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A resource queueing model for equal-rate dynamic spectrum slicing in 5G NR networks

Ibram E.Z. Ghebrial¹, Irina A. Kochetkova^{1,2}

¹ RUDN University, 6 Miklukho-Maklaya St, Moscow, 117198, Russian Federation

² Federal Research Center “Computer Science and Control” of the Russian Academy of Sciences, 44-2 Vavilova St, Moscow, 119333, Russian Federation

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Abstract. Background: In fifth-generation (5G) New Radio (NR) network slicing, a mobile network operator leases part of its spectrum to a mobile virtual network operator under service-level agreements. Under equal-rate (Round Robin) scheduling, the base station assigns time-frame shares so that every user in a slice receives the same bitrate regardless of location. Existing analytical queueing frameworks for dynamic spectrum slicing, however, cover only the fixed-power case, and no such framework yet exists for equal-rate scheduling. Purpose: To develop a resource queueing model for dynamic spectrum slicing under equal-rate scheduling, extending the authors’ prior fixed-power framework to this regime. Method: We describe each user’s channel quality by an inverse spectral efficiency (ISE) and derive its cumulative distribution function from the path-loss model. Under equal-rate scheduling, all users in a slice share a common bitrate equal to the allocated bandwidth divided by the sum of independent, identically distributed ISEs; we characterize this sum exactly through multi-fold convolution and, for computational tractability, approximate it through the central limit theorem. These distributions feed a continuous-time Markov chain (CTMC) that models the joint spectrum partition and per-slice user counts, with state-dependent admission control and stochastic frequency reallocation that preserves isolation guarantees between slices. Results: The framework yields closed-form expressions for the blocking probability, the average per-user bitrate, the average number of active users in each slice, and overall resource utilization. Conclusions: The proposed model provides an analytical tool for spectrum dimensioning and admission control in multi-tenant 5G NR networks under equal-rate scheduling.

Key words and phrases: 5G NR, CTMC, dynamic spectrum management, equal-rate scheduling, network slicing, queueing model, Round Robin

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1. Introduction

Network slicing is a cornerstone of fifth-generation (5G) New Radio (NR) architectures, enabling a mobile network operator (MNO) to partition a common radio access network into isolated logical slices, each governed by dedicated service-level agreements (SLAs) [1, 2]. In multi-tenant deployments the MNO simultaneously serves its own subscribers (Slice 1) and leases residual spectrum to a mobile virtual network operator (MVNO, Slice 2), coupling technical resource management with economic objectives [3, 4]. Two intra-slice scheduling strategies are widely studied [5]: the fixed-power (FP) model, which divides the allocated bandwidth equally among active users, and the equal-rate (Round Robin, RR) model, which adjusts per-user time-frame fractions so that every user achieves the same instantaneous bitrate [6, 7]. The FP model inherently discriminates users by location; the RR model eliminates this disparity and is therefore better suited to SLA-governed multi-tenant environments and to mobility-intensive use cases such as high-speed rail and vehicular networks [8, 9].

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A complete analytical framework for FP-based dynamic spectrum slicing—combining a continuous-time Markov chain (CTMC) resource queueing model, stochastic frequency reallocation with isolation guarantees, and MNO revenue optimization—was established in [10]. That line of research traces back to queueing and simulation analyses of dynamic slicing [11], a controllable queueing model with elastic traffic and Markov decision process (MDP) formulation [6], and an MDP–artificial neural network combination for policy approximation [12]. However, extending these results to the equal-rate scheduler requires a fundamentally different stochastic characterization of the per-user bitrate, and no prior work has provided such a framework with closed-form performance guarantees.

The present paper fills this gap. The main contributions of our study are as follows:

- Stochastic bitrate model for equal-rate scheduling. The common per-user bitrate under the RR policy is characterized as the ratio of the allocated bandwidth to the sum of independent, identically distributed (i.i.d.) inverse spectral efficiencies. A closed-form cumulative distribution function (CDF) is derived for this random variable, and a tractable Central Limit Theorem (CLT) approximation is established for use in admission control and reallocation computations.
- CTMC resource queueing model with state-dependent control. A complete CTMC over the joint state—spectrum partition, MNO user count, MVNO user count—is formulated, incorporating state-dependent admission probabilities, stochastic frequency reallocation subject to per-slice isolation thresholds. The reallocation policy can be chosen to optimize a given objective, for example MNO revenue maximization as in [10].
- Closed-form performance metrics. Steady-state expressions are derived for blocking probability, average per-user bitrate, average number of active users, and resource utilization.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 describes the system model. Section 4 presents the results—the CTMC queueing model and closed-form performance metrics. Section 6 presents conclusions and future directions.

