network slicing has been proposed. The fundamental idea of network slicing is to logically isolate network resources and functions customized for specific requirements on a common physical infrastructure [41]. A network slice as a virtual end-to-end (E2E) network for efficiently implementing resource isolation and increasing statistical multiplexing is self-contained with its virtual network resources, topology, traffic flow, and provisioning rules [17, 41]. Due to the significant role in constructing flexible and scalable future wireless networks, network slicing for mMTC, eMBB, and URLLC service (multiplexing) has received much attention from the academia [1, 4, 35]. However, most of the current work did not study the impact of time-varying channel on the creation of slices and the benefits of exploiting advanced radio access techniques (RATs) in network slicing systems as well. For example, the actual channel may vary in short timescales (e.g., milliseconds) while the creation of network slices may be conducted in relatively long timescales (e.g., minutes or hours). Therefore, network slicing needs to mitigate a multi-timescale issue. Additionally, the utilization of advance RATs (e.g., coordinated multipoint, CoMP) has been considered as a promising way of satisfying spectrum challenges and improving system throughput [18, 32]. Thus, network slicing systems are expected to deploy advance RATs.

A recent work in [47] developed a CoMP-based radio access network (RAN) slicing framework for eMBB and URLLC service multiplexing and proposed to tackle the multi-timescale issue of RAN slicing via an alternating direction method of multipliers (ADMM). However, this work assumed that URLLC traffic was uninterrupted generated and ignored the significant bursty characteristic of URLLC traffic [7]. The bursty URLLC traffic will further exacerbate the difficulty of slicing the RAN for URLLC-involved service multiplexing from the following three aspects:
we review the related work. In Section 3, we describe our system model and formulate the studied problem in Section 4. In Sections 5 and 6, we discuss the problem-solving method. Simulation results are given in Section 7, and this paper is concluded in Section 8.

2 RELATED WORK

Network slicing and resource management. Enabling network slicing in 5G and beyond networks faces many challenges, in part owing to challenges in virtualizing and apportioning the RAN into several slices. To tackle these challenges, a rich body of previous work has been developed. In the following, we introduce some of the representatives on slice virtualization and resource apportionment.

In the research domain of slice virtualization, for example, a RAN slicing system for single RAT setting was developed to enable the dynamic virtualization of base stations (BSs) in [16]. A control framework focusing on the balance of realistic traffic load and deployment of virtual network functions was designed in [39]. Based on network function virtualization services, the work in [10, 25] proposed to scale virtual network slices for content delivery automatically (e.g., eMBB and mMTC traffic). Based on SDN and NFV technologies, slow startup and virtual internet of things (IoT) network slices were created in [48] to meet different quality of service (QoS) requirements in IoT systems. To tackle the low speed of constructing virtual network slices a lightweight network slicing orchestration architecture was developed in [28].

In the research domain of resource apportionment, most of the literature focused on the resource abstraction and sharing. For instance, many recent works mapped resource sharing problems as the interaction between network resource providers and network slice brokers (or tenants). Scheduling mechanisms [33, 34], game frameworks [11, 12, 52], optimization frameworks [4, 8, 15, 22, 27, 29, 35, 43, 44], and artificial intelligence-based methods [1, 20] were then developed to help infrastructure providers improve profits (or utilities) and help tenants reap the benefits of resource sharing while guaranteeing their subscribers’ service requirements. Looking to resource abstraction, the work in [24] proposed a network slicing architecture featuring RAN resource abstraction, where a scheduling mechanism was crucial for abstracting network resources among slices. Yet, scheduling processes were not explored in more detail in this work. By leveraging diverse resource abstraction types, an approach of virtualizing radio resources for multiple services was developed in [14] with the assumption that the traffic arrival rate of each slice equalled the number of requested radio resources. However, few of the above literature researched the benefit of slicing RAN equipped with advance RATs, e.g., CoMP.

Coordinated multipoint. Recently, there are some papers separately studying the CoMP without exploiting the network slicing [2, 13, 36–38, 50]. The fundamental principle of CoMP is similar to that of a distributed multiple-input multiple-output (MIMO) system, where CoMP cells act as a distributed antenna array under a virtual BS in the MIMO system [2, 18]. In [36, 37], a CoMP architecture coupled with a user-beam selection scheme aiming at achieving high-performance gains without generating high overhead were developed, where all beams were assumed to transmit at the same power level. The work in [13] discussed the frequent inter-beam handover issue, which was caused by covering high-speed moving devices, in a CoMP mobile communication system with a single BS. To improve ground users’ QoS, fronthaul bandwidth allocation and CoMP were jointly optimized in [50] without considering the impact of time-varying channel on the scheme of

- Resource efficiency: one of the efficient proposal in future wireless communication networks to handle the uncertainty (including bursty) is to reserve network resources, which may waste a large amount of valuable network resources. Therefore, it is important to develop resource orchestration schemes with high utilization for future networks, especially for some resource-constrained networks.
- More reliable URLLC transmission: except for requiring schemes of guaranteeing low codeword error decoding probability for finite blocklength regime [42], some extra mechanisms are desired to reduce packet blocking probability as bursty URLLC traffic may lead to packet blocking.
- Immediate resource orchestration: bursty URLLC packets need to be immediately scheduled if there are available resources and the system utility can be maximized. Therefore, under the premise of improving resource efficiency, immediate resource orchestration schemes related to the number of flashing URLLC packets should be developed.

The difficulty motivates us to investigate the CoMP-enabled RAN slicing for bursty URLLC and eMBB service provision, and the primary contributions of this paper can be summarized as follows:

- We re-cut physical resource blocks (PRBs) and derive the minimum upper bound of network bandwidth orchestrated for bursty URLLC traffic transmission to guarantee that the bursty URLLC packet blocking probability is of the order of a low value.
- After correlating CoMP beamforming with channel uses according to the network capacity result for finite blocklength regime we derive the minimum upper bound of channel uses for transmitting a URLLC packet with a low codeword error decoding probability.
- We define eMBB and URLLC long-term slice utilities and formulate the CoMP-enabled RAN slicing for bursty URLLC and eMBB service multiplexing as a resource optimization problem. The objective of the problem is to maximize the long-term total slice utility under constraints of total transmit power and network bandwidth. It is highly challenging to mitigate this problem due to the requirements of future channel information and tackling a two timescale issue.
- To addressing the challenges, we propose a bandwidth and beamforming optimization algorithm. In this algorithm, we approximately transform the service multiplexing problem into a non-convex global consensus problem via a sample average approximate (SAA) technique. We exploit an ADMM method to mitigate the global consensus problem. Next, a semidefinite relaxation (SDR) scheme joint with a variable slack scheme are applied to transform the non-convex problem into a semidefinite programming (SDP) problem. We also perform theoretical analysis on the tightness and convergence of the proposed algorithm.
3 SYSTEM MODEL

We consider a CoMP-enabled RAN slicing system for URLLC and eMBB service multiplexing. In this system, the time is discretized and partitioned into time slots and minislots, and a time slot includes 7 minislots. There are $N^e$ and $N^u$ ground eMBB user equipments (UEs) and URLLC UEs and BSs. The eMBB UE set and URLLC UE set are denoted as $I^e = \{1, \ldots, N^e\}$, $I^u = \{1, \ldots, N^u\}$, respectively. We assume that eMBB and URLLC UEs are randomly distributed in a considered communication area, and BSs are regularly deployed. Besides, each BS is equipped with $K$ antennas, and each UE is equipped with a single antenna. All BSs cooperate to transmit signals to a UE such that the signal-to-noise ratio (SNR) of it can be significantly enhanced\(^3\). Meanwhile, a flexible frequency division multiple access (FDMA) technique is exploited to achieve the inter-slice and intra-slice interference isolation [47].

3.1 RAN slicing system

Figure 1 shows an architecture of a RAN slicing system adopted in this paper, which consists of four parts: end UEs, RAN coordinator (RAN-C), network slice management, and network providers. At the beginning of each time slot, the RAN-C will decide whether to accept or reject the received slice requests for serving end eMBB and URLLC UEs after checking the available resource information (e.g., PRBs and transmit power) and computing. If a slice request can be accepted, network slice management will be responsible for creating or activating corresponding types of virtual slices, the process of which is time costly and usually in a timescale of minutes to hours. Next, if a slice request admission arrives, network providers will find the optimal servers and paths to place virtual network functions to satisfy the required E2E service of the slice.

On the other hand, at the beginning of each minislot, coordinated BSs will generate beamformers matching time-varying channels for each accepted slice. In this RAN slicing system, we consider two types of slices, i.e., multicast eMBB slices and unicast URLLC slices. The set of eMBB slices is denoted by $S^e$, and the set of URLLC slice is denoted by $S^u$.

3.2 eMBB slice Model

According to the above mentioned concept of a network slice (especially from the perspective of the QoS requirement of a slice), we can define an eMBB network slice request as the following.

**DEFINITION 3.1 (Multicast eMBB slice request).** A multicast eMBB slice request can be characterized as a tuple $(I_k^e, C_k^h)$ for any multicast slice $s \in S^e$, where $I_k^e$ is the number of multicast eMBB UEs in $s$ and $C_k^h$ is the data rate requirement of each UE in $s$.

In this definition, eMBB UEs are partitioned into $|S^e|$ groups according to the data rate requirement of a UE. UEs in the same slice have the same data rate requirement. The slice request of each group of eMBB UEs will always be admitted by the RAN-C in this paper, and coordinated beamformers and PRBs will be effectively configured to accommodate data rate requirements of all eMBB UEs by way of multicast transmission.

