Machine Learning for 6G Enhanced Ultra-Reliable and Low-Latency Services

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***Abstract*—Ultra-reliable and low-latency communications (URLLC), as one of the major communication services of the fifth-generation (5G) and the sixth-generation (6G) cellular networks, is critical to supporting a variety of emerging mission-critical applications. However, the modern mobile networks could not satisfy the latency and reliability requirements as well as other Quality of Service (QoS) requirements, including spectrum efficiency, energy efficiency, capacity, jitter, round-trip delay, network coverage, and so on. To fulfill diverse QoS requirements for various URLLC applications, machine learning (ML) solutions are promising for future 6G networks. In this paper, we first categorize the 6G URLLC vision into three connectivity characteristics, including ubiquitous connectivity, deep connectivity, and holographic connectivity, with their corresponding unique QoS requirements. We then identify potential challenges in meeting these connectivity requirements, and investigate promising ML solutions to achieve the intelligent connectivity for the 6G URLLC service. We further discuss how to implement the ML algorithms to guarantee the QoS requirements for different URLLC scenarios, including mobility URLLC, massive URLLC, and broadband URLLC. Finally, we present a case study of downlink URLLC channel access problems, solved by centralized deep reinforcement learning (CDRL) and federated DRL (FDRL), respectively, which validates the effectiveness of machine learning for URLLC services.**

I. INTRODUCTION

Global telecommunications is ongoing an extraordinary transformation. The evolving network is expected to provide connectivity with extremely high speed, large-scale, tremendous capacity, low latency, low power consumption, and high reliability. Despite the deployment of the fifth-generation (5G) networks is presently well underway in many countries, 5G is unable to fully realize the vision of the Internet of Everything (IoE), due to the limited standardization time and the maturity of relevant technique development [1]. Current networks can only support the connectivity of the macro physical world with a limited spatial reach of thousands of meters above the land surface, which still has many shortcomings in the depth and breadth of information exchange [2]. The swift growth of human activities scope and the swift advancement of technical fields has increased the demand for more diverse and extensive information interaction, which motivates the research of the sixth-generation (6G) mobile cellular communication systems [2]. The vision of 6G is to largely enhance and extend the existing 5G three main services, including enhanced ultra-reliable and low latency communications (eURLLC), ultra-massive machine type communications (umMTC), and further-enhanced mobile broadband (feMBB) [3] [4].

The 6G mobile networks are expected to support an unprecedented proliferation of new IoE applications, including extended reality (XR) (including augmented, mixed, and virtual reality (AR/MR/VR)), tactile internet (TI), unmanned aerial vehicles (UAVs), brain-computer interfaces (BCI), and so on, that further exacerbate challenges for eURLLC services. These emerging applications not only substantially tougher reliability and latency criteria than those established set in 5G URLLC, but also impose massive connections and high data rate requirements. That is to say, the 6G eURLLC will conflate with both mMTC and eMBB, which disrupts the original 5G goal of offering straightforward short-packet, sensing-based classical URLLC services [3]. In a word, the 6G eURLLC is expected to support extremely reliable low latency communications (ERLLC), mobile broadband reliable low latency communications (MBRLLC), and massive-URLLC (mURLLC) services [4].

To satisfy diverse requirements for these various eURLLC applications, the 6G networks not only require new communication techniques like holography technology, haptic communications, Internet of Nano-Things (IoNT), Internet of BioNanoThings (IoBNT), space-air-ground integrated network (SAGIN), etc., but also require machine learning (ML) techniques [5]. Several existing works have focused on specific machine learning solutions, such as deep reinforcement learning (DRL) [6], federated learning (FL) [7], and transfer learning (TL) [8], for general wireless networks, and deep learning (DL) [9] for URLLC services. Yet, a comprehensive study on the vision of 6G eURLLC scenarios as well as their unique characteristics, and corresponding machine learning solutions has never been exploited.