2. Related work

The architecture and challenges of 5G network slicing are surveyed in [1, 2], covering radio access network (RAN), core, and transport domains. More recent surveys extend this to end-to-end 6G slicing [8] and to smart-city applications of beyond-5G networks [9]. These works establish a consistent taxonomy: while data-driven and optimization-based approaches dominate the recent literature, analytical and model-based methods remain indispensable for deriving closed-form admission control policies and for system dimensioning under SLA constraints. The scheduling layer—covering RR, proportional fairness (PF), and maximum throughput (MT) strategies within sliced architectures—is surveyed in [5], which identifies RR as the preferred policy when uniform per-user quality of service (QoS) is the primary requirement.

Learning-based approaches have become dominant for intra- and inter-slice resource management. A data-driven RAN slicing mechanism for enhanced mobile broadband (eMBB) and ultra-reliable and low latency communications (URLLC) coexistence was proposed in [13], providing a reference architecture for slice-orchestrator-level control. Cooperative multi-agent reinforcement learning (MARL) for flexible RAN slicing in open RAN (O-RAN), capable of handling variable slice counts, was introduced in [14]. Prediction-aided weighted deep reinforcement learning (DRL) for online resource allocation was shown to outperform static and myopic baselines in [15], and a hybrid Double Deep Q-Network with dueling architecture was proposed for 5G network slicing in [16]. The preemptive resource allocation problem in dynamic multi-tenant networks was addressed with a Dueling-DQN approach in [17]. DRL-based dynamic scheduling for LTE (long-term evolution) and eMBB slicing—with explicit comparison of PF, RR, and max-rate rules—was studied in [7]. In the domain of joint allocation and scheduling, the power-subcarrier co-allocation problem for multi-tenant multi-service systems was formulated as a mixed-integer nonlinear program with efficient heuristic decomposition in [18]. A cooperative-aware scheme for cloud RAN was developed in [19], and a QoS-aware multi-cell RAN slicing framework accounting for inter-cell interference and mobility was presented in [20]. While

DRL methods excel in complex dynamic environments, they require extensive training, offer limited interpretability, and do not produce the closed-form expressions needed for system dimensioning.

Guaranteeing strict inter-slice isolation while enabling efficient resource sharing is among the most challenging aspects of multi-tenant slicing. The isolation-aware slicing problem was formulated as a mixed-integer program in [4]. A latency-driven orchestration framework for beyond-5G networks was developed in [21], simultaneously providing latency and throughput guarantees in multi-tenancy environments. Pricing strategies for 5G multi-tenancy—Shapley value, bargaining game, and dynamic pricing—were evaluated using a game-theory framework in [3], highlighting the interplay between isolation requirements, resource efficiency, and economic incentives.

The matrix-analytic foundations for performance evaluation of multi-server queueing systems with state-dependent service rates are provided in [22], which underpins the CTMC-based methodology of the present work. State-dependent service rates and elastic traffic models have been employed to study admission control and capacity planning in sliced networks under various traffic assumptions [6]. The isolation-aware slicing model of [4] demonstrates that analytical formulations can capture the joint technical–economic trade-offs that DRL-based methods leave implicit.