We next describe data rate requirements of eMBB UEs. The generated transmit beamformers for UEs of slice $s \in S^e$ on BS $j$ at minislot $t$ is denoted by $\psi_{sj}(t) \in \mathbb{C}^K$. The channel coefficient between BS $j$ and eMBB UE $i$ of $s$ at minislot $t$ is denoted by $h_{ij,t}(s,t) \in \mathbb{C}^K$, which varies once every minislot. Suppose that the instantaneous channel coefficient $h_{ij,t}(s,t)$ can be exactly measured at the beginning of minislot $t$ and the channel fading process is ergodic over a time slot for each $(i,j)$ pair. The SNR received at UE $i$ of slice $s$ at $t$ can then be written as

$$SNR_{ijs}(t) = \frac{|\sum_{j \in I} h_{ij,s}^H(t) \psi_{js}(t)|^2}{\sigma_i^2}$$ \(\text{for all } s \in S^e, i \in I_f^e (1)\)

where $\sigma_i^2$ denotes the noise power, $I_f^e = \{1, \ldots, I_f^e\}$ is the set of eMBB UEs of $s$. Since the multicast transmission and flexible FDMA mechanism are exploited the interference is not involved [47].

According to Shannon formula, the achievable data rate $y_{ijs}(t)$ of UE $i$ of slice $s$ at $t$ is expressed as

$$y_{ijs}(t) = \omega(t) \log_2(1 + SNR_{ijs}(t))$$ \(\text{for all } s \in S^e, i \in I_f^e (2)\)

where $\omega(t)$ denotes the bandwidth allocated to $s$ at $t$.

If the service request of an eMBB UE can be admitted, then the following data rate condition should be satisfied

$$y_{ijs}(t) \geq C_{ij,s}^h, \text{for all } s \in S^e, i \in I_f^e$$ \(\text{(3)}\)

3.3 URLLC slice Model

Similar to the definition of an eMBB slice request, we define the unicast URLLC slice request as follows.

**DEFINITION 3.2 (Unicast URLLC slice request).** A unicast URLLC slice request can be characterized as four tuples $(I_v^u, D_v, \alpha, \beta)$ for any unicast slice $s \in S^u$, where $I_v^u$ denotes the number of unicast URLLC UEs in $s$, $D_v$ represents the latency requirement of each UE.
in \( s, \alpha \) and \( \beta \) are denoted as the data packet blocking probability and the packet error decoding probability of each URLLC UE, respectively.

In this definition, URLLC UEs are classified into \( |S^u| \) clusters according to the latency requirement of each UE. Owing to the ultra-low latency requirement URLLC traffic should be immediately scheduled upon arrival; thus, URLLC slice requests will always be accepted by the RAN-C in this paper. Then, coordinated beamformers will be correspondingly generated to cover UEs by way ofunicast transmission at the beginning of each minislot.

As we all know, it is challenging to design a RAN slicing system to support the transmission of URLLC traffic owing to URLLC UEs’ stringent QoS requirements. What makes the issue more difficult is that URLLC traffic may be bursty. Bursty URLLC traffic, which may cause severe packet blocking, may significantly degrade the system performance of RAN slicing when URLLC slices are not well configured. To understand the characteristic of bursty URLLC traffic and mitigate the effect of bursty URLLC traffic on RAN slicing, we will address the following two questions.

- **How to model bursty URLLC traffic?**
- **What schemes can be developed for the RAN slicing system so as to significantly reduce URLLC packet blocking probability?**

During a time slot, bursty URLLC data packets destined to UEs of each URLLC slice and aggregated at the RAN-C are modelled as a Poisson arrival process in this paper, which has the merit of simplicity and tractability. The vector of URLLC packet arrival rates is denoted by \( \lambda = \{\lambda_1, \ldots, \lambda_s, \ldots, \lambda_{|S^u|}\} \), where \( \lambda_s \) is a constant and represents the average arrival rate of packets destined to UEs of slice \( s \) during a unit of time.

On the basis of the URLLC traffic model, we next discuss how to reduce the URLLC packet blocking probability via re-cutting PRBs. To satisfy the QoS requirements of URLLC UEs, a portion of PRBs should be allocated to them. In the RAN slicing system, a URLLC UE \( i \) of \( s \) will be allocated a block of network bandwidth of size \( \omega_{i,s}^u(t) \) for a period of time \( d_s \) at minislot \( t \). Since URLLC packets in \( s \) have the deadline of \( D_s \) seconds for E2E transmission latency, we shall always choose \( d_s \leq D_s \). Besides, a packet destined to the UE \( i \) will be coded before sending out to improve the reliability; and the transmission of the packet’s codewords needs \( r_{i,s}^u(t) \) channel uses in PRBs. The channel use and bandwidth is related by \( r_{i,s}^u(t) = \kappa \omega_{i,s}^u(t) \), where \( \kappa \) is a constant representing the number of channel uses per unit time per unit bandwidth of the FDMA frame structure and numerology. We denote the channel use set of URLLC UEs as \( r(t) = \{r_1(t), \ldots, r_s(t), \ldots, r_{|S^u|}(t)\} \) with \( r_s(t) = \{r_{1,s}^u(t), \ldots, r_{t,s}^u(t)\} \).

Let us model the aggregation and departure of URLLC packets in the RAN-C as an \( M/M/|S^u| \) queueing system with a finite bandwidth \( W^u \) and arrival data rate \( \lambda \). Owing to stochastic variations in the packet arrival process, there may not be enough spare bandwidth to serve new arrival URLLC packets occasionally; As a result, URLLC packets may be blocked. Thus, the PRBs should be effectively re-cut such that the URLLC packet blocking probability can be greatly reduced. Denote \( p_b(\omega^u(t), \lambda, d, W^u(t)) \) as the blocking probability experienced by arrival packets of UEs in \( s \) at minislot \( t \) where \( \omega^u(t) = \{\omega_{1,s}^u(t), \ldots, \omega_{t,s}^u(t), \ldots, \omega_{|S^u|}(t)\} \) and \( d = \{d_1, \ldots, d_s, \ldots, d_{|S^u|}\} \). The following theorem provides us a clue of re-cutting PRBs for URLLC packets transmission.

**Theorem 3.1.** At any minislot \( t \), for the given \( \omega^u(t), d \), and a positive integer \( q \), define \( \omega^u_q(t) = (\omega_{1,s}^u(t), \ldots, \omega_{t,s}^u(t), \ldots, \omega_{|S^u|}(t)) \) and \( d_q = (d_1, \ldots, q d_s, \ldots, d_{|S^u|}) \). If \( \lambda s d_s < 1 \) that is not restrictive, then there exists a bandwidth \( W^u_q(t) \) such that for \( W^u(t) > W^u_q(t) \) we have \( p_b(\omega^u(t), \lambda, d, W^u(t)) \geq p_b(\omega^u_q(t), \lambda, d, W^u_q(t)) \).

This theorem tells us that if we shorten the packet latency, fewer resource blocks will be available in the frequency plane, which will definitely cause more severe queueing effect and significantly increases the packet blocking probability. If we narrow resource blocks in the frequency plane, then more concurrent transmission is available, which is beneficial for decreasing the packet blocking probability.

Therefore, we should scale up \( d_s \) and select \( d_s \) and \( \omega_{i,s}^u(t) \) for any URLLC slice \( s \) at any minislot according to the following equation

\[
d_s = D_s = \frac{r_{i,s}^u(t)}{\lambda_s}, \text{ for all } i \in I_s, s \in S_u
\]

With (4), we can obtain the minimum upper bound of bandwidth allocated to URLLC slices via the following lemma.

**Lemma 3.2.** At any minislot \( t \), for a given \( M/M/|S^u| \) queueing system with packet arrival rates \( \lambda \) and a family of packet transmit speeds \( \{\kappa \}/r_{i,s}(t) \), let \( W^u(r(t)) \) denote the minimum upper bound of bandwidth allocated to all URLLC slices such that \( W^u(r(t)) \leq \xi \) and \( p_b(\omega^u(t), \lambda, D, W^u(r(t))) \) is of the order of \( a \) where \( P_Q^M/W^u \) represents the queueing probability. If \( \xi > \alpha \), then

\[
W^u(r(t)) \approx A(r(t)) + c(\zeta, \alpha) \sqrt{B(r(t))}
\]

where \( A(r(t)) = \sum_{s \in S^u} \sum_{i \in I_s} \frac{\lambda_s \omega_{i,s}^u(t)}{\kappa}, B(r(t)) = \sum_{s \in S^u} \sum_{i \in I_s} \frac{\lambda_s r_{i,s}^u(t)}{\kappa D_s}, D = \{D_1, \ldots, D_s\} \), and

\[
c(\zeta, \alpha) = \alpha - \zeta \alpha \sqrt{\frac{\min_{s \in S^u} \{\lambda_s D_s\}}{\xi - \alpha}}
\]

**Proof.** Please refer to Appendix A. \( \square \)

In (5), the first summation item denotes the mean value of the bandwidth allocated to URLLC slices and the second summation item can be regarded as the redundant bandwidth allocated to mitigate the impact of stochastic variations in the arrival process.

We next discuss the relationship between URLLC capacity and channel uses. For URLLC slice \( s \in S_u \), let \( h_{ij,s}(t) \in \mathbb{C}^k \) be the transmit beamformer to UE \( i \) from BS \( j \) at \( t \), \( \bar{h}_{ij,s}(t) \) is the corresponding channel coefficient, the corresponding SNR received at \( i \) can then be expressed as

\[
SNR_{i,s}^u(t) = \frac{\sum_{j \in J} | h_{ij,s}(t) \bar{h}_{ij,s}(t) |^2}{\sigma_i^2}, \text{ for all } i \in I_s, s \in S_u
\]

The perception of channel state information (CSI) or channel fading distribution may require the signal exchange before transmission that entails extra transmit latency and potential reliability.
loss as well. Therefore it may be impossible to obtain perfect CSI for URLLC service provision, and a constant $\phi > 1$ is involved in (7) to model the SNR loss for URLLC traffic transmission [30]. Meanwhile, interference signals are not included in (7) as a flexible FDMA mechanism is exploited [47].

