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A Survey on Deep Learning for Ultra-Reliable and Low-Latency Communications Challenges on 6G Wireless Systems

ADEEB SALH[1], (Member, IEEE), LUKMAN AUDAH[1], (Member, IEEE), NOR SHAHIDA MOHD SHAH[2], (Member, IEEE), ABDULRAQEB ALHAMMADI[3], (Member, IEEE), QAZWAN ABDULLAH[1], (Member, IEEE), YUN HEE KIM[4], (Senior Member, IEEE), SAMIR AHMED AL-GAILANI[5], SHIPUN A. HAMZAH[1], BASHAR ALI F. ESMAIL[1], (Graduate Student Member, IEEE), AND AKRAM A. ALMOHAMMEDI[6], (Member, IEEE)

[1]Wireless and Radio Science Centre (WARAS), Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Parit Raja 86400, Malaysia
[2]Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia, Parit Raja 86400, Malaysia
[3]Department of Electronics and Communication Engineering, College of Engineering, A'Sharqiyah University (ASU), Ibra 400, Oman
[4]Department of Electronics Engineering, Kyung Hee University, Yongin 449-701, South Korea
[5]School of Electrical and Electronic Engineering, Universiti Sains Malaysia, Nibong Tebal 14300, Malaysia
[6]Automobile Transportation Department, South Ural State University, 454080 Chelyabinsk, Russia

Corresponding authors: Nor Shahida Mohd Shah (shahida@uthm.edu.my) and Lukman Audah (hanif@uthm.edu.my)

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ABSTRACT The sixth generation (6G) wireless communication network presents itself as a promising technique that can be utilized to provide a fully data-driven network evaluating and optimizing the end-to-end behavior and big volumes of a real-time network within a data rate of Tb/s. In addition, 6G adopts an average of 1000+ massive number of connections per person in one decade (2030 virtually instantaneously). The data-driven network is a novel service paradigm that offers a new application for the future of 6G wireless communication and network architecture. It enables ultra-reliable and low latency communication (URLLC) enhancing information transmission up to around 1 Tb/s data rate while achieving a 0.1 millisecond transmission latency. The main limitation of this technique is the computational power available for distributing with big data and greatly designed artificial neural networks. The work carried out in this paper aims to highlight improvements to the multi-level architecture by enabling artificial intelligence (AI) in URLLC providing a new technique in designing wireless networks. This is done through the application of learning, predicting, and decision-making to manage the stream of individuals trained by big data. The secondary aim of this research paper is to improve a multi-level architecture. This enables user level for device intelligence, cell level for edge intelligence, and cloud intelligence for URLLC. The improvement mainly depends on using the training process in unsupervised learning by developing data-driven resource management. In addition, improving a multi-level architecture for URLLC through deep learning (DL) would facilitate the creation of a data-driven AI system, 6G networks for intelligent devices, and technologies based on an effective learning capability. These investigational problems are essential in addressing the requirements in the creation of future smart networks. Moreover, this work provides further ideas on several research gaps between DL and 6G that are up-to-date unknown.

INDEX TERMS Artificial neural networks, artificial intelligence, Internet of Things, sixth-generation wireless communication and network architecture, URLLC.

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I. INTRODUCTION

The role of artificial intelligence (AI) in the development of intelligence-enabled edge computing, connections in the process of edge intelligence, intelligent devices for mobile users (MUs), and edge infrastructure components is a driving force behind the development of the sixth generation (6G) of wireless communications [1], [2]. The novel generation is expected to employ wide frequency bands to provide big data.