The main contributions of this paper are: 1) we first categorize the 6G eURLLC vision into three connectivity characteristics, including ubiquitous connectivity, deep connectivity, and holographic connectivity, with their corresponding unique Quality of Service (QoS) requirements in Section II; 2) we then identify potential problems and challenges in meeting these connectivity requirements, and exploit promising ML techniques to design a multi-layer intelligent system to achieve the intelligent connectivity vision in Section III; 3) we further present how to implement different ML algorithms to

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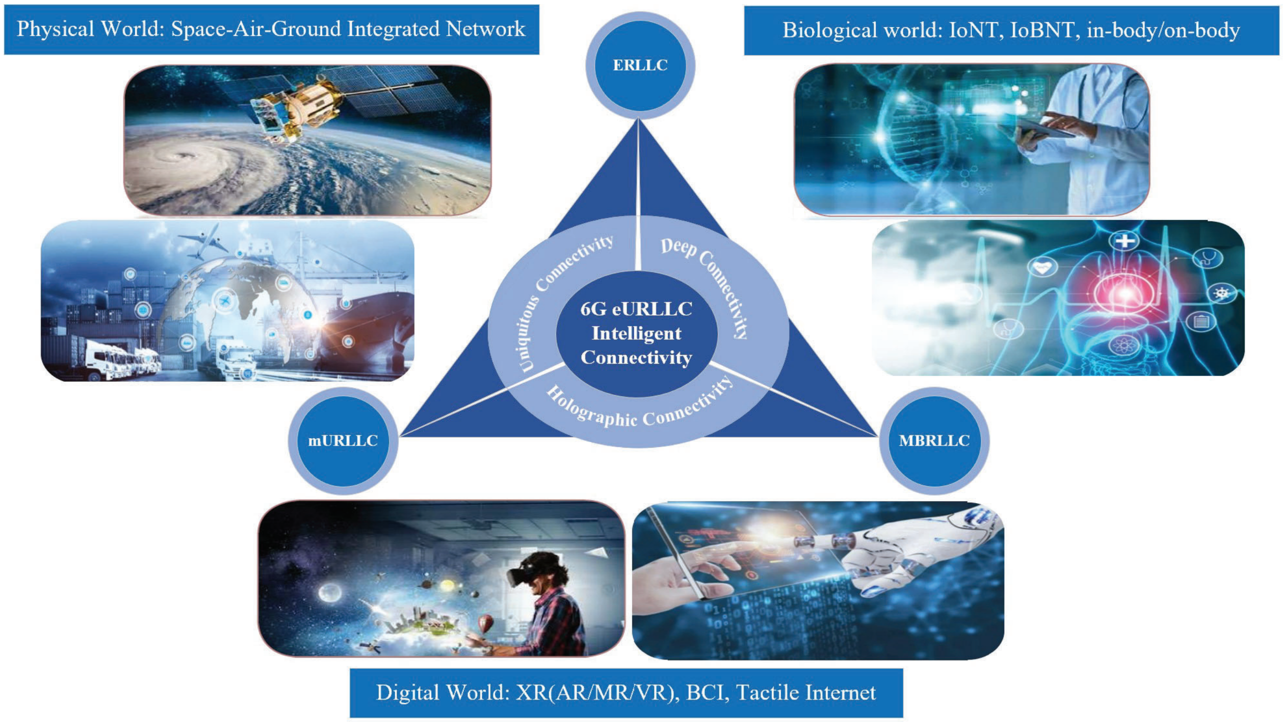

Fig. 1: Connectivity Vision and Application Scenarios for 6G eURLLC

guarantee the QoS requirements for different eURLLC applications, including mobility URLLC, massive URLLC, and broadband URLLC in Section IV; 4) in order to demonstrate the effectiveness of ML for 6G eURLLC service, we present a case study of channel access optimization problems for downlink URLLC, specifically based on the centralized deep reinforcement learning (CDRL) and federated DRL (FDRL) algorithms, respectively, in Section V. Finally, we conclude the paper in Section VI.

II. Connectivity Vision and Application Scenarios for 6G eURLLC

As illustrated in Fig. 1, the 6G eURLLC is expected to support emerging types of connectivity, including (i) ubiquitous connectivity, (ii) deep connectivity, and (iii) holographic connectivity. In this section, we will first characterize the vision of these three connectivity types and then describe the corresponding application scenarios for 6G eURLLC as well as their QoS requirements as shown in Table I.