The present paper is the latest contribution to a research program on CTMC-based analytical modeling of dynamic spectrum slicing in 5G NR. The program began with a queueing and simulation study that established the basic framework for modeling the reallocation interaction between an MNO and an MVNO [11]. This was followed by a controllable queueing system with elastic traffic and Poisson control signals, which formulated the spectrum reallocation decision as a Markov decision process (MDP) and provided resource capacity planning guidelines [6]. The MDP formulation was extended in [12] by combining it with an artificial neural network to approximate the optimal reallocation policy in larger state spaces. The most comprehensive prior framework is [10], which integrates a full CTMC resource queueing model with frequency reallocation ensuring per-slice isolation and MNO revenue maximization under the fixed-power scheduling policy. The present work extends [10] to the equal-rate (Round Robin) scheduling model. The key challenge is that the RR policy yields a per-user bitrate that is a random ratio—the allocated bandwidth divided by the sum of i.i.d. inverse spectral efficiencies—whose stochastic characterization differs fundamentally from the fixed-power case. To the best of our knowledge, no existing work has developed a complete resource queueing framework integrating equal-rate scheduling with dynamic spectrum slicing and frequency reallocation in a multi-tenant 5G NR setting.

3. System model

3.1. Network architecture and channel model

We consider a single macrocell served by one base station (BS) shared between an MNO and an MVNO under a network-slicing agreement (Figure 1). The total downlink bandwidth $F = M\Delta f$ is divided into M resource blocks of width Δf . The MNO is allocated m blocks (Slice 1, bandwidth $F_1(m) = m\Delta f$) and leases the remaining $M - m$ blocks to the MVNO (Slice 2, bandwidth $F_2(m) = (M - m)\Delta f$), with the partition constrained to $M_1 \leq m \leq M - M_2$, where M_i is the minimum block reservation for slice i .

Both operators provide broadband data services. PDU (Protocol data unit) session requests in slice i arrive according to independent Poisson processes with rates λ_1 (MNO) and λ_2 (MVNO). The traffic volume per session—the total number of bits to be transferred—is exponentially distributed with mean $1/\mu_i$ bits. Each slice enforces a minimum bitrate guarantee $b_i^{\min}$; in addition, a stricter isolation threshold $b_i^{\text{is}} > b_i^{\min}$ is maintained: a spectrum reallocation is executed only when every active user in the affected slice would receive at least b_i^{is} under the new partition. The MNO controls the partition via a Poisson reallocation signal of rate δ ; at each signal epoch the controller selects a target allocation a from the feasible set $\mathcal{A}(m, n_1, n_2)$ defined in Section 4.

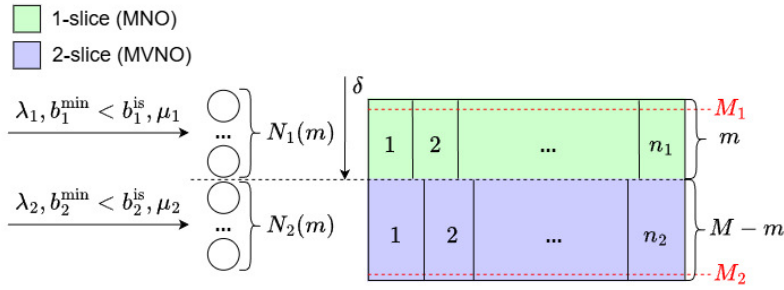


Figure 1. System model

Users are spatially distributed over the macrocell according to a two-dimensional Poisson Point Process (PPP) on the annulus $[R_{\min}, R_{\max}]$. The downlink received SNR (signal-to-noise ratio) is governed by the Friis path-loss model combined with the Shannon–Hartley capacity theorem. With BS transmit power P , antenna gains G_t and G_r , thermal noise N_0 , and background interference I_0 , the spectral efficiency (bits/s/Hz) at path loss PL is

$$r(\text{PL}) = \log_2 \left(1 + \frac{PG_t G_r}{(N_0 + I_0)\text{PL}} \right).$$

Since $r(\cdot)$ is strictly decreasing in path loss, users near the BS ($\text{PL} = \text{PL}_{\min}$, distance $R_{\min}$) achieve the maximum spectral efficiency (SE) $r(\text{PL}_{\min})$, while cell-edge users ($\text{PL} = \text{PL}_{\max}$, distance $R_{\max}$) achieve the minimum $r(\text{PL}_{\max})$. The general instantaneous bitrate of user j in slice i is

$$b_{ij}(m, n_i) = F_i(m) \cdot \tau_{ij}(m, n_i) \cdot r(\text{PL}_{ij}), \quad j = 1, \dots, n_i, i = 1, 2,$$

where $\tau_{ij}(m, n_i) \in [0, 1]$ is the downlink time-frame fraction allocated to user j .

