Artificial Intelligence in Beyond 5G and 6G Reliable Communications

Ali Nauman, Tu N. Nguyen, Yazdan A. Qadri, Zulqar Nain, Korhan Cengiz, and Sung Won Kim

Abstract

The rapid increase in heterogeneous data traffic with the ongoing development of self-organizing and self-sustaining networks exposes the limitations of the fifth generation (5G) system, which was originally aimed at enabling the realization of the Internet of Everything. This study presents flexible design agreements of beyond 5G (B5G) from the current 3GPP study and proposes an intelligent network architecture for the 5G and B5G paradigm to ensure that the network is self-sustained and self-organized. The key idea is to use machine learning (ML) to dynamically schedule flexible transmission time intervals at the slot level to optimize network performance. This study also provides an overview of the queuing model of the medium access control layer and presents how ML-enabled scheduling plays an important role in reducing queuing latency and providing reliable services of the B5G network.

Introduction

The vision of the Internet of Everything (IoE) in the sixth generation (6G), which is to connect billions of humans and machines to the Internet, shifts the paradigm from rate-centric services such as further enhanced mobile broadband (FeMBB) toward enhanced ultra-reliable low-latency communication (eURLLC) and ultra massive machine type communication (umMTC) [1]. 5G cellular communication was expected to be the key enabler for IoE with 1000× increase in data rate and network capacity. The development of 5G by the 3rd Generation Partnership Project (3GPP) has led to the standardization of New Radio (NR) in Release 15, which operates exclusively over millimeter-wave (mmWave) frequencies — a true IoE carrier yet to be achieved. However, most of the 5G versions around the globe still use sub-GHz frequencies. Although 5G readily supports eURLLC services, the aim to have a self-sustaining and self-organized network (SSN/SON) has thus far remained a mirage, and these objectives have been moved upward to the B5G networks [2].

The International Telecommunication Union (ITU) classified the services of eURLLC ranging from telemedicine to autonomous flying cars, all of which require reliability as high as 10^{-9} packet error rate and latency as low as 10–100 μs over the radio interface [3]. However, FeMBB services include high-resolution videos and extended reality (augmented, mixed, virtual) with large data packets that require high data rate of 1 Tb/s. The umMTC services encompass a massive deployment of Internet of Things (IoT) devices that require augmented network capacity to support 10^7 devices/km^2 [3]. The coexistence of these applications in network transmission disrupts the 5G goal of supporting short-packet eURLLC services. To successfully enable IoE, 5G and B5G networks should be capable of simultaneously delivering data traffic of heterogeneous (Het) devices with high reliability, low latency, and high data rate across uplink and downlink communication. The two challenges of SSN/SON and the coexistence of Het devices for emerging IoEs are therefore still open for research. To meet the stringent latency and reliability requirements in Het data traffic, 3GPP has introduced the concept of mini-slots from Release 15 onward by shortening the transmission time interval (TTI) with varying numbers of orthogonal frequency-division multiplexing (OFDM) symbols [1]. Furthermore, NR offers scalable sub-carrier spacing (SCS). Increasing the SCS reduces the TTI and consequently enhances the network capacity by accommodating a greater number of users. The amalgamation of mini-slots with scalable SCS offers a solution to optimize network performance and satisfy stringent network requirements [4].

Motivation: Recent advancements in hardware computation have allowed researchers to benefit from machine learning (ML) in wireless communications, especially for 5G networks. ML mimics the human brain to enhance its capability for computer vision, image processing, parallel and distributed processing, analytics, and prediction [5]. Resource allocation for network optimization based on ML techniques in real time can be implemented with less complexity. In this study, we present a reinforcement learning (RL)-enabled transmission rate adaptation scheme for the 5G NR network. RL is a type of ML method based on the Markov decision process (MDP) [6]. RL algorithms are less computationally complex than other supervised and unsupervised techniques because they learn from real-time experience instead of training on preexisting datasets. The selection of an RL algorithm is determined by the problem statement, and the selection is made based on the understanding of the problem. Every RL problem can be designed by identifying states, actions, and subsequent rewards.