A. 6G eURLLC Connectivity Vision

1) Ubiquitous Connectivity: The first trend of the 6G connectivity is the breadth expansion of the distribution areas of the connected things in the physical world, expanding from a limited space range of thousands of meters above the land surface to three-dimensional coverage and connection of all types of things in terrain and space. With the rapid development of science and technology in the fields of deep-sea exploration and astronautics, the human activity range is expanding quickly, which will greatly expand the geographic range of 6G networks. Thus, the 6G networks are expected to provide a broader connection anytime and anywhere, with the aim to achieve real 'ubiquitous connectivity' [10]. One scenario is that in an emergency, moving devices (e.g., UAVs and airplanes) in SAGIN can be exploited to deliver light healthcare supplies (e.g., medicines and surgical instruments) among hospitals or remote locations (e.g., rural, ocean, desert, islands, and mountain areas). This will reduce data interchange latency by assisting in the prevention of traffic congestion.

2) Deep Connectivity: The second trend of 6G connectivity is the depth expansion of the connected things, from traditional domains in the macro physical world to the complex sensing environment in the biological world. With the development of 6G technology and other interdisciplinary disciplines like materials science, bio-science, and bio-electronics medicine, it is expected to realize smart miniaturization, noninvasive biomedical measurements, and wearable in-body and on-body sensing with emerging IoBNT devices. These emerging applications could collect and sense signals from the biological environment and send them to data centers for processing through the internet. Thus, the 6G networks need to support a 'deep connectivity' vision [10]. One scenario involves IoBNT devices (e.g., implants, and on-body nano-devices), which are able to transmit data with extremely high reliability and low latency to the medical staff at hospitals by edge devices or cloud centers for medical analysis.

3) Holographic Connectivity: The third trend of 6G connectivity is the digitization of the physical world (e,g., cars, drones, transportation, factories, mobile devices, homes, cities) and the biological world (e.g., brains, organs, DNA, proteins, cells, molecules), i.e., from macro, micro to virtual, as the 'digital twin' [4]. The evolution of VR, AR, and MR technolo-

TABLE I: QoS Requirements of Different Use Cases for 6G eURLLC

Scenarios	Use cases	Qos Requirements
Healthcare IoT	Remote health monitoring	Reliability: $1-10^{-5}$, Latency: 1ms, Connectivity: 10^7 Devices/Km^2
	Telesurgery	Reliability: $1-10^{-9}$, Latency: 0.1ms, Data rate: 100–1000 Gb/s
Industrial IoT	Servo motors	Reliability: $1-10^{-7}$, Latency: 0.1ms, Jitter: $1\mu s$
	Motion control	Reliability: $1-10^{-6}$, Latency: $1\mu s$, Jitter: $1\mu s$
Automotive IoT	Delivery drones	Reliability: $1-10^{-6}$, Latency: 1ms, Mobility: >240km/h
	V2X	Reliability: $1-10^{-9}$, Latency: 0.1ms, Mobility: >1000km/h

gies towards XR in 6G communications is accelerated by the rapid development of new display and imaging technologies. This means that 6G networks will enable deep interactions for everything, and even merge several human senses (e.g., taste, smell, touch, sight, and hearing) to support a totally immersive experience at any time and place. Thus, the 6G networks are expected to support high fidelity XR and holographic communication with the aim to realize the 'holographic connectivity' vision [10]. One scenario is that surgeons could remotely oversee and control the surgery procedure via real-time video streaming with high resolution over holographic internet for accurate diagnosis, with the help of the medical devices or assistant robotics interconnected at high speed, low jitter, and low round-trip time (RTT).

B. 6G eURLLC Application Scenarios and QoS Requirements

According to the vision in Fig. 1, we present the corresponding Internet of Things (IoT) use cases for 6G eURLLC application scenarios and detailed their QoS requirements.