Through the implementation of high AI technology and a large bandwidth of terahertz (0.1-10 THz), the 6G is expected to provide a high data rate of 1,000 Gbps, and a user experience data rate of 1 Gbps. Moreover, the large bandwidth of THz offers high-data rates, which act as the driving force in optimizing 6G wireless networks, including machine learning (ML) and deep learning (DL). However, 5G wireless networks have recently led to the development of several components of 6G, whereas the 6G is expected to fully support AI, enhanced mobile broadband, massive Internet-of-Things (IoT), cell-free communications, holographic beamforming, as well as high data analytics. The ultimate goal in creating 6G, namely, providing a fully-immersive user experience that serves as a fully intelligent system, has not yet been achieved. The 6G needs to increase capacity, not only in terms of bandwidth, but also in terms of coverage. It might potentially offer more perspectives in terms of brain-computer interfaces, making it viable to "use devices via our brain. Additionally, the 5G system is not guaranteed to enhance all communication services among people and things, due to the fact that ultra-reliable and low latency communication (URLLC) has become a critical performance criterion. The open 6G network is able to provide sufficient communication services from people to things and from things to things, based on utilizing the connection intelligence for leveraging terminal and concentrated intelligence.

A. 6G TECHNOLOGY

To support a high rate and reliability, the abundant bandwidth of THz must be utilized. On the other hand, the 5G network supports various applications such as a Gbps speed of an enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), and a microsecond delay of 99.99% of the level of URLLC transmissions to meet the needs of the information civilization through 6G technology [3]–[6]. However, a guarantee of high reliability depends on redesigning the physical layer and enabling technologies, including packet and frame structure [7]–[11]. Among the major challenges in developing 6G wireless networks is supporting the ultra-broadband to increase the system's capacity by augmenting the system bandwidth to THz and improving the spectrum efficiency by decreasing the propagation loss [12]–[15]. The THz band is projected to grant a Tbps data speed to fulfill extremely high URLLC, providing 6G wireless networks with better resolution in sensing, and greater accuracy in positioning. The more the bandwidth capacity increases, the greater the big data in 6G, which can theoretically be obtained by applying a sub-THz radio spectrum over 90GHz. On the other hand, the design of 6G wireless networks is estimated to provide big data rates with low latency through employing intelligence. 6G is expected to be a paradigm shift by introducing a complete control of transmission, estimation, caching and resource areas [1], [16]–[18]. Due to its rapid development, 6G is expected to support high-quality services and satisfy the demand for improved aspects of wireless networks, including Internet of Everything (IoE), massive connectivity, low latency, high security, eMBB and reliable connectivity.

The internet protocol, new holographic media, and network architecture were all established to facilitate the development of 6G by contributing to the study of wireless equipment, and the standard improvement in the International Telecommunication Union (ITU) [19]. 6G technology is predicted to have far-reaching impacts, beyond the sphere of the mobile internet, such as supporting AI by improving protocols and architectures. The connecting networks in wireless communication depend on associate intelligence with ML capabilities. Recent developments in AI have solved some of the most daunting bottlenecks in technology in areas such as route management, topology control, security, and secrecy of the transmission network. One of the essential challenges in 6G research is the efficient utilization of transmitting up to 1 Tbps per user. The radio spectrum from 0.1 THz to 10 THz offers opportunities for massive signal bandwidths, exceptionally enhancing 6G's wireless transmission capacity [19], [20].

B. KEY CONTRIBUTIONS

This survey focuses primarily on DL for URLLC that provides a critical performance criterion 6G networks. It also provides a detailed discussion of multi-level architecture by enabling AI. Furthermore, it presents a multi-level architecture for URLLC through DL to create a data-driven AI system, 6G networks for intelligent devices, and technologies based on practical learning capability. Finally, we highlight future research based on application scenarios and a multi-level architecture that enables a data-driven DL. The contributions of this survey can be summarized as follows:

- We highlight the key requirements of URLLC and the challenges currently threatening the vision of 6G wireless networks. This vision was adopted from the recent literature on sharing directions for the 6G by incorporating achievable AI in advanced ML techniques.
- We provide a detailed discussion of the advantageous new services that will be offered by 6G wireless networks, including their fundamental principles and general applications such as holographic radio, advanced wireless channel coding, massive IoTs, integrated and haptic communication, and Tactile Internet for URLLC.
- We discuss the significant challenges that need to be addressed regarding DL's developments to provide high computation efficiency.
- We identify the research challenges and determine the fundamental concepts and technologies that 6G ML algorithms should adopt, including supervised learning, unsupervised learning, and reinforcement learning for big data. Moreover, more attention has been on

TABLE 1. List of abbreviations in alphabetical order.