On the other hand, owing to the stringent low latency requirement, URLLC packets typically have a short blocklength. We therefore utilize the capacity result for the finite blocklength regime in [40, 42] to calculate the URLLC capacity rather than the Shannon formula that cannot effectively capture the reliability of packet transmission. Particularly, for each $i$ in $s \in S^u$, the number of information bits $L^u_{t,i,s}(t)$ of a URLLC packet that is transmitted at $t$ with a codeword error decoding probability of the order of $\beta$ in $r^u_{t,i,s}(t)$ channel uses can be calculated by

$$L^u_{t,i,s}(t) \approx r^u_{t,i,s}(t)C(SNR^u_{t,i,s}(t)) − Q^{-1}(\beta)\sqrt{r^u_{t,i,s}(t)V(SNR^u_{t,i,s}(t))}$$  \hspace{1cm} (8)$$

where $C(SNR^u_{t,i,s}(t)) = \log_2(1 + SNR^u_{t,i,s}(t))$ is the channel capacity per Hz, $V(SNR^u_{t,i,s}(t)) = \text{ln}^2 2 (\frac{1}{1 + SNR^u_{t,i,s}(t)}$ is the channel dispersion, $Q(\cdot)$ is the Q-function.

The expression of (8) is complicate; yet, the following lemma gives the approximate expression of channel uses in terms of codeword error decoding probability $\beta$ and SNR.

**Lemma 3.3.** For any UE $i$ in $s \in S^u$, the required channel use $r^u_{t,i,s}(t)$ of transmitting a URLLC packet of size of $L^u_{t,i,s}(t)$ to $i$ can be approximated as

$$r^u_{t,i,s}(t) \leq \frac{L^u_{t,i,s}(t)}{C(SNR^u_{t,i,s}(t))} + \frac{(Q^{-1}(\beta))}{2C(SNR^u_{t,i,s}(t))}$$

$$+ \frac{(Q^{-1}(\beta)^2)}{2C(SNR^u_{t,i,s}(t))^2}\sqrt{\frac{1 + \frac{4C^2(SNR^u_{t,i,s}(t))}{(Q^{-1}(\beta)^2)}}}{(Q^{-1}(\beta)^2)}$$ \hspace{1cm} (9)$$

**Proof.** Please refer to Appendix B. \hfill \Box

## 4 PROBLEM FORMULATION

On the basis of the above system model, this section aims to formulate the problem of RAN slicing for URLLC and eMBB multiplexing service provision.

As each BS has a limitation on the maximum transmit power $E_j$ ($j \in J$), we can obtain the following power constraint

$$\sum_{s \in S^u} \mathbf{u}_{j,s}(t)\mathbf{u}_{j,s}(t) + \mathbf{g}_{j,s}(t)\mathbf{g}_{j,s}(t) \leq E_j$$ \hspace{1cm} (10)$$

Besides, since the multicast eMBB and the unicast URLLC service provisions are considered, and network bandwidths allocated to eMBB and URLLC slices are separated in the frequency plane, the network bandwidth constraint can be written as

$$\sum_{s \in S^u} o^u_s(\mathbf{t}) + W^u(r(t)) \leq W$$ \hspace{1cm} (11)$$

where $o^u_s(\mathbf{t})$ represents the bandwidth allocated to eMBB slice $s \in S^u$ over a time slot, $W$ denotes the maximum network bandwidth.

We next discuss the design of the objective function of service multiplexing. To achieve the maximum utility of service multiplexing, utilities of eMBB and URLLC service provisions should be maximized simultaneously. In this paper, we leverage a key performance indicator, i.e., energy efficiency, which is popularly exploited in resource allocation problems to model the utility.

On the one hand, as network states of any two adjacent slots can be seen as independent in the time-discrete RAN slicing system, we focus on the problem formulation in a time slot of duration of $T$. On the other hand, during a time slot, channel coefficients followed by the beamforming may change over minislots; as a result, time-varying utility functions in terms of channel coefficients and beamforming should be designed. Specifically, the following two definitions describe the expression of objective function.

**DEFINITION 4.1 (eMBB Long-Term Utility).** Over a time slot, the eMBB long-term utility is defined as the time-average energy efficiency of serving all eMBB UEs, which is calculated as

$$\bar{U}^e = \bar{T} \sum_{t=1}^{T} U^e_t(t) = \frac{1}{T} \sum_{t=1}^{T} \sum_{s \in S^e} u^e_{t}(\mathbf{v}_{j,s}(t))$$

$$= \frac{1}{T} \sum_{t=1}^{T} \sum_{s \in S^e} \sum_{i \in I_s^e} SNR^e_{t,i,s}(t) - \eta \sum_{j \in J} \sum_{i \in I_s^e} H^e_{j,s}(t)g_{j,s}(t)$$ \hspace{1cm} (12)$$

where $\eta$ is an energy efficiency coefficient reflecting the tradeoff between energy consumption and gain.

**DEFINITION 4.2 (URLLC Long-Term Utility).** Over a time slot, the URLLC long-term utility is defined as the time-average energy efficiency of serving all URLLC UEs, which can be calculated as

$$\bar{U}^u = \frac{1}{T} \sum_{t=1}^{T} U^u_t(t) = \frac{1}{T} \sum_{t=1}^{T} \sum_{s \in S^u} u^u_{t}(\mathbf{g}_{j,s}(t))$$

$$= \frac{1}{T} \sum_{t=1}^{T} \sum_{s \in S^u} \sum_{i \in I_s^u} SNR^u_{t,i,s}(t) - \eta \sum_{j \in J} \sum_{i \in I_s^u} g_{j,s}(t)$$ \hspace{1cm} (13)$$

With the above models, constraints, and definition of utility, we can formulate the problem of RAN slicing for bursty URLLC and eMBB service multiplexing as follows

$$\begin{align*}
\text{maximize} & \quad \hat{U} = \bar{U}^e + \hat{\rho} \bar{U}^u \\
\text{subject to:} & \quad \text{constraints (3), (10), (11) are satisfied.} \quad (14a) \\
& \quad \hat{\rho} \omega^u_s(\mathbf{t}) \geq 0, \forall s \in S^u \\
\end{align*}$$

subject to:

$$\text{constraints (3), (10), (11) are satisfied.} \quad (14a)$$

$$\hat{\rho} \omega^u_s(\mathbf{t}) \geq 0, \forall s \in S^u$$

where $\hat{\rho}$ is a slice priority coefficient representing the priority of serving inter-slices, $\bar{U}$ denotes the long-term total slice utility, beamformers $\mathbf{v}_{s}(t) = [\mathbf{v}_{1,s}(t); \ldots; \mathbf{v}_{J,s}(t)] \in \mathbb{C}^{K \times 1}$, and $\mathbf{g}_{s}(t) = [\mathbf{g}_{1,s}(t); \ldots; \mathbf{g}_{J,s}(t)] \in \mathbb{C}^{K \times 1}$.

The mitigation of (14) is highly challenging mainly because

1. future channel information is needed; the optimization should be conducted at the beginning of the time slot; yet the objective function needs to be exactly computed according to channel information during the time slot.
2. two timescale issue: the bandwidths $\{\omega^u_s(\mathbf{t})\}$ and the beamformers $\{\mathbf{v}_{s}(t)\}$ and $\{\mathbf{g}_{s}(t)\}$ should be optimized at two different time scales. $\{\omega^u_s(\mathbf{t})\}$ needs to be optimized at the beginning of the time slot. $\{\mathbf{v}_{s}(t)\}$ and $\{\mathbf{g}_{s}(t)\}$ should be optimized at the beginning of each minislot.

In the following sections, we discuss how to address the challenging problem effectively.
5 PROBLEM SOLUTION WITH SYSTEM GENERATED CHANNEL COEFFICIENTS

To tackle the issue of requiring future channel information at the beginning of the time slot, we resort to an SAA technique [23]. Based on the results of the SAA, we exploit an ADMM method [9] to address the two timescale issue.

5.1 Sample average approximation

Owing to the ergodicity of channel fading process over the time slot, the objective function can be approximated as

\[ \frac{1}{T} \sum_{t=1}^{T} U^*(t) + \frac{1}{T} \sum_{t=1}^{T} \beta U^U(t) \approx E_{\hat{h}} [ \hat{U}^* + \beta \hat{U}^U ] \]  

where \( \hat{h} \) denotes a set of all channel coefficient samples collected at the beginning of the time slot.

For SAA, its fundamental idea is to approximate the expectation of a random variable by its sample average. The following proposition shows that if the number of samples \( M \) is reasonably large, then for all \( m \in M = \{\ldots, M\} \), \( \{\hat{U}_m\} \) converges to \( \hat{U} \) uniformly on the feasible region constructed by constraints (14b) and (14c).

**Proposition 5.1.** Let \( \Theta \) be a nonempty compact set formed by constraints (14b) and (14c), \( \{Y, \hat{h}\} = \{\hat{U}^* + \beta \hat{U}^U, \hat{U}\} \). For any \( x \in \Theta \), suppose that there exists \( \epsilon > 0 \) such that the family of random variables \( \{Y, \hat{h}\} : Y \sim B(x, \epsilon) \) is uniformly integrable, where \( B(x, \epsilon) = \{y : ||y - x|| \leq \epsilon\} \) denotes the closed ball of radius \( \epsilon \) around \( x \). Then \( \{\hat{U}_m\} \) converges to \( \hat{U} \) uniformly on \( \Theta \) almost surely as \( M \to \infty \).