3.2. Equal-rate scheduling

Under the equal-rate scheduling policy the BS assigns time fractions $\tau_{ij}(m, n_i)$ so that every active user in slice i achieves the same instantaneous bitrate:

$$b_{ij}(m, n_i) = b_i(m, n_i), \quad j = 1, \dots, n_i, \quad i = 1, 2.$$

Substituting the equal-rate condition into the general bitrate expression and solving for the time fraction gives

$$\tau_{ij}(m, n_i) = \frac{b_i(m, n_i)}{F_i(m) \cdot r(\text{PL}_{ij})}, \quad j = 1, \dots, n_i, \quad i = 1, 2.$$

Applying the frame normalization constraint $\sum_{j=1}^{n_i} \tau_{ij}(m, n_i) = 1$ yields the common bitrate:

$$b_i(m, n_i) = \frac{F_i(m)}{\sum_{j=1}^{n_i} 1/r(\text{PL}_{ij})}, \quad i = 1, 2,$$

where $1/r(\text{PL}_{ij})$ is the inverse spectral efficiency (ISE) of user j . Users with poor channel conditions (large ISE) are compensated by a larger time-frame share, so every user in the slice receives the same bitrate regardless of location.

Since user positions are random (PPP), the path loss ξ_{PL} is a random variable with CDF $F_{\xi_{\text{PL}}}(\cdot)$ on $[\text{PL}_{\min}, \text{PL}_{\max}]$. Consequently, $\xi_j^{\text{ISE}} = 1/r(\xi_{\text{PL}})$ are i.i.d. random variables with support $[\text{ISE}_{\min}, \text{ISE}_{\max}]$, where $\text{ISE}_{\min} = 1/r(\text{PL}_{\min})$ and $\text{ISE}_{\max} = 1/r(\text{PL}_{\max})$. The equal-rate bitrate $\xi_i^b(m, n_i)$ is therefore itself a random variable:

$$\xi_i^b(m, n_i) = \frac{F_i(m)}{\sum_{j=1}^{n_i} \xi_j^{\text{ISE}}}, \quad i = 1, 2.$$

Its stochastic characterization—the CDF of ξ_{ISE} , the CLT approximation for the sum $\eta_i(n_i) = \sum_{j=1}^{n_i} \xi_j^{\text{ISE}}$, and the resulting admission and reallocation probabilities—is developed in Section 4.

4. Results: Resource queueing model

4.1. CTMC and transition rates

The system is modeled as a CTMC with state (m, n_1, n_2) , where $m \in \{M_1, \dots, M - M_2\}$ is the current spectrum partition and $n_i \geq 0$ is the number of active users in slice i . Under the equal-rate policy the worst-case channel realization (all users at $R_{\min}$, path loss $\text{PL}_{\min}$) determines the maximum admissible occupancy:

$$N_i(m) = \left\lfloor \frac{F_i(m) \cdot r(\text{PL}_{\min})}{b_i^{\min}} \right\rfloor, \quad i = 1, 2.$$

The finite state space is accordingly

$$\mathcal{X} = \{(m, n_1, n_2) : 0 \leq n_1 \leq N_1(m), 0 \leq n_2 \leq N_2(m), M_1 \leq m \leq M - M_2\}.$$

A Poisson reallocation signal of rate δ triggers a candidate partition change from m to target $a \in \mathcal{A}(m, n_1, n_2)$. To protect both slices, the feasible set $\mathcal{A}(m, n_1, n_2)$ is constructed from the isolation-safe minimum block counts

$$m_i^{\text{is}}(n_i) = \max \left\{ M_i, \left\lceil \frac{b_i^{\text{is}} \cdot n_i}{\Delta f \cdot r(\text{PL}_{\min})} \right\rceil \right\}, \quad i = 1, 2,$$

and equals:

$$\begin{aligned} \mathcal{A}(m, n_1, n_2) &= \emptyset, \quad m < m_1^{\text{is}}(n_1), \quad M - m < m_2^{\text{is}}(n_2), \\ \mathcal{A}(m, n_1, n_2) &= \{m, \dots, M - m_2^{\text{is}}(n_2)\}, \quad m < m_1^{\text{is}}(n_1), \quad M - m \geq m_2^{\text{is}}(n_2), \\ \mathcal{A}(m, n_1, n_2) &= \{m_1^{\text{is}}(n_1), \dots, m\}, \quad m \geq m_1^{\text{is}}(n_1), \quad M - m < m_2^{\text{is}}(n_2), \\ \mathcal{A}(m, n_1, n_2) &= \{m_1^{\text{is}}(n_1), \dots, M - m_2^{\text{is}}(n_2)\}, \quad m \geq m_1^{\text{is}}(n_1), \quad M - m \geq m_2^{\text{is}}(n_2). \end{aligned}$$

When $\mathcal{A}(m, n_1, n_2) = \emptyset$ no safe reallocation exists and the partition remains at m .

Let $p_i(m, n_i)$ denote the state-dependent admission probability and $p(m, n_1, n_2, a)$ the reallocation success probability; both quantities depend on the CDF of the equal-rate bitrate $\xi_i^b(m, n_i)$ and are derived below. The non-zero off-diagonal transition rates are:

$$\begin{aligned} \mathbf{Q}[(m, n_1, n_2), (m, n_1 + 1, n_2)] &= \lambda_1 \cdot p_1(m, n_1), \quad n_1 + 1 \leq N_1(m), \\ \mathbf{Q}[(m, n_1, n_2), (m, n_1, n_2 + 1)] &= \lambda_2 \cdot p_2(m, n_2), \quad n_2 + 1 \leq N_2(m), \\ \mathbf{Q}[(m, n_1, n_2), (m, n_1 - 1, n_2)] &= n_1 \mu_1 \cdot \mathbb{E}[\xi_1^b(m, n_1)], \quad n_1 > 0, \\ \mathbf{Q}[(m, n_1, n_2), (m, n_1, n_2 - 1)] &= n_2 \mu_2 \cdot \mathbb{E}[\xi_2^b(m, n_2)], \quad n_2 > 0, \\ \mathbf{Q}[(m, n_1, n_2), (a, n_1, n_2)] &= \delta \cdot p(m, n_1, n_2, a), \quad a \in \mathcal{A}(m, n_1, n_2) \setminus \{m\}. \end{aligned}$$

The first two rates correspond to arrivals: an arriving user in slice i is admitted with probability $p_i(m, n_i)$ and blocked (no state change) when $n_i = N_i(m)$. The third and fourth rates describe service completions, which occur at the elastic rate $n_i \mu_i \mathbb{E}[\xi_i^b(m, n_i)]$: since each session volume is exponentially distributed with mean $1/\mu_i$ bits and the equal-rate scheduler allocates bitrate $\xi_i^b(m, n_i)$, the expected service rate per user is $\mu_i \mathbb{E}[\xi_i^b(m, n_i)]$. The last rate governs reallocation transitions, which fire at each Poisson epoch of rate δ when the controller selects target a and the affected slice passes the isolation check with probability $p(m, n_1, n_2, a)$.

4.2. Performance metrics

The CTMC over $\mathcal{X}$ is irreducible and ergodic. All metrics are expectations over the stationary distribution $\pi(m, n_1, n_2)$. Blocking probability of a request in slice i :

$$p_i^{\text{bl}} = \sum_{m=M_1}^{M-M_2} \sum_{n_1=0}^{N_1(m)} \sum_{n_2=0}^{N_2(m)} [1 - p_i(m, n_i)] \cdot \pi(m, n_1, n_2), \quad i = 1, 2.$$

Average bitrate per user in slice i :

$$\bar{b}_1 = \frac{\sum_{m=M_1}^{M-M_2} \sum_{n_1=1}^{N_1(m)} \mathbb{E}[\xi_1^b(m, n_1)] \sum_{n_2=0}^{N_2(m)} \pi(m, n_1, n_2)}{\sum_{m=M_1}^{M-M_2} \sum_{n_1=1}^{N_1(m)} \sum_{n_2=0}^{N_2(m)} \pi(m, n_1, n_2)}, \quad \bar{b}_2 = \frac{\sum_{m=M_1}^{M-M_2} \sum_{n_2=1}^{N_2(m)} \mathbb{E}[\xi_2^b(m, n_2)] \sum_{n_1=0}^{N_1(m)} \pi(m, n_1, n_2)}{\sum_{m=M_1}^{M-M_2} \sum_{n_2=1}^{N_2(m)} \sum_{n_1=0}^{N_1(m)} \pi(m, n_1, n_2)}.$$