Contribution: A massive amount of Het data is generated across massive devices. An RL-enabled next generation nodeB (gNB) can learn the traffic patterns and the required TTI with scalable SCS and number of OFDM symbols to reduce physical/medium access control (PHY/MAC) layer latency and increase reliability. This article discusses the applications of the B5G network and a few emerging PHY/MAC layer issues. This article also provides the stringent network service requirements and presents how RL-enabled flexible TTI scheduling at the slot level plays a role in satisfying these service requirements. The article concludes by highlighting some limitations and open research issues.

5G and B5G Driving Applications

This section provides a brief overview of three application categories defined by ITU in 5G and B5G: FeMBB, umMTC, and eURLLC. This section also highlights a few emerging PHY/MAC layer issues. Figure 1 illustrates the three application categories.

FeMBB

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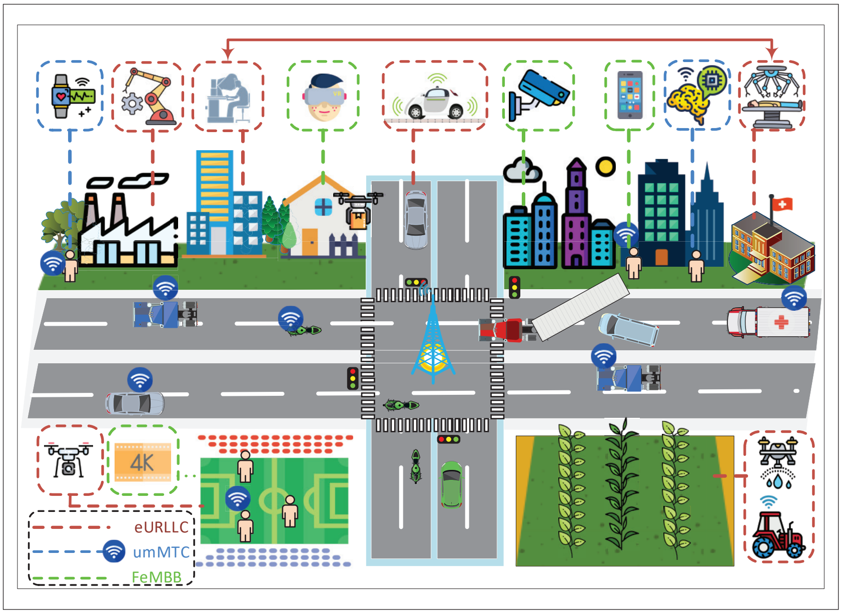


FIGURE 1. Application scenario of 5G and B5G networks.

is not considered efficient, because 60 percent of the resources are wasted on control overheads. Thus, a complete redesign of the PHY/MAC layer is required.

Service Requirements

With the objective of providing viable solutions for 5G and B5G networks, it is vital to understand the critical requirements. This section provides a brief overview of the requirements of and challenges faced by B5G Het traffic.

Latency Requirement: The PHY layer latency includes transmission, propagation, retransmission, and processing latency. The MAC layer latency encompasses scheduling delay, queuing delay, processing, multiple hybrid automatic repeat requests (HARQs), and decoding delay [2]. The queuing and processing delays result from the statistical multiplexing of data destined for multiple Het users. As the data traffic increases with the number of Het users, the queuing effect would worsen to maximize the spectral efficiency [2]. As per 3GPP, the eURLLC applications have a stringent average latency over the radio that should be less than 1 ms. Therefore, a new frame structure is required to reduce transmission delay. The key performance indicator (KPI) to determine latency is time, which is denoted by *L* and measured in seconds.

Ultra-High Reliability: The eURLLC services have the strictest reliability requirements. The reliability required for eURLLC services should be at least 99.99999 percent packet delivery ratio (PDR) within 10–100 μs of the latency period. Mission-critical applications such as robotic surgery require reliability as high as 1×10^{-9} packet error rate [8]. To achieve ultra-reliability, efficient channel coding and retransmission of HARQs are the essential ingredients. Advanced channel coding with an efficient channel estimation technique for short packet transmission can be exploited. For short slot lengths, retransmission schemes using time-domain resources could be a viable option [8]. The KPI to measure the reliability is the PDR. In this study, we use *R* to denote PDR.