**Proof.** We omit the proof here as a similar proof can be found in the convergence proof of SAA in [23]. □

Then, given a set of samples of channel coefficients \( \{h_m\} \) with \( h_m = [h_{11,m}, \ldots, h_{1j,m}, \ldots, h_{N^m,N^m}]; |S^m|+|S^m| \) that are assumed to be independent and identically distributed, the original problem (14) is approximated as

\[ \begin{align*}
\text{maximize}_{\{\omega^e_{sm}, \nu_{sm}, \xi_{sm}\}} & \quad \{N_m\} = \frac{1}{M} \sum_{m=1}^{M} U^e_m + \frac{\beta}{M} \sum_{m=1}^{M} U^u_m \\
\text{subject to:} & \\
\omega^e_{sm} = \omega^s_{m}, & \forall s \in S^e, \forall m \in M \\
\sum_{s \in S^e} \nu^H_{js,m} \nu_{js,m} + \sum_{s \in S^e} \sum_{i \in I^u_s} g_{ij,s,m} g_{ij,s,m} \leq E_j, & \forall j \in J, m \in M \\
\sum_{s \in S^e} \omega^e_{sm} + W^U(r_m) \leq W, & \forall m \in M \\
\nu^H_{js,m} \geq c^H_{js}, & \forall s \in I^c_s, \forall m \in M \\
\omega^e_{sm} \geq 0, & \forall s \in S^e, \forall m \in M
\end{align*} \]  

where \( \{N_m\} \) denotes a variable corresponding to the \( m \)-th coefficient sample \( h_m \). The constraint (16b) is imposed to explicitly describe the two timescale issue of the original problem (14).

(16) can be considered as a global consensus problem with \( \{\omega^e_s\} \) being a family of local variables. Therefore, an ADMM method can be exploited to mitigate the problem effectively.

5.2 Alternating direction method of multipliers

According to the fundamental principle of ADMM method, ADMM for the problem (16) can be derived from the following augmented partial Lagrange problem

\[ \begin{align*}
\text{minimize}_{\{\omega^e_{sm}, \omega^e_{s}, \nu_{sm}, \xi_{sm}\}} & \quad \frac{1}{M} \sum_{m=1}^{M} \left\{ U^e_m + \beta U^u_m \right\} \\
& \quad \sum_{s \in S^e} \left\{ \psi_{sm} \left( \omega^e_{sm} - \omega^e_s \right) + \mu \left\| \omega^e_{sm} - \omega^e_s \right\|_2^2 \right\} \\
\text{subject to:} & \\
\text{constraints (16c) - (16f) are satisfied.}
\end{align*} \]  

where \( \psi_{sm} \) is a Lagrangian multiplier, \( \mu \) is a penalty coefficient.

For all channel samples, the ADMM-based framework of mitigating (17) can then be summarized to alternatively calculate equations from (18) to (20).

\[ \begin{align*}
\begin{cases}
\omega^e_{s}(k+1) \\
\nu_{s}(k+1)
\end{cases}
= \arg \min \left\{ \hat{L}(\omega^e_{s}, \nu_{s}, \xi_{s}) \right\} \\
\text{subject to:} \\
\text{for a sample } s, (16c) - (16f) \text{ are satisfied.}
\end{align*} \]  

\[ \begin{align*}
\omega^e_{s} = \frac{1}{M} \sum_{m=1}^{M} \left( \psi_{sm} + \frac{1}{\mu} \nu_{sm} \right), & \forall s \in S^e
\end{align*} \]  

\[ \begin{align*}
\psi_{sm} = \nu_{sm} + \mu \left( \omega^e_{sm} - \omega^e_s \right), & \forall s \in S^e
\end{align*} \]  

where,

\[ \hat{L}(\omega^e_{sm}, \nu_{sm}, \xi_{sm}) = -\frac{U^e_m}{M} - \frac{\beta U^u_m}{M} + \sum_{s \in S^e} \left( \psi_{sm} \left( \omega^e_{sm} - \omega^e_s \right) + \frac{\mu}{2} \left\| \omega^e_{sm} - \omega^e_s \right\|_2^2 \right) \]  

In our RAN slicing system, the RAN-C is responsible for executing the ADMM-based framework, and M virtual machines (VMs) are activated to conduct (18) and (20). A central VM (CVM) is utilized to calculate the consensus variable. Additionally, in this framework, local dual variables \( \{\psi_{sm}\} \) are updated to drive local variables \( \{\omega^e_{sm}\} \) into consensus, and quadratic items in (18) help pull \( \{\omega^e_{sm}\} \) towards their average value.

Unfortunately, the mitigation of (18) is difficult due to the existence of non-convex constraints. We next attempt to tackle the non-convexity of (18).

5.3 Semidefinite relaxation scheme

Let \( V_{sm} = \nu_{sm} \nu^H_{sm} \in \mathbb{R}^{J^s \times J^s} \) for all \( s \in S^e, m \in M \), and \( g_{i,s,m} = g_{i,s,m} \nu^H_{sm} \in \mathbb{R}^{J^s \times J^s} \) for all \( i \in I^u_s, s \in S^e, m \in M \). Next, if we recall the properties: \( V_{sm} \Rightarrow V_{sm} \geq 0, \text{rank}(V_{sm}) \leq 1 \), and \( g_{i,s,m} \Rightarrow g_{i,s,m} \nu^H_{sm} \Rightarrow g_{i,s,m} \geq 0, \text{rank}(g_{i,s,m}) \leq 1 \) with \( V_{sm} \) being a family of local variables. Therefore, an ADMM method can be exploited to mitigate the problem effectively.
\[ \begin{align*}
&\varnothing \subseteq 0 \text{ denoting that the matrix } V_{sm} \text{ is Hamiltonian positive semidefinite}, (18) \text{ can then be reformulated as} \\
&\begin{bmatrix}
\omega_{sm}^{(k+1)}, V_{sm}(k+1), G_{i,sm}(k+1)
\end{bmatrix} = \arg\min \left\{ \tilde{L}(\omega_{sm}, V_{sm}, G_{i,sm}) \right\} \\
&\text{subject to:} \\
&\frac{\omega_{sm}^{(k+1)}}{\sigma_{l,s}^{(k+1)}} \geq C_{th}, V_{sm} = S^e_i, i \in I^e \\
&\sum_{s \in S^e} \sum_{i \in I^u} \text{tr}(Z_{i}^s) + \sum_{s \in S^u} \text{tr}(Z_{i}^s)g_{i,sm}) \leq E_j, \forall j \in J \\
&V_{sm} \geq 0, \forall s \in S^e \\
&G_{i,sm} \geq 0, \forall i \in I^u, s \in S^u \\
&\text{rank}(V_{sm}) \leq 1, \forall s \in S^e \\
&\text{rank}(G_{i,sm}) \leq 1, \forall i \in I^u, s \in S^u \\
&\text{constraints} (16d), (16f) \text{ are satisfied} \\
\end{align*} \]

where \( \text{tr}(\cdot) \) represents an operator of trace, \( H_{i,sm} = h_{i,sm}h_{i,sm}^H \in \mathbb{R}^{J \times J}, H_{i,sm} = [h_{i,sm}, ..., h_{i,sm}] \in \mathbb{C}^{J \times 1}, Z_{j} \in \mathbb{R}^{K \times K} \) is a square matrix with \( J \times J \) blocks, and each block in \( Z_{j} \) is a \( K \times K \) matrix. Besides, in \( V_{sm} \), the block in the \( j \)-th row and \( j \)-th column is a \( K \times K \) identity matrix, and all other blocks are zero matrices.

As power matrices \( V_{sm} \) and \( G_{i,sm} \) are the feasible set of the relaxed (22) is a supererset of the (non-convex) feasible set of (22). Certainly, if they satisfy, then the relaxation is tight; if not, then some manipulation, e.g., a randomization/scale method [31], should be performed on them to obtain their approximate solutions.

Although non-convex constraints are removed, constraints related to \( W^{u}(r_{m}) \) are complicated which hinder the optimization of the relaxed (22). Therefore, we next discuss how to equivalently transform the complicated constraints via a variable slack scheme.

5.4 Variable slack scheme

From (5), we observe that \( W^{u}(r_{m}) \) is a quadratic function with respect to (w.r.t) \( r_{m} \). Therefore, via introducing a family of slack variables \( f_{m} = \{f_{i,sm}\}, i \in I^u, s \in S^u, m \in M \), the following lemma shows the equivalent expressions of (16d).

**Lemma 5.2.** Given the family of slack variables \( f_{m} = \{f_{i,sm}\} \), \( (16d) \) is equivalent to the following inequalities

\[ \sum_{s \in S^u} \omega_{sm}^{(k+1)} + A(f_{m}) + c(\zeta, \alpha) \sqrt{B(f_{m})} \leq W \]

and

\[ f_{i,sm} \geq r_{i,sm}^{(k)} \]

for all \( i \in I^u, s \in S^u, m \in M \).

5.5 Performance analysis

In this subsection, we analyze the performance of DBO. We first present a lemma about the optimality of solving (22) and then state the computational complexity and the convergence of DBO.
If we denote $G^*_{i,s,m}$ and $V^*_{i,s,m}$ as solutions to (25), then the following lemma shows the tightness of exploring the SDR scheme on (22).