1) Healthcare IoT: 6G eURLLC could support healthcare applications since continuous low-latency and high-reliability communications are essential for services related to remote health and disaster response. For instance, in order to accomplish a quick and reliable remote diagnosis to provide real-time healthcare, the remote health monitoring applications require high reliability ($1-10^{-5}$) and low latency ($<$ 1ms) [11]. The telesurgery applications require continuous connectivity with ultra-reliability ($1-10^{-9}$) and ultra-low latency (sub-ms), due to a small latency and poor connectivity will cause severe fatal consequences in case of emergencies.

2) Industrial IoT: 6G eURLLC could further promote the manufacturing revolution (e.g., Industry 5.0), where most industrial applications rely on frequently updated control loops in an extremely reliable environment as well as low latency. In order to accommodate these high-frequency updates (e.g., 100 times per second updating of servo motor's closed control loop), extreme reliability ($1-10^{-7}$) and sub-millisecond latency ($<$ 0.1ms) are needed. The motion control applications (e.g., machine tools or packaging machines) in the industrial automation field, require reliability ($1-10^{-6}$) and microsecond level (ideally $1\mu s$) end-to-end latency (across the radio access, core, and transport networks) [12]. Low jitter is another crucial factor for such low latency industrial applications. In order to control industrial actuators, a jitter delay of $1\mu s$ is required to achieve real-time communications.

3) Automotive IoT: 6G eURLLC could transform the entire transportation ecosystem by supporting vehicle-to-everything (V2X) communication, which will contribute to autonomous vehicles in the future. The V2X communications will have far-reaching effects on vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), vehicle-to-infrastructure (V2I), and vehicle-to-cloud (V2C) by providing low latency, high reliability, and high throughput communications. In V2X communications, each communication channel requires extreme network parameters. Extremely low latency (1ms) and high reliability ($1-10^{-9}$) [12] are needed for connectivity among medical facilities delivery drones and connectivity among the roadside infrastructures.

III. Challenges and Machine Learning Solutions

The 6G networks are envisioned to be large-scale, multi-layered, ultra-dense, high dimensional, dynamic, and heterogeneous. These characteristics pose great challenges to 6G eURLLC services: 1) the massive amounts of highly heterogeneous data collected from 6G mobile networks makes it hard to extract meaningful and useful information for further network optimization and eURLLC performance improvement; 2) the complicated time-variant hybrid communication environment makes it hard to achieve the automated operation of 6G eURLLC applications via conventional network optimization techniques; and 3) the formulated eURLLC optimization problems usually require trade-offs among multiple objectives (e.g., latency, reliability, mobility, capacity, and data rate) in order to achieve a suitable solution, which is hard to handle using conventional mathematical techniques.

These challenges make it vital to explore emerging adaptive and flexible techniques to achieve intelligent 6G eURLLC communications with ultra-reliability, ultra-low latency, ultra-massive access, and ultra-broadband. In recent years, as a key paradigm, artificial intelligence (AI) could support coordinating communication and information systems from bottom to top. In order to overcome the aforementioned challenges, ML approaches, as a significant branch of AI, are able to establish an intelligent system operating in complicated environments, thanks to their tremendous learning, optimizing, and intelligent recognition capabilities. The intelligent system