Coexistence of Het Traffic: According to the recommendation of 3GPP, whenever there is an eURLLC service either in scheduling or during FeMBB or umMTC transmission, the base station (BS) should give priority to eURLLC. To support eURLLC, the ongoing FeMBB and umMTC services should be stopped immediately without any notification [7]. Since the interruption is not notified to mobile users, the quality of service (QoS) of FeMBB and umMTC degrade severely. This problem, associated with heterogeneous applications in 5G and B5G networks, is referred to as coexistence by 3GPP. Therefore, an efficient mechanism to protect all ongoing services should be introduced. The KPI to measure the fair balance of the coexistence of Het traffic is fairness. One of the popular indices used to determine fairness is Jain's fairness index (JFI), denoted by *F* [5]. In this study, fairness is determined using the method described in [9].

The service applications of FeMBB include high-resolution video streaming and extended (augmented, virtual, mixed) reality with large packet sizes (approximately four times those of the other two application types), which in turn require high bandwidths [7]. The major challenge faced by previous generations of communication technology was related to the improvement of system throughput and data rate with a 100–1000-fold increase in capacity. The current PHY/MAC technologies enable efficient multiplexing, high-order encoding and modulation, cell densification, and multiple-input multiple-output (MIMO) transmission. However, to achieve a 1000× higher data rate, more aggressive approaches are needed, which remain unexplored for SON and SSN networks. Some viable solutions include terahertz (THz) communication, millimeter-wave (mmWave) communication, full dimension MIMO, and ML-enabled networks [8].

umMTC

The service applications of umMTC include massive deployment of machine-type devices, such as tagging, localization, sensing, metering, and monitoring, which require efficient spectrum access and energy conservation mechanisms [8]. The B5G network should support network density of 10^7 devices/km^2. 3GPP introduced narrowband IoT, which is a low- power wide area network (LPWAN) radio technology, in 5G capable of operating over a licensed band for umMTC devices with a life expectancy of more than 10 years and coverage area of 1–10 km. LPWAN technologies offer low power consumption, improved coverage, and low operational cost. However, when the number of devices significantly exceeds capacity related to available resources, an aggressive spectrum access mechanism is required to accommodate additional users [8].

eURLLC

The eURLLC service applications include services that are latency-sensitive and require high reliability such as autonomous driving, Tactile Internet, telemedicine, and industrial automation. The end-to-end latency of packet transmission in mission-critical applications should be 10–100 μs. To reduce the latency, a fundamental change in both backhaul and wireless networks is needed. Software-defined networking (SDN) can be used to improve the backhaul network by exploiting virtual network slicing. In a wireless network, overhead increases the latency due to control signals, which takes almost 0.3–0.4 ms per scheduling [8]. Therefore, utilizing low latency for packet transmission

Problem Formulation

In this section, we discuss the queuing model of the B5G architecture and highlight the relationship between the MAC queue model and the service requirements of the 5G network. The concepts and frame structure of 5G NR are illustrated to define the objective. The main objective of our approach is to reduce the overall MAC layer latency and augment reliability by optimizing the queuing delay and fulfilling the service requirements.

Queueing Model

This section describes the queuing model, which shows the behavior of the PHY/MAC layer when a gNB schedules Het traffic at the downlink. The data packets of Het users are buff-