ITEM	DESCRIPTION
5G	Fifth Generation
6G	Sixth Generation
URLLC	Ultra-Reliable and Low Latency Communication
AI	Artificial Intelligence
DL	Deep Learning
ML	Machine learning
MU	Mobile Users
IoT	Internet-of-Things
THz	Terahertz
eMBB	Enhanced Mobile Broadband
mMTC	Massive Machine-Type Communication
IoE	Internet of Everything
ITU	International Telecommunication Union
QoS	Quality of Service
E2E	End-to-End
PDCCH	Physical Downlink Control Channel
PDSCH	Physical Downlink Shared Channel
DTX	Discontinuous Transmission
NACK	Negative Acknowledgment
ACK	Acknowledgment
PER	Packet Error Rate
SVC	Sparse Vector Coding Technique
CC	Convolution Code
PC	Polar Code
CSI	Channel State Information
KPI	Key Performance Indicators
DNNs	Deep Neural Networks
NB-IoT	Narrowband IoT
LTE-M	Long Term Evaluation Machine
MEC	Mobile Edge Computing
SON	Self-Organizing Networks
AoA	Angle-of-Arrival
ToA	Time-of-Arrival
SDN	Software Defined Networking
LTE	Long Term Evolution
BLER	Block Error Rate
ANN	Artificial Neural Network
ELU	Exponential Linear Unit activation
ReLU	Rectified Linear Unit
Deep-RL	Deep Reinforcement Learning
NR	New Radio

a URLLC design that enables precise predictions of channels and high traffic data speed, which is essentially predictive and controls the new development in DL.

- We suggest several future research directions that enable a data-driven DL to support slices in 6G networks, thus improving network performance based on its effective learning capabilities.

C. PAPER ORGANIZATION

The work is further structured as shown in Fig. 1. We begin by discussing the importance of URLLC for 6G networks compared to 5G networks, based on AI-enabled technology. In Section II, we present the literature of prior work on smart data-driven base in URLLC using DL. Section III discusses the requirements, frame, and packet structures of URLLC. Section IV presents the potential key technologies and new services that 6G offers. Section V discusses the various types of ML-enabled intelligent 6G networks. Section VI explains the multi-level architecture that enables a data-driven network for URLLC. Future research directions for AI technologies that are predicted to improve 6G network performance are outlined in Section VII. Finally, Section VIII concludes the paper.

II. RELATED WORKS

There a number of previous studies have been conducted on the development of a smart data-driven base for improving traffic-flow prediction. Besides, DL plays an important role in URLLC through addressing the critical applications scenario. This development in smart data-driven networks depends on applying the short-term correlation prediction to the intelligent Internet of Things (IoTs) and control architecture to achieve URLLC.

A. CURRENT RESEARCH PROGRESS FOR URLLC TOWARDS 6G

Increased management of traffic flow provides efficient, reliable data-driven predictions for transmitting packets in real-time networks to improve the multi-level architecture for data-driven networks. In addition, it allows for transmitting packets by learning from data-traffic demand predictions under a non-stationary and predictable environment based on URLLC, as proposed in [21]. The multi-level architecture of URLLC for IoT devices is forced to rely on unnecessary power and process capabilities that are unsuitable for the lifetime of IoT devices [16], [17], [19]. However, the peak throughput and DL networks improved the data-driven network based on a large quantity of training data, to enhance the parameters of training samples by implementing allocated, intelligent wireless computing, as proposed in [22], [23].

The greater the number of devices that IoTs are able to provide, the more suitable the small power devices, and the more they provide high reliability for long-range communication. Furthermore, based on the high number of collisions in the IoT access network, the developing ultra-dense IoT networks are able to address ML to enable devices to regularly learn the random-access channel in cellular IoT networks [23]–[25]. The AI in question is an advanced ML technique, optimized edge computing networks based on the proposed advancement of URLLC, as well as the distributed AI, which all work together to achieve high reliability and throughput in the URLLC [26], [27].