TABLE II: Challenges and Machine Learning Solutions for 6G eURLLC

ML-enabled Intelligent Wireless System for 6G eURLLC Services			
Layers	**Issues**	**Challenges**	**ML Solutions**
Intelligent Perception Layer	Data Gathering	Massive Devices	CNN: improve sensing accuracy and reliability; SVM&K-means clustering: achieve real-time sensing.
	Environment Monitoring	Varying Environment	
Intelligent Analytics Layer	Compress and Filter	High Dimensiona	PCA, ISOMAP: compress and filter high-dimensional data; RBM, DBN, CNN, GNN: address large-scale heterogeneous data fusion.
	Knowledge Discovery	Heterogeneous	
Intelligent Control Layer	Decision Making	Multiple Objectives	Constrained DRL: latency and reliability requirements formulated as constraints.
	Performance Optimization	High-quality Requirements	
Intelligent Application Layer	Service Provisioning	Resource Utilization	Knowledge-assisted DL: improve utilization efficiency of manufacturing resources; FL: trade-off between learning accuracy, communication latency, and computation latency.
	Performance Evaluation	Effectiveness	
Implement ML Solutions for Different eURLLC Application Scenarios			
Scenarios	**Challenges**		**ML Solutions**
Mobility URLLC:	High-speed mobility, Frequent handovers		Precise Prediction: knowledge-assisted DL-based predictive algorithms, RNN based DL predictive algorithms, TL adapted on DNNs, LSTM Method; Decision Making: fuzzy Q-learning, DRL-based algorithm.
Massive URLLC:	Simultaneously deliver several critical QoS requirements, Massive devices lead to network congestion with degraded QoS performance		Scheduling and Allocation: DRL approach, distributed multi-agent DRL; Multiuser Detection: DNN-aided GF-NOMA system with deep auto-encoder, DNN-aided message-passing-based block sparse Bayesian Learning algorithm.
Broadband URLLC:	Data rate of up to terabits per second, Boost the need for spectrum		Channel Modeling and Estimation: RL-based Bayesian filter for angle-of-arrival (AoA) estimation in terahertz channels; Spectrum Sharing: DRL-based occupied spectrum predict algorithms, FL approaches improve learning performances

can be applied to intelligently achieve knowledge discovery, complex decision-making, and performance optimization, to fulfill diverse QoS requirements of emerging eURLLC applications [13]. This section focuses on the ML-enabled intelligent wireless system for 6G eURLLC services with multiple layers: sensing layer, analytics layer, control layer, and application layer [13], as illustrated in Table II.

A. *Intelligent Perception Layer*

In the first perception (sensing) layer, a massive number of devices (e.g., cameras, robots, drones, and vehicles) will sense and detect data from physical or biological environments in real-time and then communicate to the Access Point (AP) [13]. It is noteworthy that highly reliable sensing in real-time for 6G eURLLC services is important but challenging for massive connectivity devices to collect data in a continuously varying environment. In this context, cutting-edge ML approaches are needed in this layer to achieve intelligent environmental monitoring, data collection, dynamic spectrum access and interference management, that have ultra-low latency and ultra-reliability requirements of eURLLC services. Cooperative sensing based on convolutional neural networks (CNN) can increase sensing accuracy and reliability with low complexity. By training low-dimensional input samples, the support vector machine (SVM) and K-means clustering could be exploited to do reliable sensing in real time [13].

B. *Intelligent Analytics Layer*

In the second analytics layer, the AP will process (reduce and filter), analyze (useful and valuable), compute, and store a large amount of raw data produced by the massive number of devices from the first perception layer in the networks [13]. It is important to discover valuable patterns or rules during data analytics, known as ‘knowledge’, to provide useful information for protocol adaptation, architecture slicing, resource management, and so on for eURLLC services [13]. However, for massive URLLC services, the heterogeneous, nonlinear, and high dimensional nature of massive acquired data poses challenges in processing and analyzing data to achieve semantic derivation and knowledge discovery. Large-scale heterogeneous data fusion can be addressed by ML-based data analysis and mining techniques, such as advanced neural networks (ANNs) including deep belief network (DBN), CNN, graph neural network (GNN), and restricted Boltzmann machine (RBM), to get meaningful information. The massively gathered high-dimensional data (e.g., channel information, photos, and videos) could be compressed and filtered using two additional traditional dimension reduction algorithms, principal component analysis (PCA) and isometric mapping (ISOMAP) [13]. As a result, it may be possible to significantly reduce model complexity, storage space, and processing latency.