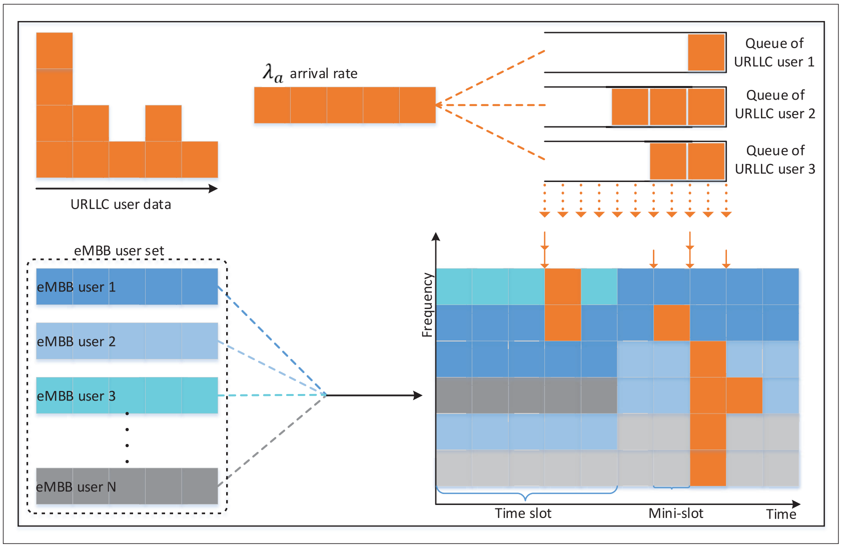


FIGURE 2. Queuing model describing the PHY/MAC layer behavior with the puncturing mechanism at gNB for B5G applications.

ered at the gNB in the first transmission queue and awaits for the scheduler to schedule the first HARQ transmission [2]. Upon failure of the first HARQ transmission, the packet is available for retransmission after a round-trip time (RTT). Whenever the packet in the buffer at the gNB misses its deadline, it is dropped, resulting in a loss of reliability. Moreover, when a packet cannot be decoded at the receiver after *N* HARQ transmissions, it is declared as a failure resulting in a loss of reliability [2]. The finite size of the buffer in a queuing model refers to the fact that the packets are dropped at the transmitter side if the queuing delay exceeds the latency requirement. At each time instant, the scheduler at the gNB allocates time and frequency resources for transmissions and retransmissions to fulfill the service requirements of every user [2].

3GPP in Release 15 introduced mini-slots to reduce the latency by shortening the TTI from 1 ms to only a few OFDM symbols while maintaining the overall channel structure [3]. Reducing the TTI enhances the network capacity and allows for a larger number of retransmissions within latency constraints. Moreover, it allows precise rate control. In addition, 3GPP agrees with scalable SCS for NR scaled by a power of 2, that is, $2^n \times 15$ kHz, where $n = \{0, 1, 2, 3, ..., n\}$ [3]. Until now, $n = 4$ has been standardized in NR. Moreover, 3GPP standardized the mechanism of puncturing in NR for the eURLLC traffic to meet stringent latency and reliability requirements, categorically halting the ongoing FeMBB traffic to transmit eURLLC traffic mini-slots without notifying FeMBB user equipment (UE), as shown in Fig. 2. The data traffic of FeMBB users is continuous, and for eURLLC users the data packets follow a Poisson point process (PPP) with arrival rate λ(packets/s). The priority weight of each FeMBB and eURLLC user is defined as ratio of product of queue weight, arrival rate, packet size in bits per packet, and channel state information (CSI) of each user. The queue weight is the ratio of number of packets of a particular user and sum of all the queues (FeMBB and eURLLC). Normalized load (NL) is defined as the objective of the problem. NL is the ratio of product of arrival rate with size of packet and the product of number of symbols allocated with length of slot in seconds. Therefore, the problem is defined as to select the optimal SCS and number of symbols for mini-slots to transmit eURLLC traffic of a priority user using a puncturing mechanism to minimize the NL so that the QoS requirements for both FeMBB and eURLLC can be met. If the priority of the FeMBB user is high, very small mini-slot or no mini-slot should be given to the eURLLC user. To better understand how shortening the TTI and scalable SCS can meet the service requirement, we now look into the frame structure of 5G NR.