The ultra-dense IoT networks are able to process intermittent transmissions, a large number of data packet transmissions, and unsuitable transmission scheduling, by utilizing a distributed cache of IoT devices to manage their irregular transmissions. The high throughput and reliability are improved by enabling modern random access for IoT systems based on advanced signal processing and increasing the intelligence to fulfill the least long-term costs up to 56% in improvement in 6G to provide big data [28]–[32]. The DL uses reliable predictive models of URLLC to enhance the implementation of space air-ground by selecting the correct

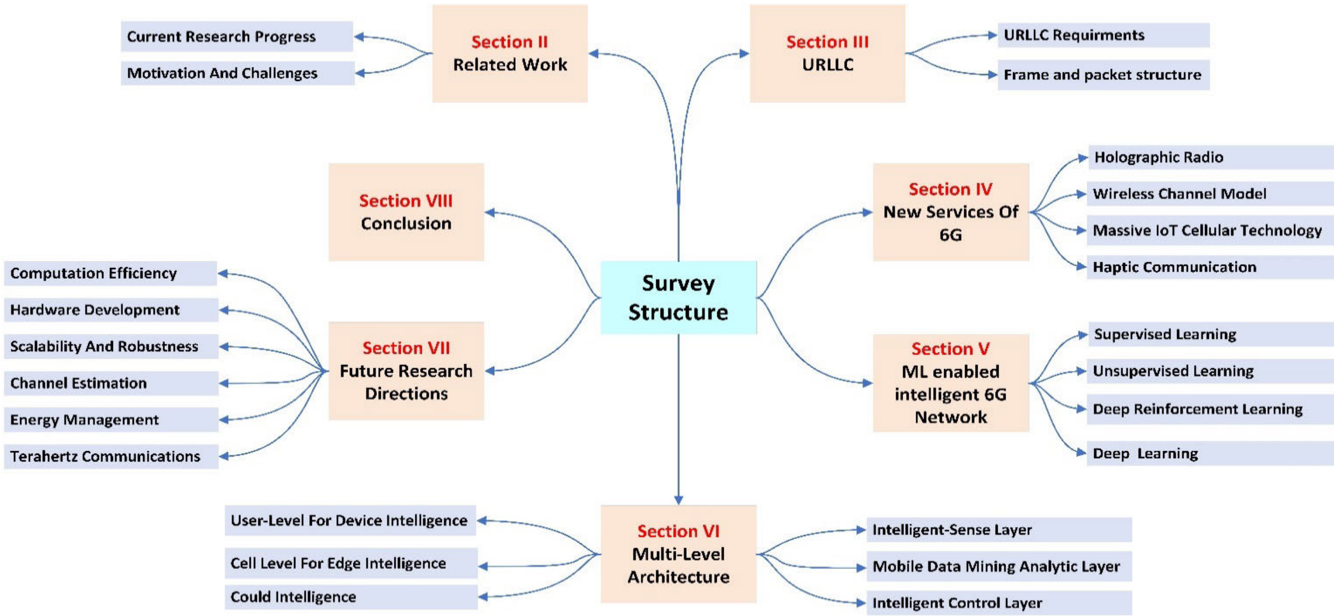


FIGURE 1. Diagrammatic view of survey structure.

paths and increasing the big data communication requirements, and supporting DL in the physical layer network. The high quality of service (QoS) and capacity depend on the rate and latency-reliability space that supports the connectivity for a large number of devices in physical environments. However, the improved QoS for MU depends on the implementation of intelligence for ML in 6G to provide high throughput and ultra-low latency [16]–[18], [31]–[34]–[45]. This study aims to fill the gaps found in the application scenarios of multi-level architectures for 6G networks, including mobility and traffic prediction for all MU, scheduler design at each access point, user connection in a multi-access point [46]–[49], [50]–[53], [54]–[58], and multi-level architecture for URLLC in DL [18], [65], [61]. This involves carrying out the following steps: providing a fresh and in-depth look at URLLC based on the AI-enabled intelligence active in 6G networks; highlighting the importance of URLLC; discussing the efficiency of the developing network that can process large quantities of data with the smallest delay possible and addressing the challenges faced in application scenarios, and discussing six key technologies that provide a survey on various ML techniques that are realistically capable of improving communication. Table 2 displays the summary of several related works to the URLLC.