**Lemma 5.4.** For all $i \in I^u$, $s \in S^u$, $m \in M$, the SDR for both $V_{i,s,m}$ and $G^*_{i,s,m}$ in problem (22) tight, that is,

$$\begin{align*}
\text{rank}(V^*_{i,s,m}) &\leq 1, \forall i \in I^u, s \in S^e, m \in M, \\
\text{rank}(G^*_{i,s,m}) &\leq 1, \forall i \in I^u, s \in S^u,
\end{align*}$$

(26)

Moreover, $G^*_{i,s,m}$ and $V^*_{i,s,m}$ are optimal solutions to (22).

**Proof.** Please refer to Appendix D.

The computational complexity of DBO is dominated by that of solving the SDP problem. The SDP problem has $(|S^e| + |I^u|)$ matrices of size of $JK \times JK$ and $(3|S^e| + 11|I^u|)$ one-dimensional variables. An interior-point method can then be exploited to efficiently mitigate the worst-case computational complexity of $O((|S^e| + |I^u|)J^3K^3 + 3|S^e| + 11|I^u|)^{3/2} [51]$. Nevertheless, the actual complexity will usually be much smaller than the worst case.

The following lemma presents the convergence of the algorithm.

**Lemma 5.5.** Let $(\omega^*_{s,m}, \psi^*_{s,m}, \theta^*_{i,s,m})$ denote the optimal solutions, under the ADMM-based distributed algorithm, $\forall k \in \mathbb{Z}$, $m \in M$, we have that $\tilde{L}(\omega^*_{s,m}, \psi^*_{s,m}, \theta^*_{i,s,m})$ is lower-bounded and

$$\tilde{L}(\omega^*_{s,m}, \psi^*_{s,m}, \theta^*_{i,s,m}) = \lim_{k \to \infty} \tilde{L}(\omega^*_{s,m}, \psi^*_{s,m}, \theta^*_{i,s,m})$$

(27)

**Proof.** For all $m \in M$, to proof that $\tilde{L}(\omega^*_{s,m}, \psi^*_{s,m}, \theta^*_{i,s,m})$ (or $\tilde{L}(\omega^*_{s,m}, \psi^*_{s,m}, \theta^*_{i,s,m})$) for notation lightening) is lower-bounded, we should proof that variables $\omega^*_{s,m}$, $\psi^*_{s,m}$ and $\theta^*_{i,s,m}$ are bounded as $\tilde{E}^k$ is convex. Next, we should proof that there exist non-positive coefficients $a_{s,m}$ and $b_{s,m}$ such that $|\tilde{L}^k - \tilde{E}^k| = \sum_{s \in S^e} a_{s,m} \omega^*_{s,m} - \sum_{s \in S^e} b_{s,m} \psi^*_{s,m} |

\sum_{s \in S^e} a_{s,m} \omega^*_{s,m}$, by solving the SDP problem. The SDP problem has $O((|S^e| + |I^u|)J^3K^3 + 3|S^e| + 11|I^u|)^{3/2}$ [51]. Nevertheless, the actual complexity will usually be much smaller than the worst case.

By leveraging the presented SDR scheme and variable slack scheme in Section 5, (28) can be equivalently transformed into a standard SDP problem that is able to be effectively mitigated by CVX or MOSEK.

Recall that the SDR for both $V_{i,t}$ and $G_{i,t}$ is tight, we therefore can perform the eigenvalue decomposition on $V_{i,t}$ and $G_{i,t}$ to obtain the optimal beamforming vectors $\psi_{i,t}$ and $\theta_{i,t}$.

Then, the bandwidth and beamforming optimization algorithm designed for the RAN slicing system can be summarized as follows.

| Algorithm 2 Bandwidth and beamforming optimization algorithm based on ADMM, B²O-ADMM |
|---|
| 1: Input: $\{H_{i,t}(s)\}$, for all $i \in I^e \cup I^u$, $s \in S^e \cup S^u$ |
| 2: Output: $\{\omega^*_{i,t}\}, \{\psi_{i,t}\}$, and $\{\theta^*_{i,s,m}\}$ |
| 3: Call Algorithm 1 to generate $\{\omega^*_{i,t}\}$, for all $s \in S^e$. |
| 4: for $t = 1 : T$ do |
| 5: Given $\{\omega^*_{i,t}\}$, the RAN-C mitigates (28) to obtain beamformers $\{\psi_{i,t}\}$ for all $s \in S^e$ and $\{\theta^*_{i,s,m}\}$ for all $i \in I^e$, $s \in S^u$. |
| 6: end for |

**7 SIMULATION RESULTS**

In this section, we evaluate the performance of bandwidth allocation and beamforming algorithms in the RAN slicing system. We compare i) the proposed B²O-ADMM algorithm; ii) the IRHS algorithm [47], which enforces all slices requests and optimizes the same objective function as B²O-ADMM; iii) the proposed resource allocation algorithm without ADMM, NaADMM. Specifically, NaADMM algorithm generates the bandwidth allocated to eMBB slices based on sensed channel gains at the beginning of the 1st minislot.

**Simulation setup.** In the simulation, three BSs are deployed on a circle with a radius of 0.5km, and the distance between each of them is equal. eMBB and URLLC UEs are randomly and uniformly distributed in the circle. The transmit antenna gain at each BS is set to be 5dB, and a log-normal shadowing path loss model is utilized to simulate the path loss between a BS and a UE. Particular, a downlink path loss is calculated as $H(dB) = 128.1 + 37.6 \log_{10} d$, where $d$ is the distance between the BS and UE.

Further, simulation results show that Algorithm 1 can converge in several iterations.

**6 OPTIMIZATION OF BEAMFORMING WITH SENSED CHANNEL GAIN**

With the system generated channel coefficient samples, Section 5 obtains the approximate solution $\{\omega^*_{i,t}\}$ to (14). In this section, we continue to optimize minislot variables $\{V_{i,t}(s), G_{i,t}(s)\}$ according to sensed channel gains $\{H_{i,t}(s)\}$, $i \in I^e \cup I^u$, $s \in S^e \cup S^u$, at the beginning of each minislot $t$.

Given $\{\omega^*_{i,t}\}$ and system sensed channel gains $\{H_{i,t}(s)\}$, as the maximization of $U^e(t) + \tilde{U}^u(t)$ at each minislot will lead to the maximization of the time average utility over the whole time slot, the original problem (14) can be reduced to the following beamforming optimization problem at each minislot $t$: 

$$\begin{align*}
\text{maximize} & \quad U^e(t) + \tilde{U}^u(t) \\
\text{subject to:} & \quad \omega^*_{i,t} \log_2(1 + \frac{\text{tr}(H_{i,t}(s) V_{i,t}(s))}{\sigma^2_{i,t}}) \geq \frac{C^t_{i,t}}{N_0} \forall s \in S^e, i \in I^e, \\
& \quad \sum_{s \in S^e} \text{tr}(Z_{i,t} V_{i,t}(s)) + \sum_{s \in S^u} \text{tr}(Z_{i,t} G_{i,t}(s)) \leq E_j, \forall j \in J, \\
& \quad V_{i,t} \succeq 0, \forall s \in S^e, \\
& \quad G_{i,t} \succeq 0, \forall s \in I^u, \\
& \quad \text{rank}(V_{i,t}(s)) \leq 1, \forall s \in S^e, \\
& \quad \text{rank}(G_{i,t}(s)) \leq 1, \forall s \in I^u, \\
& \quad \text{constraint} (11) \text{ is satisfied.}
\end{align*}$$

(28a, 28b, 28c, 28d, 28e, 28f, 28g, 28h)
ADMM can well support URLLC transmission with higher arrival rate \( \lambda \) in the system. The log-normal shadowing standard deviation is set to be 10 dB. Besides, we let \( E_\lambda = E_\eta = E_3 = 1 \) W. \( \sigma_{d,i}^2 = -110 \) dB for all \( i \in I^e \cup I^u, \ s \in S^e \cup S^u \), \( I^u_s = 160 \) bits, \( \lambda_\text{unit} = 0.1 \) packet per unit time for all \( i \in I^u_s, \ s \in S^u \). \( K = 2, \eta = 1000, \hat{\lambda} = 500, M = 100, T = 60 \) minislots, \( \kappa = 5 \times 10^{-3} \) channel uses per unit time per unit bandwidth, \( W = 4 \) MHz, \( \phi = 1.5 \). Other slice configure parameters are listed as below: \( \zeta = 2 \times 10^{-5}, \alpha = 10^{-5}, \beta = 2 \times 10^{-8}, |S^e| = 3, |S^u| = 2, \{I^e_s, I^u_s\} = \{4, 6, 8\} \) UEs, \( C_s^\text{up} = \{6, 4, 2\} \) Mb/s, \( \{H_s^u\} = \{3, 5\} \) UEs, and \( \{D_s\} = \{1, 2\} \) milliseconds [47].

**Results.** Figure 2 depicts the convergence of DBO with \( \Delta_{\text{dB}} = \sum_{e \in S^e} \omega_{z,e}^{k+1} - \omega_{z,e}^k \). It shows that DBO can converge in several iterations. To understand the impact of packet arrival rate on the performance of comparison algorithms, we plot the relationship between the bandwidth allocated to URLLC slices and the packet arrival rate \( \lambda \) with \( \lambda = \{0.1, 0.2, \ldots, 1.0, 1.1\} \) packets per unit time in Figure 3. We can see that the bandwidth allocated to URLLC slices monotonously increases with an increasing arrival rate when the RAN slicing system provides URLLC and eMBB multiplexing services. When the system does not provide eMBB services, B^2O-ADMM and NoADMM algorithms recommend to allocate the total network bandwidth to URLLC slices to guarantee more reliable URLLC transmission. As the IRHS algorithm does not design some schemes to reduce the packet blocking probability of URLLC traffic, it suggests to keep the bandwidth allocated to URLLC slices at a low constant value. We can also see that B^2O-ADMM can well support URLLC transmission with higher arrival rates without significantly decreasing the achieved long-term total slice utility \( \bar{\Upsilon} \). Compared with B^2O-ADMM and NoADMM, although IRHS needs less network bandwidth to ensure the ultra-low URLLC error decoding probability, it consumes more energy \( E^u = \sum_{s \in S^u} \sum_{i \in I^u_s} \text{tr}(G_{i,s}) \).