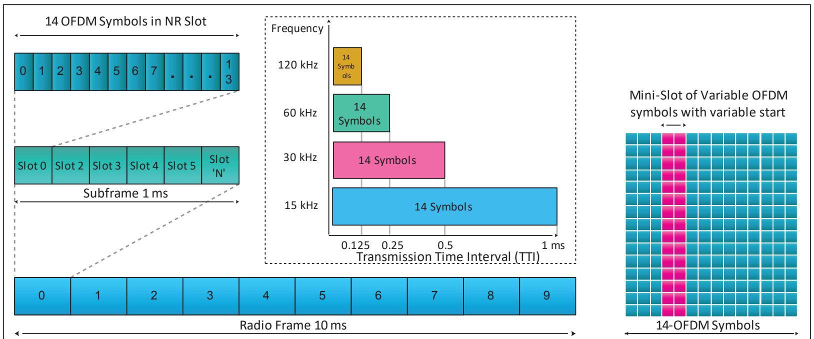
NR Frame Structure

The frame length of NR in the time domain is 10 ms, which is composed of 10 subframes of 1 ms, as shown in Fig. 3. The subframe is sub-divided into 2^n numbers of radio slots. The radio slot is defined as the smallest time unit that fits into one TTI [10]. Each slot encompasses 14 OFDM symbols with a normal cyclic prefix (CP) [1]. The number of radio slots varies depending on the SCS. Each slot comprises control signaling at the start and/or end of the OFDM symbols. In NR, the mini-slot concept has been adopted, which allows more flexible TTI size with a variable number of OFDM symbols. A mini-slot can start from any OFDM symbol with a variable symbol length of two, four, or seven symbols. The length of the time slot is 1 ms/2^n. When $n = 1$, the time slot becomes 0.5 ms at 30 kHz, as depicted in Fig. 3. The mini-slot provides the opportunity to transmit fast for eURLLC traffic. The mini-slots are independently scheduled with control signals, allowing lower scheduling latency. This means that the mini-slot is the smallest time domain unit for the MAC scheduler in NR, and enables dynamic scheduling with variable TTI.

Numerologies of NR

NR has a scalable numerology with SCS of $2^n \times$ 15 kHz, where $n = \{0, 1, 2, 3, ..., n\}$. At higher SCS, the time duration of symbols decreases, resulting in a reduction in the length of radio slots, which is beneficial for lower latency. Moreover, NR supports mixing of numerologies on the same carrier. The subframe of 1 ms at 15-kHz SCS is 125 μs at 120-kHz SCS, as depicted in Fig. 3. However, higher SCS is more vulnerable to the Doppler effect and inter-carrier interference (ICI), as CP is also scaled down by scaling up the SCS. Application of the windowing prevents changes between OFDM symbols to confine them in the frequency domain, which promotes the use of mixed numerology with short guard bands.

In addition, increasing the SCS increases the available bandwidth, as depicted in Fig. 3. The maximum bandwidth available becomes 400 MHz at 120 kHz SCS from 50 MHz at 15 kHz SCS [5]. In NR, the number of sub-carriers (SCs) in a physical resource block (PRB) is fixed, that is 12. The number of SCs are defined by SCS, therefore, the total number of PRBs are also defined by SCS. The bandwidth of a PRB also varies with SCS, which is 180 kHz at $n = 0$ and 2.88 MHz at $n = 4$, as shown in Fig. 3. The NR offers both time-division duplex (TDD) and frequency division duplex (FDD) for Het traffic. For FDD, all the slots are for downlink or uplink transmission. For all the slots in TDD, NR supports bidirectional (uplink and downlink) transmission. Het users can be scheduled dynamically with a variable size of mini-slots and scalable SCSs to reduce latency. The MAC scheduler can freely schedule Het users independently with different SCS numerologies with different TTI sizes [4]. At each time instance, the scheduling allocation is announced to the UE by a PHY downlink control channel, which can be multiplexed easily with other downlink PHY channels and can be mapped contiguously or non-contiguously in the frequency domain. This highly adaptive design can reduce the downlink control channel overhead to a sub-one-percent value [4]. One of the solutions proposed for eURLLC application is the principle of punctured scheduling, where when a eURLLC data packet arrives at gNB, the MAC scheduler overwrites the ongoing transmission using mini-slots [2]. However, punctured scheduling comes with a price of interrupting ongoing transmission, which degrades the system's performance. Therefore, the size of the mini-slot and SCS should be chosen carefully with an efficient MAC



n	SCS (kHz)	Slots/Sub-frame	Slots/Frame	Symbols/Slot	OFDM Symbol Duration including CP (µs)	Max. BW (MHz)	No. of SCs, No. of PRB	Size of PRB (kHz)
0	15	1	10	14	71.35	49.5	3300, 275	180
1	30	2	20	14	35.68	99	3300, 275	360
2	60	4	40	14	17.84	198	3300, 275	720
3	120	8	80	14	8.92	396	3300, 275	1440
4	240	16	160	14	4.46	397.4	3300, 275	2880

FIGURE 3. Frame structure for NR DL/UP transmission.

scheduling mechanism. In this study, we model the problem of selecting the TTI and SCS at gNB for downlink transmission as a multi-arm bandit (MAB) problem, which is an MDP. To satisfy the service requirements (L, R, F), we provide the RL-based NR MAC scheduler framework.