In the process, this review also provides a comprehensive discussion of DL systems for several reasons. First, the lack of proposing different enabled AI technologies for use in URLLC that should provide the community with an important research area to embark upon for the vision for 6G wireless networks. The second reason is to shed light on 6G technologies such as holographic radio, advanced wireless channel coding, massive integrated IoT, and haptic communication and tactile internet that enhance the predictive leveraging of new developments in ML. Third, we highlight the challenges underlying 6G, which is necessary for designing an efficient AI in the framework based on the effective learning capability and a multi-level architecture. Also, the implementation of the training process in an unsupervised learning setting is vital to enhance performance and enable a data-driven network in the AI based on the proposed DL. Finally, the final reason is to identify the strategies used to evaluate, and the disciplinary techniques for supervised, unsupervised, and reinforcement learning (RL) through improving the multi-level architecture to decrease the treating time and prevent delays. The capability of ML to provide accurate traffic packets for URLLC depends on efficient distributed training for computation complexity, and guarantees the QoS requirements on the end-to-end (E2E) latency and reliability for every user.

B. MOTIVATION AND CHALLENGES

Recently, the 5G wireless network was developed to support eMBB, mMTC, and URLLC, based on the report of ITU-R [2]. Based on such excellent characteristics of 5G, it has opened new opportunities towards developing applications. The main drawback of 5G is its low data rate if implemented within AI technology. However, the 6G communication technologies will unveil certain unique features, namely ultrahigh data rate, broadband multiple services, scalable bandwidth, and flexible communications for manifold end-users, which requires higher data rates of Tb/s, than augmented reality and impending virtual reality. So to fulfill the noted unique features of the network, AI with a high level of intelligence will be the main driver of mobile technology

TABLE 2. A Summary of several works reared to URLLC.