In Figure 4, we plot the impact of slice priority coefficient \( \hat{\lambda} \) on the obtained total slice utility \( \bar{\Upsilon} \) with \( \hat{\lambda} = \{1, 50, 100, \ldots, 500\} \), \( \lambda = 0.1 \), and \( \eta = 1000 \). We can observe that B^2O-ADMM achieves the greatest \( \bar{\Upsilon} \) and the obtained \( \bar{\Upsilon} \) increases almost linearly with \( \hat{\lambda} \) for all comparison algorithms. For B^2O-ADMM and NoADMM, the bandwidth allocated to URLLC slices increases following with an increasing URLLC service priority. For IRHS, the bandwidth orchestrated for URLLC slices is insensitive to \( \hat{\lambda} \).

**Figure 2:** A convergence curve of the DBO algorithm.

**Figure 3:** Trend of bandwidth allocated to URLLC slices vs \( \lambda \).

**Figure 4:** Trend of achieved long-term total slice utility vs \( \hat{\lambda} \).

**Figure 5:** Trend of achieved long-term total slice utility vs \( \eta \).

At last, to understand the effect of energy efficiency coefficient \( \eta \) on \( \bar{\Upsilon} \), we plot the relationship between \( \bar{\Upsilon} \) and \( \eta \) with \( \eta = \{100, 250, 500, \ldots, 2500\} \), \( \lambda = 0.1 \), and \( \hat{\lambda} = 500 \) in Figure 5. We can see that B^2O-ADMM obtains the greatest \( \bar{\Upsilon} \) and the achieved \( \bar{\Upsilon} \) of all algorithms monotonously decrease with an increasing \( \eta \). A great \( \eta \) indicates that the power consumption dominates the total slice utility. As a result, all algorithms reduce the power consumption, and the corresponding achievable SNR received at each end UE. In addition, compared with NoADMM, B^2O-ADMM suggests to apportion greater network bandwidth to URLLC slices as the B^2O-ADMM...
needs to obtain a global consensus bandwidth to ensure an ultra-
low packet blocking probability over the whole time slot.

8 CONCLUSION
In this paper, we considered a CoMP-enabled RAN slicing system
simultaneously supporting bursty URLLC and eMMB traffic trans-
mission. In the presence of eMMB traffic, we orchestrated the shared
network resources of the system to guarantee a more reliable bursty
URLLC service provision from the perspectives of lowering both
URLLC packet blocking probability and codeword error decoding
probability. We formulated the problem of RAN slicing for bursty
URLLC and eMMB service multiplexing as a resource optimization
problem and developed a joint bandwidth and CoMP beamforming
optimization algorithm to maximize the long-term total slice utility.

There are some interesting directions to explore in the future
such as discussing the URLLC packet retransmission to improve
the reliability further, validating the performance of the proposed
algorithm through experiments, conducting the concrete prototype
implementation of the RAN slicing system.

A PROOF OF LEMMA 3.2
Given an $M/M/W^u$ queuing system with a URLLC packet arrival
rate $\lambda$ and a family of packet transmit speeds $\{\kappa_j \}$, the QoS
goal of configuring URLLC slices is that the queuing probability
$P^{M/M/W^u}_Q$ in the $M/M/W^u$ system is lower than a given value $\zeta$
and the packet blocking probability $p_b(\alpha^u, \lambda, D, W^u(t_i))$ for $p_b$
notation lightening) is of the order of $\alpha$. To achieve this goal,
we exploit the square-root staffing rule [21] to derive the needed
network bandwidth.

If we let
\[
A(r(t)) = \sum_{s \in S^u} \sum_{i \in I^u} \lambda_s r_i^u(t_i),
B(r(t)) = \sum_{s \in S^u} \sum_{i \in I^u} \lambda_s \times \frac{r_i^u(t_i)}{\kappa_s^2 D_s^2},
\]
then the minimum network bandwidth needed to satisfy
the QoS goal can be approximately expressed as [21]
\[
W^u(r(t)) \approx A(r(t)) + c(\zeta, \alpha) B(r(t))
\]  
(29)

For the $M/M/W^u$ queuing system, the expression of $P^{M/M/W^u}_Q$
with respect to $p_b$ can be written as [21]
\[
P^{M/M/W^u}_Q = \frac{A(r(t)) + c(\zeta, \alpha) B(r(t))}{c(\zeta, \alpha) B(r(t)) + A(r(t)) p_b}
\]  
(30)

Since $P^{M/M/W^u}_Q \leq \zeta$ and $\zeta > \alpha$, (30) can take the following
form
\[
c(\zeta, \alpha) \geq \frac{A(r(t)) - \zeta A(r(t))}{B(r(t)) - \zeta A(r(t))} \approx \alpha
\]  
(31)

According to Cauchy-Schwarz inequality, we can scale up $A(r(t))$
as
\[
A(r(t)) \leq \sum_{s \in S^u} \sum_{i \in I^u} \lambda_s^2 D_s^2 \left( \sum_{s \in S^u} \sum_{i \in I^u} \frac{r_i^u(t_i)}{\kappa_s^2 D_s^2} \right)^2
\]  
(32)

For $B(r(t))$, it can be scaled down as
\[
B(r(t)) \geq \min_{s \in S^u} \{ \lambda_s D_s \} \sum_{s \in S^u} \sum_{i \in I^u} \frac{r_i^u(t_i)^2}{\kappa_s^2 D_s^2}
\]  
(33)

It can be observed that $W^u(r(t))$ monotonously increases with
$c(\zeta, \alpha)$. A big $c(\zeta, \alpha)$ indicates that more bandwidth should be cut
and apportioned to URLLC slices, and $W^u(r(t))$ will obtain the mini-
imum value when (31) is active. Therefore, on the basis of (31)-(33),
to save network bandwidths while ensuring a low packet blocking probability we have
\[
c(\zeta, \alpha) = \frac{\alpha - \zeta A(r(t))}{\zeta A(r(t))} \approx \frac{\sum_{s \in S^u} I^u_s \lambda_s^2 D_s^2}{\min_{s \in S^u} \{ \lambda_s D_s \}}
\]  
(34)

This completes the proof.

B PROOF OF LEMMA 3.3
By calculating the first order derivation of $r_{i,s}^u(t)$ over $V(SN^R_i^u(t))$, we
observe that $r_{i,s}^u(t)$ monotonously increases with $V(SN^R_i^u(t))$.
Since $\ln^2 2$ is the maximum value of $V(SN^R_i^u(t))$, if we let $V(SN^R_i^u(t)) = \ln^2 2$, then we can obtain the minimum upper bound of
$r_{i,s}^u(t)$.

Let $\lambda_{i,s}^u(t) = x$ and $V(SN^R_i^u(t)) = \ln^2 2$, then (8) becomes a quadratic equation w.r.t $x$. Solving it we can achieve the closed-
form expression for the minimum upper bound of $r_{i,s}^u(t)$ that is
shown in (9). This completes the proof.

C PROOF OF LEMMA 5.3
In this subsection, we exploit the variable slack scheme to trans-
form non-linear constraints into convex cones.

For the constraint (22b), we introduce a variable $\tilde{\lambda}_{i,s}$ and let
\[
\ln \left( 1 + \frac{\text{tr}(H_{i,s}V_{s,m})}{\sigma_{i,s}^2} \right) \geq \tilde{\lambda}_{i,s}, \forall s \in S^e, i \in I_s^e
\]  
(35)

By introducing a family of variables $\{ \tilde{\theta}_{i,s} \}$, we can obtain
\[
\text{tr}(H_{i,s}V_{s,m})/\sigma_{i,s}^2 \geq \tilde{\theta}_{i,s}, s \in S^e, i \in I_s^e
\]  
(36)

(35) can then be rewritten as a standard convex expression, i.e.,
\[
(1 + \theta_{i,s} \neq 1, \tilde{\lambda}_{i,s} \ln 2) \in K_{s,m}, s \in S^e, i \in I_s^e
\]  
(37)

where $K_{s,m} = \{ (x_1, x_2, x_3) : x_1 \geq \sqrt{x_2^2 + x_3^2}, x_2 > 0 \}$ is an exponential
cone of $\mathbb{R}^3$.

The $\omega_{s,m}$ can then be correlated with $\tilde{\lambda}_{i,s}$ by the following
quadratic cone
\[
(\omega_{s,m}, \tilde{\lambda}_{i,s}, \sqrt{2C^2_{s,m}}) \in Q_2^3, s \in S^e, i \in I_s^e
\]  
(38)

where $\mathbf{Q}_2^3 = \{ x \in \mathbb{R}^3 : x_1 \geq \sqrt{x_2^2 + x_3^2}, x_2, x_3, x_4 \geq 0 \}$ is a rotated
quadratic cone of $\mathbb{R}^3$.