C. Intelligent Control Layer

In the third control layer, the controllers will make decisions based on the 'knowledge' obtained from the lower layers [13]. Those decisions include power control, spectrum access, routing management, resource allocation, edge computing, network association, network slicing, and so on. For various eURLLC applications with high-quality requirements, specific efficient decision-making objectives include the appropriate routing strategy management in dynamic SAGIN for mobility URLLC service, the flexible spectrum access for massive URLLC service, and the parameter selection of Terahertz (THz) transmission for broadband URLLC service. The ML techniques, instead of traditional algorithms that have heavy mathematical models, need to be investigated to achieve parameter optimization based on global objectives (e.g., reliability, latency, connectivity, and coverage) for various eURLLC services. The problem is generally multi-objective optimization due to that in 6G eURLLC applications, multiple performance metrics need to be jointly optimized. Most of the existing works solve this problem by maximizing or minimizing a weighted sum of different performance metrics, where the weighting coefficients are determined manually. Another possible solution is constrained DRL, where the latency and reliability requirements could be formulated as constraints and other variables including weighting coefficients could be optimized iteratively with the primal-dual method.

D. Intelligent Application Layer

In the fourth application layer, the primary duty is to deliver specific vertical eURLLC application services according to their diverse requirements including latency, reliability, mobility, coverage, and data rate, as well as evaluate the provisioned services [13]. These emerging specific vertical eURLLC applications, including XR for automated industry, UAVs for smart health, and autonomous vehicles for smart transportation, etc., introduce diverse tasks with stringent requirements pose critical challenges to traditional bit-oriented communications. ML algorithms are required to scale up performance as well as save energy and resources in order to serve a variety of smart eURLLC applications. For instance, the knowledge-assisted DL methods could significantly improve the QoS of smart factories and the utilization efficiency of resources. As such, the experts or engineers can transfer their skills remotely through remote supervision, maintenance, and management using various types of XR and teleoperation equipment with super-fast, ultra-low latency, and ultra-reliable connections. The FL approaches could be designed to balance the trade-off between learning accuracy, communication latency, and computation latency for object recognition in autonomous vehicles. Efficient FL approaches could decrease the model size to satisfy latency constraints via federated dropout, federated pruning, and model compression, where the loss functions with latency constraints could be utilized to evaluate the effectiveness of service.

IV. Machine Learning Implementation in Different Application Scenarios

Based on the ML-based intelligent system described in Section III, we discuss how to implement the ML solutions for different eURLLC application scenarios, including mobility URLLC, massive URLLC, and broadband URLLC in this section, as illustrated in Table II.

A. Mobility URLLC

A large number of high-speed mobility devices (e.g., vehicles, satellites, and UAVs) in 6G SAGIN will contribute to frequent handovers. Efficient mobility and handover management are two main challenging issues of 6G eURLLC services that require continuous communication with low latency and high reliability. ML techniques could be exploited to intelligently execute mobility prediction and handover optimization for 6G eURLLC services.

- Precise Prediction: In order to void frequent handovers or handover failures to reduce latency as well as increase reliability, the knowledge-assisted DL-based predictive algorithms could efficiently predict the mobility patterns of high-speed vehicles or trajectories of UAVs. The DL predictive algorithms could be based on the recurrent neural network (RNN) to improve the accuracy of state estimation. The pre-trained deep neural network (DNNs) could adopt the transfer learning (TL) algorithms to fine-tune non-stationary 6G mobile networks for improving learning efficiency and performance. Another effective DL technique is the long short-term memory (LSTM) method, which may be exploited to learn a series of future time-dependent mobility states and predict future trajectories in order to optimize handover parameters and improve mobility URLLC performance.
- Decision Making: In order to avoid frequent handovers and reduce connectivity failures for URLLC performance guarantee, the DRL can be exploited to optimize the handover strategies for high-speed mobility devices in time-varying environments. In the DRL-based algorithm, each device can be treated as an agent to observe the environment states (e.g., movement velocity, channel quality, and device location) and then choose the best actions (e.g., parameters related to mobility or handover) to obtain the greatest reward defined by the transmission latency, reliability, and so on. [13].

B. Massive URLLC

The massive URLLC must simultaneously deliver several critical QoS requirements, including high reliability, low latency, and massive connectivity. Such applications include reliable massive health data delivery in real time to facilitate remote healthcare as well as reliable massive information sharing among V2X to enhance road safety and improve traffic efficiency. However, these massive devices will lead to network congestion with degraded QoS performance, which poses a big challenge for 6G eURLLC applications. As a result of recent developments in ML techniques, it is an outstanding tool for supporting mURLLC in 6G to provide excellent solutions for user scheduling, resource allocation, and user detection [11].