Reference	Short Description	AI		URLLC		Technology	
		DL	Other ML	IoT	Mobile Network	5G	6G
Letaief Khaled [22]	Presented an AI-empowered by designing and optimizing 6G architectures of URLLC to provide a massive low-latency control (less than 1 msec E2E latency.		√		√		√
Murtaza Ahmed Siddiqi [23]	Highlights the implementation issues of URLLC with IoT devices. It discusses the recent progress 3GPP standardization for URLLC and the role of URLLC in operating IoT, in terms of massive device connectivity, on-device AI, vehicle-to-vehicle, IoT energy efficiency and device-to-device communications.		√	√	√	√	
Mehdi Bennis [24]	Provides a background on latency and reliability, and examines several URLLC enablers and their inherent tradeoffs. It also focuses on various methodologies that pay attention to the URLLC requirements. The paper also discusses several URLLC applications through selected use cases.		√		√	√	
Mohammed S. Elbamby [30]	Focuses on edge computing in terms of applications provided by the network edge, and the challenges on enabling low latency and ultra-reliable edge computing services for mission critical applications such as edge AI, vehicle-to-everything, and virtual reality.	√	√	√		√	
Changyang She [34]	Addresses several open issues in multi-level architecture for URLLC. It developed a multi-level architecture that enables edge intelligence, cloud intelligence and device intelligence for URLLC.	√		√			√
Xukan Ran [43]	Presents a framework to tie together weak front-end devices with more powerful backend helpers which allow DL to select local or remote execution. It determines the optimal offloading strategy by considering a complex interaction between video quality, model accuracy, network data usage, network conditions and battery constraints.	√		√		√	
Chaoyun Zhang [45]	This paper provides a study that discusses the gap between mobile wireless networks and DL. It also discusses several DL techniques with potential applications.	√	√	√		√	
Jimmy Jessen Nielsen [47]	Optimizes system reliability by finding the payload allocation weights. It also proposes an analytical framework that combines technology specific latency with traditional reliability models, to estimate the performance of latency and reliability.				√	√	
Changyang She [48]	Proposes a cross-layer framework based on transmission and queueing delay to optimize the radio access networks in terms of URLLC.				√	√	
Quang DuyLa [52]	Focuses on fog computing systems that address the issues of energy efficiency and latency requirements for time-critical IoT applications. It also proposes an intelligent approach that is human-driven and device-driven to reduce latency and energy consumption in fog computing systems.		√	√		√	
Rui Dong [58]	Discusses the mobile edge computing (MEC) systems in terms of delay tolerant services and URLLC services. It also aims to minimize the normalized energy consumption by optimizing various parameters such as resource allocation, user association and offloading probabilities.	√			√	√	
Changyang She [62]	Fulfill the E2E delay and largely reliability depend on improving learning algorithms supervised/unsupervised deep learning and deep reinforcement learning(deep-RL) in URLLC.	√	√				√
Sumudu Samarakoon [63]	Investigates the issues of resource allocation and joint power for URLLC in vehicular networks in order to minimize power consumption of vehicular users. It also presents a novel distributed approach based on federated learning for estimating the tail distribution of the queue lengths.				√	√	
Chen-Feng Liu [64]	Investigates the power delay tradeoff in terms of task offloading for a multi-user MEC scenario. It also proposes a novel network design for task execution, resource allocation task and offloading, based on latency and reliability constraints.		√		√	√	
Haojun Yang [65]	Presents challenges and solutions of latency and reliability in vehicular networks and sheds light on underlying applications, URLLC requirements and potential challenges.			√		√	
Renato Abreu [66]	Focuses on a scheme that allows a group of users to share rescheduled resources for retransmission and provides retransmission opportunities without any need for scheduling control information.				√	√	

for the design and optimization of 6G networks which 5G cannot fulfill due to its low data rates drawback as compared to 6G as shown in Table 3.

To achieve the targeted key performance indicators (KPIs) concerning networks, the reliability and latency should be improved. The improvement can be achieved by including

TABLE 3. Key AI performance comparison between 5G and 6G networks [67]–[72].

Performance AI	Applications	5G	6G
Intelligent Ultra broadband Transmission in 6G	Dynamic power	Medium	Relatively low
	Power consumption	Relatively low	Ultra low
	THz	Very limited	Widely
	Transmit power of small cell	Medium	Relatively low
AI-/ML-Based Energy and Security Management for Super IoT	Connected IoT	Massive IoT,	Super IoT systems
	Energy/bit	Not Specified	1 pJ/bit
	Authentication and Access Control	Medium	High
	Security	Medium	High
	Ultra-sensitive application	Not feasible	Feasible
AI-/ML-Enabled Ultra reliable/Low-Latency Applications	QoS	Partial uRLLC	Fully intelligence (muRLLC)
	Haptic Communication	Partially	Fully
	Reliability	Not extreme	Extreme
	True AI	Absent	Present

hyperparameters to the self-organizing networks (SON) algorithms and algorithms mobility for the purpose of coordination algorithms. To achieve E2E delay less than 1ms and the overall packet loss probability less than 10^{-5}, the whole system needs to be developed to provide a multi-level architecture that enables device intelligence. The task of SON is to transform data into more illegal information, whereas the DL is used to predict, analyze and able to regulate the probability of future events. Moreover, the AI in SON optimizes some targeted network KPIs. Whereas the SON is a type of artificial ANN that is trained using unsupervised learning that enables the developing data to learn from regular unlabeled data so as to improve the QoS [73], [74]. In addition, high E2E reliability and low E2E latency is guaranteed by applying allocated power and resource allocation of users based on the proposed model-free deep-RL framework for URLLC [75]. The model-free deep-RL can go better performed in terms of delay and reliability by achieving the minimum decoding error probability and controlling jitter caused by signal processing in the network.