For $x \in \mathbb{R}^n$, as $t \geq \| x \|_2 \Leftrightarrow (t, x) \in \mathbf{Q}^{n+1}$, the constraint (23) is
equivalent to the following expression
\[
(c^{-1}(\zeta, \alpha)W - \sum_{s \in S^e} \omega_{s,m} - A(f_m), \frac{\sqrt{C_{s,m}^2}}{\kappa V_{s,m}}) \in Q_{\infty}^{S^e} + 1
\]  
(39)

where $\mathbf{Q}_2^{S^e} = \{ x \in \mathbb{R}^n : x_1 \geq \sqrt{x_2^2 + \ldots + x_{n+1}^2} \}$ is a quadratic cone of $\mathbb{R}^n$. 
Next, we let \( e^{d_{u,s,m}} \geq \frac{1}{1 + 4L_u e^{-d_{u,s,m}}} \), \( \forall i \in I_u^u \), \( s \in S^u \) and introduce the variable \( \{ \tau_{i,s,m}^u \} \). In this way, we can obtain,

\[
\text{tr}(H_{i,s,m}G_{i,s,m})/\phi_{i,s,m} \geq \tau_{i,s,m}^u, \forall i \in I_u^u, s \in S^u
\]

(40) and

\[
\left\{ \begin{array}{l}
\phi_{i,s,m}^u, 1, -d_{u,s,m} + \ln 2 \in \mathcal{K}_{\text{exp}}, \\
1 + \tau_{i,s,m}^u, \phi_{i,s,m}^u \in \mathcal{K}_{\text{exp}}, \\
\end{array} \right. \forall i \in I_u^u, s \in S^u
\]

(41)

where (41) stems from the fact that \( \ln x \geq 1, x > 1 \) \( \Rightarrow \{(u, 1, t) \in \mathcal{K}_{\text{exp}}, (x, 1, u) \in \mathcal{K}_{\text{exp}} \} \).

For constraint (24), we introduce the variable \( \{ \nu_{i,s,m}^u \} \) with \( \nu_{i,s,m}^u \geq \frac{4L_u e^{-d_{u,s,m}}}{1 + 4L_u e^{-d_{u,s,m}}} \), where \( Y = (Q^{-1}(\beta) \ln 1/2)^2 \). Then we have

\[
2\nu_{i,s,m}^u \geq \ln(e^0 + e^{-d_{u,s,m}} + \ln(4L_u e^{-d_{u,s,m}}))^2
\]

(42)

Since \( t \geq \ln(\sum_i e^{x_i}) \Rightarrow \{(\sum_i e^{x_i}) \leq 1; (\mu_i, 1, x_i - t) \in \mathcal{K}_{\text{exp}}, \forall i, (42) \) can be rewritten as

\[
\left\{ \begin{array}{l}
\mu_{i,s,m}^u, 1, -d_{u,s,m} \in \mathcal{K}_{\text{exp}}, \\
\mu_{i,s,m}^u, 2, -d_{u,s,m} \in \mathcal{K}_{\text{exp}}, \end{array} \right. \forall i \in I_u^u, s \in S^u
\]

(43)

Besides, by letting \( \tau_{i,s,m}^u \geq \nu_{i,s,m}^u, \) (24) can be transformed into the following inequality

\[
x_{i,s,m}^u \geq \ln(e^{d_{u,s,m}} + 4L_u e^{-d_{u,s,m}} + \ln(Y/2)) + e^{2d_{u,s,m}} / \sum_j \nu_{i,j,s,m}^u
\]

(45)

Likewise, (45) can take the following forms

\[
\left\{ \begin{array}{l}
\nu_{i,s,m}^u, 1, x_{i,s,m}^u \leq 1, \\
\nu_{i,s,m}^u, 2, x_{i,s,m}^u \leq 1, \\
\nu_{i,s,m}^u, 3, x_{i,s,m}^u \leq 1,
\end{array} \right. \forall i \in I_u^u, s \in S^u
\]

(46)

At last, for the inequality \( f_{i,s,m}^u \geq \nu_{i,s,m}^u, \) we can take the following exponential cone expression

\[
f_{i,s,m}^u, 1, x_{i,s,m}^u \in \mathcal{K}_{\text{exp}}, \forall i \in I_u^u, s \in S^u
\]

(48)

Next, we should prove the equivalence of transforming the above non-linear constraints. As a similar proof for the equivalent transformation of constraints via the variable slack scheme can be found in subsection 5.4, we omit the proof here for space-saving.

At this point, we may say that the problem (22) without low-rank constraints can be equivalently transformed into the problem (25). Further, it can observe that (25) consists of a quadratic objective function, a set of affine constraints, (rotated) quadratic cone constraints and convex cone constraints of positive semidefinite matrices. Next, by referring to the fact that semidefinite optimization is a generalization of conic optimization, which allows the utilization of matrix variables belonging to the convex cone of positive semidefinite matrices, we can conclude that the problem (25) is an SDP problem. This completes the proof.

D PROOF OF LEMMA 5.4

Although some standard optimization tools were leveraged to mitigate (25), they could not capture structural features (e.g., the rank) of the optimal solution. Therefore, we resort to the Lagrange dual method to proof the tightness of SDR for power matrices.

The Lagrange dual problem of (25) can be formulated as

\[
\text{max} \quad \text{min} L(...) \quad (49a)
\]

subject to:

\[
\sum_j \mu_{i,j,s,m}^u \leq 0, \Phi_{i,s,m} \geq 0, \forall i \in I_u^u, s \in S^u
\]

(49b)

\[
\mu_{i,s,m}^u \geq 0, \forall i \in I_u^u, s \in S^u
\]

(49c)

\[
\mu_{j,m} \geq 0, j \in J
\]

(49d)

where \( F_m \) is the feasible region configured by constraints (25c)-(25e), (44), and (46), and the partial Lagrangian function

\[
L(...) = -\left( \frac{\sum_j \mu_{i,j,s,m}^u}{M} + \sum_j \sum_{i \in I_u^u} \frac{\text{tr}(H_{i,s,m}G_{i,s,m})}{\phi_{i,s,m}} + \right.
\]

\[
\sum_j \mu_{i,j,s,m}^u \text{tr}(V_{i,s,m}) + \sum_i \sum_{j \in J} \mu_{i,j,m} \text{tr}(Z_{i,j}V_{i,s,m}) - \Phi_{i,s,m}V_{i,s,m}
\]

(50)

It is noteworthy that only terms related to power matrices \( V_{i,s,m} \) and \( G_{i,s,m} \) are involved in (50) for brevity as we aim at calculating their ranks via Karush-Kuhn-Tucker (KKT) conditions [46].

By applying KKT conditions, the necessary conditions for achieving the optimal \( V_{i,s,m}^* \) and \( G_{i,s,m}^* \) can be arranged as

\[
\frac{\partial L(...)}{\partial V_{i,s,m}^*} = -\left( \frac{1}{M} + \sum_j \mu_{i,j,s,m}^u \frac{H_{i,s,m}G_{i,s,m}}{\phi_{i,s,m}} + \sum_j \mu_{i,j,s,m}^u E_{i,s,m} \right) + \sum_j \mu_{i,j,s,m}^u \text{tr}(Z_{i,j}V_{i,s,m}) - \Phi_{i,s,m}V_{i,s,m} = 0
\]

(51)

\[
\frac{\partial L(...)}{\partial G_{i,s,m}^*} = -\left( \frac{1}{M} + \sum_j \mu_{i,j,s,m}^u \frac{H_{i,s,m}G_{i,s,m}}{\phi_{i,s,m}} + \sum_j \mu_{i,j,s,m}^u E_{i,s,m} \right) + \sum_j \mu_{i,j,s,m}^u \text{tr}(Z_{i,j}G_{i,s,m}) - \Phi_{i,s,m}G_{i,s,m} = 0
\]

(52)

where \( E_{i,s,m} \) and \( E_{i,s,m}^* \) are \( J \times K \) identity matrices.

As the Lagrangian multiplier \( \mu_{i,j,m} \) for all \( j \in J \) is nonnegative, matrices \( \sum_j \sum_{i \in I_u^u} \mu_{i,j,s,m}^u Z_{i,j} \) and \( \sum_j \sum_{i \in I_u^u} \mu_{i,j,s,m}^u E_{i,s,m} \) are full rank. Besides, as \( \mu_{i,s,m}^u \) and \( X_{i,s,m}^u \) are nonnegative and rank \( H_{i,s,m}G_{i,s,m} \) = rank \( (h_{i,s,m}H_{i,s,m}) \leq 1 \), we can conclude that rank \( \Phi_{i,s,m} \leq J - 1 \) and rank \( X_{i,s,m}^u \leq J - 1 \).

On the other hand, the optimal \( V_{i,s,m}^* \) and \( G_{i,s,m}^* \) will always satisfy the following complementary slackness conditions

\[
X_{i,s,m}G_{i,s,m}^* = 0, \forall i \in I_u^u, s \in S^u
\]

(53)

\[
X_{i,s,m}G_{i,s,m}^* = 0, \forall i \in I_u^u, s \in S^u
\]

(54)

Since all matrices \( \Phi_{i,s,m}, V_{i,s,m}, X_{i,s,m}, \) and \( G_{i,s,m}^* \) are of size of \( J \times K \), we have rank \( (\Phi_{i,s,m}) \leq J \text{ and rank}(X_{i,s,m}) \leq J \text{ and rank}(G_{i,s,m}^*) \leq J \) according to the property of the rank of a matrix. To this end, we obtain the conclusion that rank \( V_{i,s,m}^* \leq 1 \text{ and rank}(G_{i,s,m}^*) \leq 1 \).
Besides, recall that (25) is an SDP problem, we may say that the optimal solutions $\mathbf{V}_s^*$ and $\mathbf{G}_{s,m}^*$ to (25) can be obtained by utilizing some methods such as interior-point methods. This completes the proof.