- Scheduling and Allocation: For the grant-free non-orthogonal multiple access (GF-NOMA) schemes that are available for 6G massive URLLC, the collision problem (two or more users choose the same pilot sequence) is the bottleneck for reliability performance. In GF-NOMA systems, the DRL approach can be exploited to optimize pilot sequence selection and scheduling in GF-NOMA since it does not need tractable mathematical models. The choice of the pilot sequences should be carried out by the users in a distributed way because it is impractical for users to share their information with each other in reality [14]. As a result, distributed multi-agent DRL is a promising method to learn about the contention status (collision or not) at resource blocks and exploit potential superior resource blocks with fewer collisions to achieve higher reliability in an uncoordinated manner.
- Multiuser Detection: GF-NOMA schemes for massive URLLC also pose challenges in terms of user detection at the receiver. This is owing to the fact that in cases with massive connectivity, the receiver cannot identify the user activity because of the significant correlation between the pilot sequences. Therefore, ML approaches could be exploited to solve user detection problems in the scenarios of massive number of devices and strict latency limitations. The data decoding could be performed by a deep auto-encoder, and the spreading signature selection could be optimized by a DNN-aided GF-NOMA system [14]. The user activity detection as well as channel estimation could be accomplished by DNN-aided message-passing-based block sparse Bayesian learning methods.

C. Broadband URLLC

The emerging broadband URLLC applications may require up to terabits per second data rate to make these devices operate smoothly not only in the uplink but also in the downlink. Such applications include autonomous vehicles, which will require a high data rate for reliable data (e.g., high-definition images and videos). Providing broadband URLLC with rate and capacity guarantees for such applications boost the need for spectrum. It is necessary to explore both wider communication bandwidths (e.g., terahertz channel) and spectrum sharing (e.g., unlicensed bands sharing) as well as their corresponding ML solutions.

- Channel Modeling and Estimation: The reliability of the terahertz channels may be compromised due to free-space path loss, molecular absorption attenuation, and limited communication range. Especially for dynamic scenarios with high-speed moving devices, traditional channel models based on stationary or quasi-stationary assumptions will no longer be appropriate for terahertz channels that are seen as non-stationary. The challenges of terahertz channel modeling and estimation for 6G eURLLC services can be addressed by a wide variety of ML methods. For the angle-of-arrival (AoA) estimation of terahertz channels, the RL-based Bayesian filter might be exploited to improve estimation accuracy under dynamic conditions for applications (e.g., MR and XR). The RL algorithms can also be exploited for channel modulation, channel tracking, channel selection, and channel coding design [14].
- Spectrum Sharing: The coexistence of existing use cases like satellite services and future terahertz communications requires spectrum sharing. The DRL-based prediction methods can be exploited to help to make decisions about accessing or releasing the spectrum band, in order to guarantee priority access for URLLC devices [14]. In contrast to centralized algorithms, distributed algorithms can save a significant amount of network spectrum resources for data training in complex scenarios. By avoiding the offloading of a massive number of data to the remote server during the training process, the FL methods could be exploited to provide low-latency network interactions [14]. Furthermore, the cooperation of a large number of devices for FL could hasten the convergence rate and thereby enhance 6G eURLLC learning performances.

V. Case Study

Due to the increase in traffic and bandwidth requirements for new URLLC applications, the licensed spectrum is in shortage and the unlicensed spectrum becomes a promising alternative considering its high flexibility and availability of bandwidth. As such, in this section, we validate the effectiveness of ML methods in optimizing downlink URLLC channel access problems about unlicensed spectrum sharing between New Radio Unlicensed (NR-U) and WiFi systems.