RL-Enabled NR: MAC Scheduler

To formulate the RL problem, we model the environment as an MDP. An MDP comprises four basic elements, in other words, (S, A, P, R). In a finite MDP, S refers to the number of finite states $s \in S$, the action A to the set of actions $a \in A$ taken by an agent, P to the transitional probability from one state to the other by taking an action, and R is the reward function for evaluating the action. One of the essential sub-elements is policy π, which is a set of rules (e.g., algorithms) that are followed by an agent during decision making. The MDP problem represents the mathematical expression to assist in making decisions for the RL process. Figure 4 presents the agent–environment interaction and its elements.

In this study, S is defined as a set of all possible combinations of TTI and SCS, as depicted in Fig. 4. We named a state $s \in S$ as the *rate adaption scheme*. The agent is defined as an intelligent MAC scheduler at gNB equipped with RL capabilities. Action a is the selection of the optimal rate adaption scheme S at time instant t to minimize the queuing delay and satisfy the service requirements. P is the transitional probability. For instance, at time instance t, the probability of selecting an $s_{(t+1)}$, given that the action a taken at s_t can be expressed as $P(s_{t+1} | s_t, a)$. The reward R is the quantitative measure of how well the action is taken by the agent. In this study, a positive reward r^+ is given to the scheduler when the data packet is delivered without compromising the reliability and satisfies the service requirements (L, R, F); otherwise, the reward is negative r^-. The *value function* is the element of RL that is the quantitative accumulation of reward over time of a state s. The value function of a state identifies the long-term intrinsic desirability of a state. A state can have a low immediate reward but still have a high-value function because it is regularly followed by r^+ [6]. The initial state can be randomly selected by the scheduler, and the reward is computed. The state transition probability is considered and executes the next action to select the state or remain in the same state based on the value function. The objective is for a given scheduling policy to select the best sequence of actions to maximize the cumulative reward.

MAC Scheduler with RL

RL algorithms such as Q-learning and SARSA provide an end-to-end solution to deployment problems. These algorithms can be implemented easily and converge quickly; however, to explore the environment for a better reward, the ε-greedy approach is adopted. In this approach, the agent randomly explores the selection of an action with probability ε or chooses an action a_t with the largest value function with a probability of (1 – ε). However, there is a dilemma as exploration and exploitation, which refers to trade-off to balance the probability of exploration and exploitation to find the optimal solution. We therefore formulate the problem as a MAB, and solve it using an upper confidence bound (UCB_1). A MAB problem involves the use of RL techniques in which an agent (player) repeatedly decides to choose a state k (machine) from K states (machines), that is, $K \in \{1, 2, ..., K\}$, at a discrete time $t = \{0, 1, 2, ..., t\}$ based on their corresponding reward [22]. Notably, the agent (player) is interested in choosing the state (machine) that provides the maximum reward. The associated rewards with the states (machines) are independent and identically distributed (i.i.d) and accompany an unknown and fixed distribution law d_K. The reward distributions $\{d_1, d_2, ..., d_K\}$ vary from one state to the other, and the player has no prior knowledge about the distribution. The UCB_1 algorithms balance the exploration and exploitation autonomously by working in an iterative manner on a basic principle by selecting and calculating the numerical UCB index of each state in the environment sequentially at each time step, which reflects how well the state has performed [11]. The agent selects the state with the maximum UCB index, which is the summation of the average reward (value function) and upper confidence bias [12].