REFERENCES

[1] Haider D Resin Albonda and Jordi Pérez-Romero. 2019. An efficient RAN slicing strategy for a heterogeneous network with eMBB and V2X services. IEEE Access 7 (2019), 44771–44782.

[2] Md Shipon Ali, Ekram Hossain, and Dong In Kim. 2018. Coordinated multipoint transmission in downlink multi-cell NOMA systems: Models and spectral efficiency performance. IEEE Wireless Communications 25, 2 (2018), 24–31.

[3] NGMN Alliance. 2016. Description of network slicing concept. NGMN SG P 1 (2016).

[4] Madyun Alsenwi, Nguyen H Tran, Mehdi Bennis, Anupam Kumar Bairagi, and Choon Seon Hong. 2019. eMBB-URLLC Resource Slicing: A Risk Sensitive Approach. IEEE Communications Letters 23, 4 (2019), 740–743.

[5] Arjun Anand and Gustavo de Veciana. 2018. Optimization and HARQ optimization for URLLC traffic in 5G wireless networks. IEEE JSAC 36, 11 (2018), 2411–2421.

[6] MOSEK ApS. 2018. MOSEK optimization toolbox for MATLAB 8.1.0.67. https://docs.mosek.com/8.1/toolbox/index.html.

[7] Amin Azari, Mustafa Ozer, and Cicek Cevdaz. 2019. Risk-aware resource allocation for URLLC: Challenges and strategies with machine learning. IEEE Communications Magazine 57, 3 (2019), 42–48.

[8] Dario Bega, Marco Gramaglia, Albert Banchs, Vincenzo Sciancalepore, Konstantinos Samadinis, and Xavier Costa-Perez. 2017. Optimising 5G infrastructure markets: The business of network slicing. In IEEE INFOCOM. 1–9.

[9] Stephen Boyd, Neal Parikh, Eric Chu, Borja Peleato, Jonathan Eckstein, et al. 2011. Distributed optimization and statistical learning via the alternating direction method of multipliers. Foundations and Trends® in Machine learning 3, 1 (2011), 1–122.

[10] Tulja Yamshi Kiran Buyakar, Amogh PC, Bheemarju Reddy Tamma, et al. 2018. Poster: Scalable network slicing architecture for 5G. In ACM Mobicom. 684–686.

[11] Pablo Caballero, Albert Banchs, Gustavo de Veciana, and Xavier Costa-Pérez. 2017. Network slicing games: Enabling customization in multi-tenant networks. In IEEE INFOCOM. 1–9.

[12] Pablo Caballero, Albert Banchs, Gustavo De Veciana, Xavier Costa-Pérez, and Arturo Azcorra. 2018. Network slicing for guaranteed rate services: Admission control and resource allocation games. IEEE TWC 17, 10 (2018), 6419–6432.

[13] Seung Hyun Cha, Jun Suk Kim, and Min Young Chung. 2017. Coordinated-beam selection scheme using mobility pattern of mobile device in 5G mobile communication systems. In Proceedings of the 11th International Conference on Ubiquitous Information Management and Communication. ACM, 53.

[14] Chia-Yu Chang, Navid Niakein, and Thrasysvoulos Syropoulos. 2018. Radio access network resource slicing for flexible service execution. In IEEE INFOCOM WKSHPS. 668–673.

[15] Salvatore D’Oro, Francesco Restuccia, Tommaso Melodia, and Sergio Palazzo. 2018. Low-complexity distributed radio access network slicing: Algorithms and experimental results. IEEE/ACM TON 26, 6 (2018), 2815–2828.

[16] Xenofon Foukas, Mahesh K Marina, and Himanshu K Dhillon. 2013. On the relative performance of different network slicing approaches. In IEEE/ACM TON 26, 1 (2017), 61–75.

[17] Xenofon Foukas, Georgios Patounas, Ahmed Elmokashfi, and Mahesh K Marina. 2018. A resource allocation framework for network slicing. In Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. ACM, 13–22.

[18] Yury Polyanskiy, H Vincent Poor, and Sergio Verdú. 2010. Channel coding rate in the finite blocklength regime. IEEE ITT 56, 5 (2010), 2307.

[19] Peter Rost, Christian Mannwiler, Diomidis S Michalopoulou, Cinzia Sartori, Vincenzo Sciancalepore, Nishanth Sastry, Oliver Holland, Shreya Tayade, Bin Han, Dario Bega, et al. 2017. Network slicing to enable scalability and flexibility in 5G mobile networks. IEEE Communications Magazine 55, 5 (2017), 72–79.

[20] Sebastian Schiessl, James Gross, and Husenir Al-Zoubaidy. 2015. Delay analysis for wireless fading channels with finite blocklength channel coding. In Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. ACM, 13–22.

[21] Giada Landi, Pietro Giardina, Marco Capitani, Koteswar Rao Kondepu, Luca Valcarcegli, and Giuseppe Avri. 2019. Provisioning and automated scaling of network slices for virtual Content Delivery Networks in 5G infrastructures. In ACM Mobicom. 397–398.

[22] Matti Latva-aho and Kari Leppänen. Sep. 2019. White paper: Key drivers and research challenges for 6G ubiquitous wireless intelligence. Technical Report Vers. 1. University of Oulu. http://urn.fi/urn:nbn:fi:uu-9789526223544.

[23] Mathieu Lecoule, Georgios S Paschos, Panayotis Mertikopoulos, and Ulaj C Kozat. 2018. A resource allocation framework for network slicing. In IEEE INFOCOM. 2177–2185.

[24] Biyi Li, Bo Cheng, Meng Wang, Meng Niu, and Junliang Chen. 2019. A lightweight Network Slicing Orchestration Architecture. In Proceedings of the 17th Annual International Conference on Mobile Systems, Applications, and Services. ACM, 596–597.

[25] Quang Liu and Tao Han. 2019. DIRECT: Distributed Cross-Domain Resource Orchestration in Cellular Edge Computing. In ACM Mobicom. 181–190.

[26] Ying-Wing K. Han, Shengqiang Han, and Chengyang Yang. 2018. Energy-efficient training-assisted transmission strategies for closed-loop MISO systems. IEEE TET 47, 6 (2018), 2846–2860.

[27] Hendrik D Resin Albonda and Jordi Pérez-Romero. 2019. An efficient RAN slicing strategy for a heterogeneous network with eMBB and V2X services. IEEE Access. 7, 2019, 44771–44782.

[28] Zhiyang Chen, Mengling Zhang, Sheng Li, Jin Chen, and Jun Chen. 2013. On the relative performance of different network slicing approaches. In Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. ACM, 13–22.

[29] Shengqiang Han, Ying-Wing K. Han, and Chengyang Yang. 2018. Energy-efficient training-assisted transmission strategies for closed-loop MISO systems. IEEE TET 47, 6 (2018), 2846–2860.

[30] Hendrik D Resin Albonda and Jordi Pérez-Romero. 2019. An efficient RAN slicing strategy for a heterogeneous network with eMBB and V2X services. IEEE Access. 7, 2019, 44771–44782.

[31] Zhiyang Chen, Mengling Zhang, Sheng Li, Jin Chen, and Jun Chen. 2013. On the relative performance of different network slicing approaches. In Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. ACM, 13–22.

[32] Shengqiang Han, Ying-Wing K. Han, and Chengyang Yang. 2018. Energy-efficient training-assisted transmission strategies for closed-loop MISO systems. IEEE TET 47, 6 (2018), 2846–2860.

[33] Hendrik D Resin Albonda and Jordi Pérez-Romero. 2019. An efficient RAN slicing strategy for a heterogeneous network with eMBB and V2X services. IEEE Access. 7, 2019, 44771–44782.

[34] Zhiyang Chen, Mengling Zhang, Sheng Li, Jin Chen, and Jun Chen. 2013. On the relative performance of different network slicing approaches. In Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. ACM, 13–22.

[35] Shengqiang Han, Ying-Wing K. Han, and Chengyang Yang. 2018. Energy-efficient training-assisted transmission strategies for closed-loop MISO systems. IEEE TET 47, 6 (2018), 2846–2860.

[36] Hendrik D Resin Albonda and Jordi Pérez-Romero. 2019. An efficient RAN slicing strategy for a heterogeneous network with eMBB and V2X services. IEEE Access. 7, 2019, 44771–44782.

[37] Zhiyang Chen, Mengling Zhang, Sheng Li, Jin Chen, and Jun Chen. 2013. On the relative performance of different network slicing approaches. In Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems. ACM, 13–22.

[38] Shengqiang Han, Ying-Wing K. Han, and Chengyang Yang. 2018. Energy-efficient training-assisted transmission strategies for closed-loop MISO systems. IEEE TET 47, 6 (2018), 2846–2860.

[39] Hendrik D Resin Albonda and Jordi Pérez-Romero. 2019. An efficient RAN slicing strategy for a heterogeneous network with eMBB and V2X services. IEEE Access. 7, 2019, 44771–44782.
How Should I Orchestrate Resources of My Slices for Bursty URLLC Service Provision?

[50] Xiongwei Wu, Xiuhua Li, Qiang Li, Victor CM Leung, and PC Ching. 2019. Latency Driven Fronthaul Bandwidth Allocation and Cooperative Beamforming for Cache-enabled Cloud-based Small Cell Networks. In IEEE ICASSP. 4594–4598.

[51] Yinyu Ye. 1997. Interior point algorithms: theory and analysis. Springer.

[52] Jiaxiao Zheng, Pablo Caballero, Gustavo De Veciana, Seung Jun Baek, and Albert Banchs. 2018. Statistical multiplexing and traffic shaping games for network slicing. IEEE/ACM TON 26, 6 (2018), 2528–2541.