Revisit analysis tools and design methodologies in a wireless network are very important factors to achieve the targeted KPIs, and these can be satisfied by achieving the KPI as follows:

1) ANALYSIS TOOLS

The performance of wireless networks in terms of a variety of theoretical tools is enhanced based on reducing the transmission delay and channel coding with the help of short block length channel codes in URLLC as suggested by [76], [77]. Improving the reliability of the cellular network reduces the probability of error or, in other words, an increase in the data rate depends on when the block length is shorted, it too depends on when the decoding error probability does not disappear for randomly limited SNR. As suggested by [75], this work proposes a deep-RL framework based on the balancing of the tradeoff between reliability, latency, and data rate to each end-user. This is done to reduce power problems under E2E reliability, E2E latency, and rate constraint in terms of a deep-RL based resource allocation scheme.

2) OPTIMIZATION CROSS-LAYER

Performing cross-layer optimization frameworks in the whole system needs to be optimized in different layers of open systems interconnection such as physical- and link-layer and the optimization depending on reducing E2E delay and the overall packet loss probability. To achieve a better E2E regarding wireless network in terms of delay components and packet losses in different layer, the optimization of cross-layer algorithms is implemented based on several issues as;

1- adjust resource allocation regularly due to channel fading and traffic load variations,

2- persistent problems are created due to difficult models from different layers and cross-layer optimization problems; from different layers, which are usually non-convex or non-deterministic polynomial time, which take a long tim to implement non-deterministic polynomial time and become hardly be implemented in real-time.

3) DEEP LEARNING

The radio resources are allocated in each Transmission Time Interval (TTI) with a duration of 0.125 ms to 1 ms. According to the 6G requirements, to support emerging mission-critical applications, the E2E delay is expected to be less than 1 ms and the E2E reliability in terms of packet loss probability less than 10^{-5} [62]. Transmission delay, such as queueing delay and processing delay only donates to a small fraction of the E2E delay. These delays are important bottlenecks for achieving URLLC. According to some review articles [1], [42], [78], the deep-RL with 6G new radio (NR) has resulted in high potential to address radio resources allocated within every TTI ($0.125 \sim 1$ ms). The basic idea is proposed by enabling DL to be obtained in the DNN output every TTI by approximating the optimal policy with a DNN. As given by [79] the processing delay and queueing delay must be less than the duration of one TTI so as to optimize the framework for URLLC. Apply supervised DL within URLLC-6G and optimizing offloading probabilities subjects to the reliability requirement which will be able to minimize E2E computing delay for short packets [34]. Moreover, applying a deep-RL algorithm to schedule the URLLC transmissions results in the improvement of QoS, as suggested by [80]. A two-phase-framework, including eMBB resource allocation and URLLC scheduling is obtained due to the dynamic nature of both URLLC traffic and channel