Average number of active users in slice i :

$$\bar{n}_1 = \sum_{m=M_1}^{M-M_2} \sum_{n_1=1}^{N_1(m)} n_1 \sum_{n_2=0}^{N_2(m)} \pi(m, n_1, n_2), \quad \bar{n}_2 = \sum_{m=M_1}^{M-M_2} \sum_{n_2=1}^{N_2(m)} n_2 \sum_{n_1=0}^{N_1(m)} \pi(m, n_1, n_2).$$

Average resource utilization:

$$\bar{m} = \sum_{m=M_1}^{M-M_2} m \sum_{n_1=0}^{N_1(m)} \sum_{n_2=0}^{N_2(m)} \pi(m, n_1, n_2), \quad \bar{F}_1 = \Delta f \cdot \bar{m}, \quad \bar{F}_2 = F - \bar{F}_1.$$

The metrics above require the quantities $p_i(m, n_i)$, $p(m, n_1, n_2, a)$, and $\mathbb{E}[\xi_i^b(m, n_i)]$, all of which depend on the CDF of the equal-rate bitrate $\xi_i^b(m, n_i)$. The next subsection derives this CDF.

4.3. CDF of the equal-rate bitrate

As defined in Section 3, the ISE of a user is the random variable $\xi_{\text{ISE}} = 1/r(\xi_{\text{PL}})$ with support $[\text{ISE}_{\min}, \text{ISE}_{\max}]$. Since $r(\cdot)$ is strictly decreasing, $\xi_{\text{ISE}} \leq s$ if and only if $r(\xi_{\text{PL}}) \geq 1/s$, i.e. $\xi_{\text{PL}} \leq r^{-1}(1/s)$. Substituting the inverse of r in closed form gives the CDF of the ISE:

$$F_{\xi_{\text{ISE}}}(s) = F_{\xi_{\text{PL}}}\left(\frac{PG_t G_r}{(N_0 + I_0)(2^{1/s} - 1)}\right), \quad s \in [\text{ISE}_{\min}, \text{ISE}_{\max}].$$

Let $\mu_{\text{ISE}} = \mathbb{E}[\xi_{\text{ISE}}]$ and $\sigma_{\text{ISE}}^2 = \text{Var}(\xi_{\text{ISE}})$ be the first two central moments computed from $F_{\xi_{\text{ISE}}}(s)$.

With n_i active users, the survival function of ξ_i^b is therefore:

$$\Pr(\xi_i^b(m, n_i) \geq b) = \Pr\left(\eta_i(n_i) \leq \frac{F_i(m)}{b}\right) = F_{\xi_{\text{ISE}}}^{*n_i}\left(\frac{F_i(m)}{b}\right), \quad n_i > 0, \quad i = 1, 2,$$

where $F_{\xi_{\text{ISE}}}^{*n_i}$ denotes the n_i -fold convolution of $F_{\xi_{\text{ISE}}}$. While exact, evaluating this convolution for large n_i is computationally intensive.

By the CLT, $\eta_i(n_i)$ is approximately normal with mean $n_i\mu_{\text{ISE}}$ and variance $n_i\sigma_{\text{ISE}}^2$, so the survival function takes the form:

$$\Pr(\xi_i^b(m, n_i) \geq b) \approx \Phi\left(\frac{F_i(m)/b - n_i\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_i}}\right), \quad n_i > 0, \quad i = 1, 2,$$

and the CDF is equivalently:

$$F_{\xi_i^b(m, n_i)}(b) \approx 1 - \Phi\left(\frac{F_i(m)/b - n_i\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_i}}\right), \quad n_i > 0, \quad i = 1, 2,$$