It should be noted that each node in NR-U and WiFi has to perform the Listen-Before-Talk (LBT) and Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) before transmission to avoid collisions among different nodes, respectively. During the LBT and CSMA/CA, the node senses the channel and compares the received power with a pre-determined energy detection (ED) threshold to determine if the channel is idle. The channel access over the sharing unlicensed spectrum can be modeled as a Markov decision process. In this process, the agents at NR-U gNodeBs (gNBs) and WiFi APs take actions to choose the ED thresholds from $[-82\text{dBm}, -52\text{dBm}]$, respectively, according to the current state and strategy, and receive rewards from the environment. The goal of our study case is to maximize the long-term successfully served packets for downlink URLLC.

We consider an indoor downlink transmission scenario defined by 3GPP [15] for the coexistence between the NR-U and WiFi systems in the 5 GHz band, which is located in a 120m × 80m area and a distance between two neighbors gNB/AP nodes of 40m. In particular, WiFi and NR-U systems share a single 20-MHz channel, and each of them deploys three small cells in a one-floor building The gNB/AP nodes are mounted at a height of 3m on the ceiling and 200 NR-U user equipments (UEs)/WiFi stations (STAs) are uniformly distributed in this layout with a height of 1m. The small packets are generated according to random inter-arrival processes over the subframes. This type of traffic is also known as FTP-3 traffic in 3GPP scope. The packet size is assumed to be fixed to 32 bytes for URLLC service.

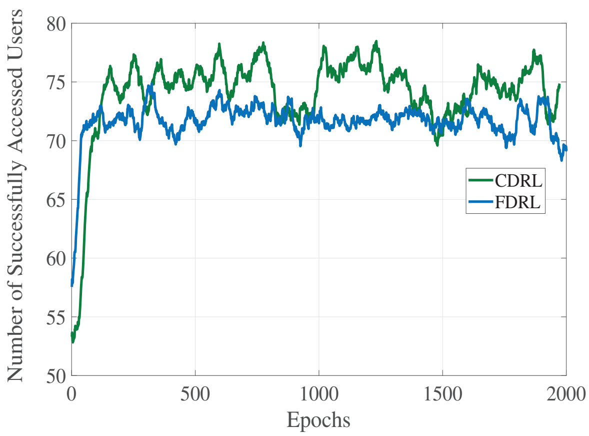

Fig. 2: Average number of successfully accessed users

Fig. 2 plots the convergence performances of centralized DRL (CDRL) and federated DRL (FDRL) algorithms, respectively. We can see that the convergence speed of the FDRL is a little bit faster than that of the CDRL. Table III compares the reliability performance of the converged CDRL and FDRL trained model with that of the fixed ED threshold setting. We observe that both system and NR-U achieve expected more than 100% reliability performance gain by applying the CDRL or FDRL. But the WiFi performance gain in FDRL (130.82%) is much larger than that in CDRL (13.48%). The simulation results show that the node cooperation in the FDRL would hasten the overall training process convergence rate and enhance intelligent 6G eURLLC learning performances. This demonstrates the advantages of FDRL for concurrent local data training and experience sharing via the server with the model aggregation technique.

TABLE III: Reliability of CDRL and FDRL

Reliability	NR-U + WiFi System	NR-U	WiFi
Fix	13.61%	40.41 %	5.19 %
CDRL	52.17%	86.79 %	5.89 %
FDRL	50.43%	81.05 %	11.98 %
Reliability Gain	NR-U + WiFi System	NR-U	WiFi
CDRL Gain	+283.32%	+114.77%	+13.48%
FDRL Gain	+270.54%	+100.57%	+130.82%

VI. Conclusions

In this paper, we first categorized the 6G eURLLC vision into three connectivity characteristics, including ubiquitous connectivity, deep connectivity, and holographic connectivity, with their corresponding unique QoS requirements. We then identified potential challenges in meeting these connectivity requirements, and investigated promising ML solutions in a designed multi-layer intelligent system to achieve the intelligent connectivity vision. We further discussed how to implement ML solutions for different eURLLC applications including mobility URLLC, massive URLLC, and broadband URLLC to guarantee their QoS requirements, respectively. Finally, in order to verify the efficacy of ML solutions, we applied both CDRL and FDRL algorithms for downlink URLLC channel access optimization problems. This work provides inspiration for future research to develop ML solutions that take into account aspects of the 6G eURLLC connectivity vision with strict QoS requirements.

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