Algorithm 1 describes the intelligent rate-adaptive scheduler based on RL. Step 1 is to determine priority weight and NL of each user. Then in step 2, the number of states, exploration coefficient, and (L, R, F) are first initialized. The input of the model is the action-value function of each state, NL, and priority matrix of users. For all Het users in the queue to be scheduled for downlink transmission at gNB, the RL-enabled intelligent rate adaption model iteratively selects each state of the environment and determines the UCB index. The model checks whether there is any rate adaptation scheme that has not yet been explored. Then the validity of the action to select the rate adaptation scheme (state s) is determined by calculating the reward at each time schedule. If all the states are explored, the model selects the rate adaptation scheme with a maximum UCB index, and determines whether the scheme is still valid or not. The model balances exploration and exploitation by updating the value function and upper confidence bias. As the number of times a specific selected state increases, the upper confidence bias decreases. Therefore, the model moves toward the state with the highest upper confidence bias to explore. The upper confidence bias refers to the uncertainty of the state that is not explored. However, the UCB index is the summation of the value function (average reward) and upper confidence bias. The value function ensures that the state with the highest upper confidence bias also has the highest accumulated reward in the past, which makes the exploration more beneficial. The model at each time step continuously explores and acts greedily simultaneously to select the state with the highest accumulated reward and highest upper confidence bias. The output of the intelligent rate adaptation model at each time step is the state with a maximum UCB index. The agent (gNB scheduler) learns the traffic pattern of Het users and also learns the rate adaptation scheme to satisfy the Het traffic in the queue.

Open Research Issues

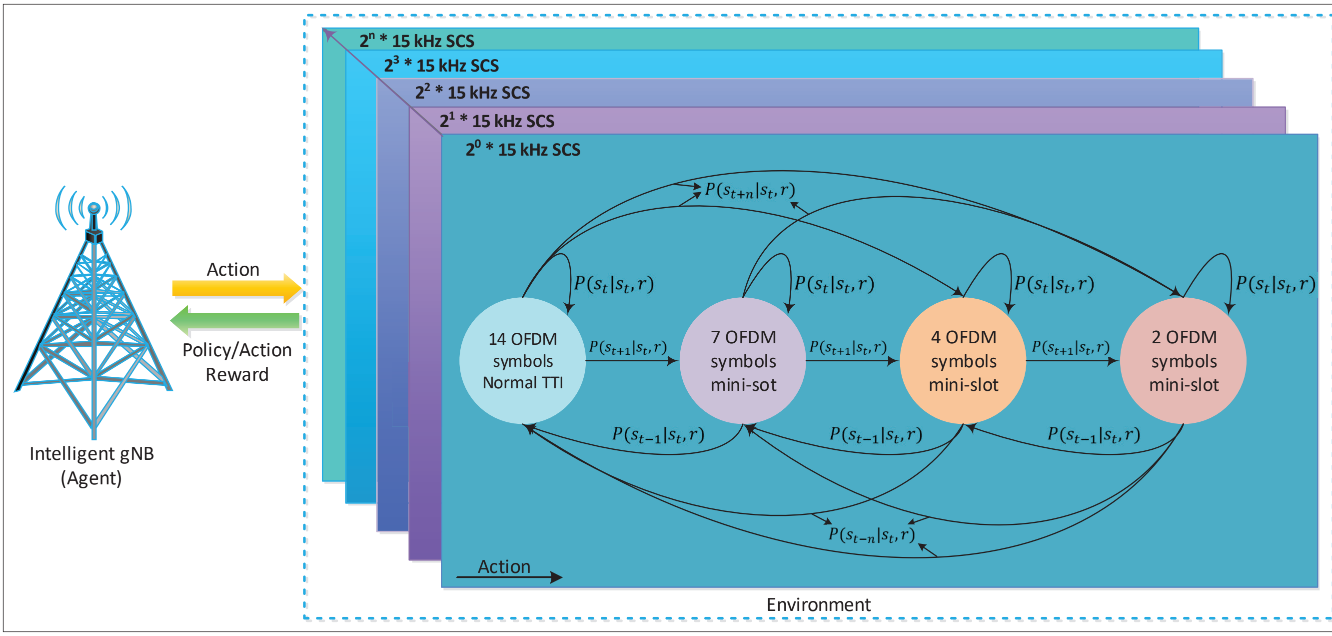


FIGURE 4. Agent–environment interaction in RL-enabled 5G and B5G NR networks.