where $\Phi(x)$ denotes the standard normal CDF. For $n_i = 1$ the CLT approximation reduces to $\Pr(\xi_i^b(m, 1) \geq b) = F_{\xi_{\text{ISE}}}(F_i(m)/b)$, which is exact. The expected equal-rate bitrate used in the service-completion rates is $\mathbb{E}[\xi_i^b(m, n_i)] = \int_{B_i^{\min}(m, n_i)}^{B_i^{\max}(m, n_i)} b dF_{\xi_i^b(m, n_i)}(b)$, where $B_i^{\min}(m, n_i) = F_i(m) \cdot r(\text{PL}_{\max})/n_i$ and $B_i^{\max}(m, n_i) = F_i(m) \cdot r(\text{PL}_{\min})/n_i$ are the minimum and maximum achievable equal-rate bitrates, corresponding to all users being at the cell edge and all users being at the cell center, respectively.

4.4. Admission and reallocation probabilities

A new arrival to slice i is admitted if and only if all $n_i + 1$ users simultaneously satisfy the minimum bitrate constraint: $\eta_i(n_i + 1) \leq F_i(m)/b_i^{\min}$. Conditioning on the current n_i users already being admitted yields the admission probability:

$$p_i(m, n_i) = \frac{\Pr(\xi_i^b(m, n_i + 1) \geq b_i^{\min})}{\Pr(\xi_i^b(m, n_i) \geq b_i^{\min})}, \quad n_i > 0, \quad i = 1, 2,$$

and $p_i(m, 0) = \Pr(\xi_i^b(m, 1) \geq b_i^{\min})$. Substituting the CLT approximation for the survival function gives:

$$p_i(m, n_i) \approx \frac{\Phi\left(\frac{F_i(m)/b_i^{\min} - (n_i + 1)\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_i + 1}}\right)}{\Phi\left(\frac{F_i(m)/b_i^{\min} - n_i\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_i}}\right)}, \quad n_i > 0, \quad i = 1, 2.$$

A reallocation from m to $a \neq m$ succeeds if all n_i users in the affected slice achieve at least the isolation threshold b_i^{is} under the new allocation. Applying the CLT survival function with b_i^{is} in place of $b_i^{\min}$:

$$p(m, n_1, n_2, a) = \frac{\Pr(\xi_1^b(a, n_1) \geq b_1^{\text{is}})}{\Pr(\xi_1^b(m, n_1) \geq b_1^{\min})} \approx \frac{\Phi\left(\frac{F_1(a)/b_1^{\text{is}} - n_1\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_1}}\right)}{\Phi\left(\frac{F_1(m)/b_1^{\min} - n_1\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_1}}\right)}, \quad a < m, \quad n_1 > 0,$$

$$p(m, n_1, n_2, a) = \frac{\Pr(\xi_2^b(a, n_2) \geq b_2^{\text{is}})}{\Pr(\xi_2^b(m, n_2) \geq b_2^{\min})} \approx \frac{\Phi\left(\frac{F_2(a)/b_2^{\text{is}} - n_2\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_2}}\right)}{\Phi\left(\frac{F_2(m)/b_2^{\min} - n_2\mu_{\text{ISE}}}{\sigma_{\text{ISE}}\sqrt{n_2}}\right)}, \quad a > m, \quad n_2 > 0,$$

with $p(m, n_1, n_2, a) = 1$ when the affected slice is empty ($n_1 = 0$ for $a < m$; $n_2 = 0$ for $a > m$).

5. Discussion

Unlike the fixed-power model [10], where each user's bitrate depends only on their own path loss, the equal-rate policy couples all users within a slice through the sum $\eta_i(n_i)$: a single cell-edge user lowers the bitrate of every other user in the slice. This coupling is what necessitates the CDF derivation in Section 4—admission and reallocation decisions cannot be made per-user, only for the slice as a whole.

The CLT approximation is exact for $n_i = 1$ and improves as n_i grows, so its main practical value is for slices with several simultaneous users, precisely the regime where the exact n_i -fold convolution becomes too costly to evaluate at each arrival or reallocation epoch.

The isolation-aware set $\mathcal{A}(m, n_1, n_2)$ protects already-admitted users but narrows the range of feasible reallocations under high load in either slice. Because this constraint now operates on a stochastic bitrate rather than a fixed allocation, reallocation decisions under equal-rate scheduling are inherently more conservative than under the fixed-power scheme.