Step 1:
Determine Normalized Load (NL) and priority weight of each user
Step 2:
Objective: To minimize NL and meet service requirements
Initialize parameters: States K, exploration coefficient, (NL), priority matrix
Input: Action reward value for all states (a_t, r_t)
Output: a_t with maximum UCB index
for all users in priority matrix
  If $t \leq K$ **then**
    Select the next state as current rate adaption and determine it's UCB index
    If service requirements (L, R, F) are satisfied and $NL_k(t+1) - NL_k(t) < 0$ **then**
      reward r^+
    else
      reward r^-
  else
    select the state with maximum UCB index
    If service requirements (L, R, F) are satisfied and $NL_k(t+1) - NL_k(t) < 0$ **then**
      reward r^+
    else
      reward r^-
  Update reward r_t of state k_t
  Update value function and upper confidence bias of state k_t
  Update UCB index of state k_t
  Return $a_t = arg \max_k (UCB\ index)$

ALGORITHM 1. Intelligent rate adaption model.

The success of an ML-defined network relies on the satisfaction of the service requirements discussed above by solving numerous open research challenges. Some critical issues related to the MAC layer are listed below.

Resource Allocation

For the coexistence of FeMBB, umMTC, and eURLLC services, users are required to share radio resources. Static or semi-static multiplexing wastes constitute 49.1 percent of the system's resources [2]. Deep RL (DRL)-defined dynamic multiplexing in frequency as well as time domain, offers efficient resource sharing over the entire system bandwidth by preventing puncturing phenomena to augment spectral efficiency and system throughput [13].

Multiple Access

Uplink transmission has more limitations than downlink transmission. The user has to follow the handshaking procedure, which refers to a grant-based method to request resources from the gNB. The gNB grants resources to users by performing dynamic scheduling to maximize system capacity. The initial handshake procedure should be critically reliable to detect the presence of uplink data, which increases the overhead of the uplink control channel. One viable solution is the grant-free approach, which utilizes semi-statistical allocation. However, in the grant-free approach, users are not aware of CSI, which increases the block error code [1]. Exponential increase in connected devices and umMTC deployment further enhance the spectral scarcity. Device-to-device (D2D) communication standardized by 3GPP is gaining much attention to improve the spectral efficiency and cater massive access problem. RL-based D2D communication has proven to be a viable solution [9].

Synchronization

The position of the signal synchronization block (SSB) in the time and frequency domains directly depends on the numerology N of the SCS. The SSB is mapped to four continuous OFDM symbols in the time domain and 240 SCs in the frequency domain. The SSB carries primary SS (PSS), secondary SS (SSS), physical broadcast control channel, and a demodulation reference signal. The PSS and SSS constitute cell and sector identification, which are critical for initial cell search. The length of the PSS is increased to 127, which is double that of LTE. The scalable numerology and increased PSS length complicate the detection of initial cell search, which degrades the reliability and latency [14].

Inter-Numerology Interference

Although shortening the TTI using high numerology of SCS is accepted as a potential solution for service requirements by 3GPP, it comes at the cost of inter-numerology interference (INI). The length of the CP scales according to the SCS; in other words, increasing the SCS reduces the CP. SCs with the same SCS are orthogonal to each other; however, SCs of different SCSs and CPs may interfere with each other. One of the potential solutions is to place fixed guard bands between subbands, which reduces spectral efficiency. The INI-power-aware resource allocation based on ML provides a solution to improve reliability and reduce interference [15].

Conclusion

In this study, we investigate the adaptive rate scheduling framework for 5G NR. The objective is to satisfy the service requirements from the perspective of latency, reliability, and coexistence of Het traffic in the 5G network. The rate adaption on the scheduler at the gNB is formulated as a MAB problem, which is also an MDP, and we propose to solve it using the UCB_1 algorithm.

The proposed intelligent rate adaption model learns the pattern of the Het traffic and determines the optimal rate deployment scheme at the gNB scheduler such that all the data of Het users in queue can be satisfied, and the latency and reliability requirements of the network can be improved. In the future, we will consider validating our framework in a real-time 5G network and further extend it for collaborative multi-agent RL at the gNB as well as the user equipment for both uplink and downlink transmissions to optimize the 5G NR network.

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