6. Conclusion

This paper has developed a complete resource queueing model for dynamic spectrum slicing in two-operator 5G NR networks under the equal-rate (Round Robin) scheduling policy, where the base station adjusts per-user time-frame fractions so that every active user within a slice achieves the same instantaneous bitrate. The CTMC is formulated with state-dependent arrivals, elastic service completions, and Poisson-triggered reallocation transitions subject to per-slice isolation thresholds. Closed-form steady-state expressions are derived for blocking probability, average per-user bitrate, average number of active users, and resource utilization.

Several directions remain open for future research. First, the numerical validation of the CLT approximation against exact n_i -fold convolution and Monte Carlo simulation across a range of cell radii, load levels, and path-loss exponents would establish practical accuracy bounds. Second, extending the model to more than two slices, to heterogeneous minimum bitrate requirements across user classes, and to non-Poisson arrival processes would broaden its applicability to emerging 5G-Advanced and 6G multi-tenant deployments.

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Information about the authors

Ghebrial, Ibram E. Z.—Junior Researcher and PhD Student with the Department of Probability Theory and Cyber Security of RUDN University (e-mail: ghebrial-ie@rudn.ru, ORCID: 0009-0007-2682-8577, ResearcherID: OKS-6645-2025, Scopus Author ID: 58848551900)

Kochetkova, Irina A.—Doctor of Sciences in Physics and Mathematics, Associate Professor with the Department of Probability Theory and Cyber Security of RUDN University; Senior Researcher with the Federal Research Center “Computer Science and Control” of the Russian Academy of Sciences (e-mail: kochetkova-ia@rudn.ru, ORCID: 0000-0002-1594-427X, ResearcherID: E-3806-2014, Scopus Author ID: 35332169400)

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Ресурсная система массового обслуживания для динамической нарезки радиочастот с равной скоростью в сетях 5G NR

И. Е. З. Гебриал¹, И. А. Кочеткова^{1,2}

¹ Российский университет дружбы народов, ул. Миклухо-Маклая, д. 6, Москва, 117198, Российская Федерация

² Федеральный исследовательский центр “Информатика и управление” Российской академии наук, ул. Вавилова, д. 44, корп. 2, Москва, 119333, Российская Федерация

Аннотация. Предпосылки: В сетях 5G NR с нарезкой радиочастот оператор мобильной сети предоставляет часть спектра в аренду виртуальному оператору по соглашению об уровне обслуживания. При планировании с равной скоростью (Round Robin) базовая станция распределяет доли временного кадра так, что каждый пользователь слайса получает одинаковую скорость передачи данных независимо от местоположения. Существующие аналитические модели массового обслуживания для динамической нарезки спектра, однако, охватывают только вариант с фиксированной мощностью, и аналогичной модели для планирования с равной скоростью пока не существует. Цель: Построение ресурсной модели массового обслуживания для динамической нарезки спектра при планировании с равной скоростью, расширяющей ранее разработанную авторами схему с фиксированной мощностью на этот режим. Методы: Качество канала каждого пользователя описывается случайной величиной обратной спектральной эффективности, функция распределения которой выводится из модели затухания радиосигнала. При планировании с равной скоростью все пользователи слайса получают общую скорость передачи данных, равную отношению выделенной полосы пропускания к сумме независимых одинаково распределённых величин обратной спектральной эффективности; эта сумма описывается точно через многократную свёртку и для снижения вычислительной сложности приближается с помощью центральной предельной теоремы. Полученные распределения используются при построении непрерывной марковской цепи (СТМС), описывающей совместную динамику распределения спектра и числа пользователей в каждом слайсе, с зависящим от состояния управлением доступом и стохастическим перераспределением частот, сохраняющим изоляцию между слайсами. Результаты: Модель даёт аналитические выражения для вероятности блокировки, средней скорости передачи данных на пользователя, среднего числа активных пользователей в каждом слайсе и общей занятости ресурсов. Выводы: Построенная модель является аналитическим инструментом для расчёта параметров спектра и управления доступом в мультитенантских сетях 5G NR при планировании с равной скоростью.

Ключевые слова: 5G NR, СТМС, динамическое управление спектром, планирование с равной скоростью, сетевой слайсинг, система массового обслуживания, Round Robin