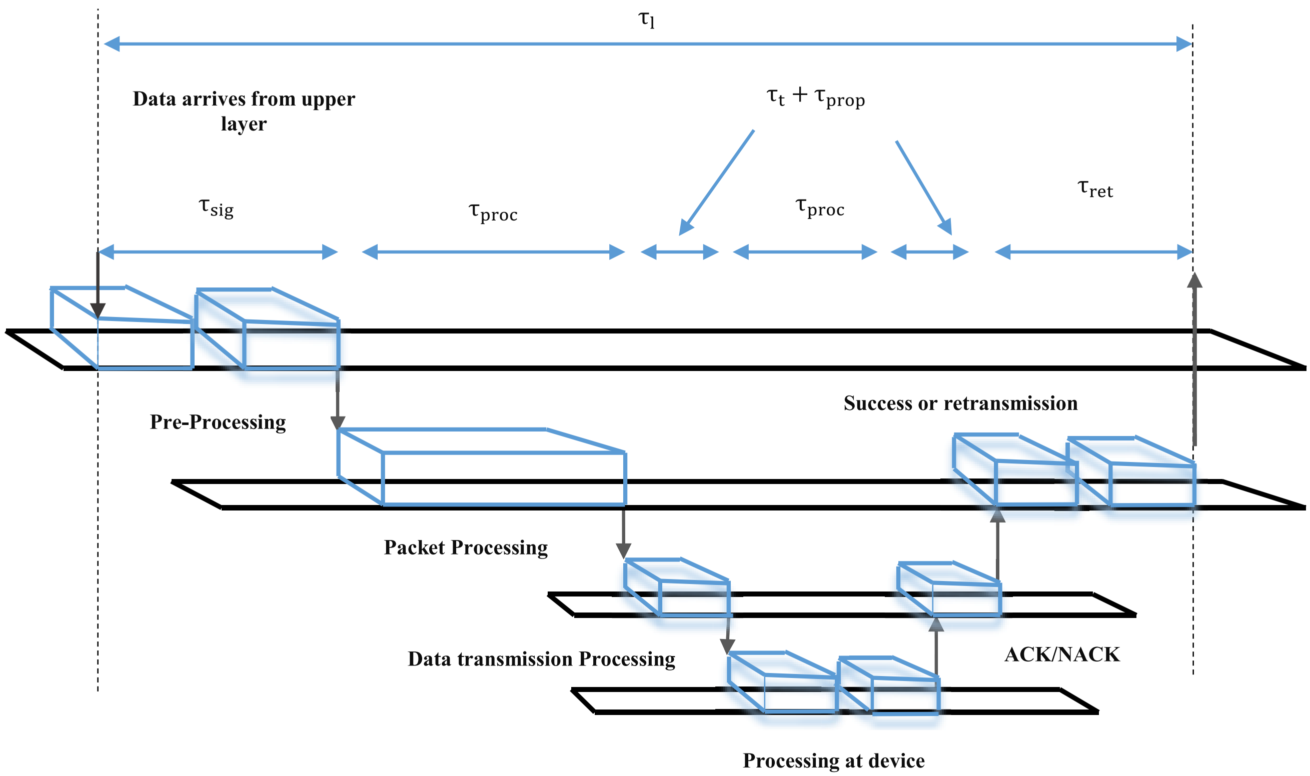


FIGURE 2. Five latency components of URLLC.

variations which is proposed to maximize the average data rate. The trail probability of delay in URLLC is evaluated based on a collection of the estimated parameters taken from each end-user in terms of Federated learning. In addition, Federated learning is an empowered wireless technology to support devices to be connected within 6G networks to run a variety of intelligent applications; the Federated learning model in the wireless networks system optimizes a global model by repeating the processes of users and update the trained weights to the access point. This proposed algorithm which is used to train a Federated learning is capable to provides a good expression of the convergence rate, which takes into account the transmission scheduling policy and inter-cell interference [81].

III. URLLC

In future 6G networks, the provision of URLLC, a novel service paradigm, is predicted to allow for the establishment of emerging mission-critical applications that have more stringent requirements for both the E2E latencies and the reliability aspect. Reliability refers to achieving its target function sufficiently for a specified duration, while latency refers to the time required for a packet of data [63], [64]. The URLLC is able to schedule a packet design by reducing the latency in terms of packet processing and the time needed to acquire a packet and to check for errors. The multiple transmissions should be unified to achieve reliable latency when the specific transmission buffer allows all users to have reliable latency [65]. To meet the stringent delay requirements of URLLC, designing a short packet transmission system with low latency is taken into account for resource allocation. A deep-RL-based learning algorithm is used to intelligently distribute the URLLC traffic across the ongoing eMBB transmission users. Providing high data rate, low latency and more reliability to the traffic with shorter packet sizes depend on applying deep-RL for URLLC.

The novel physical layer such as channel code design, full-duplex transmission, and multi-access are established for spectrally-effective URLLC. Tactile internet and self-driving cars have improved based on using the feasibility of URLLC. The packet transmission time must be on the order of tens to hundreds of microseconds for a mission-critical application, while the time it takes for the human reaction is on the stability of tens of milliseconds. Improving the software-defined network and virtual network slicing in a wireless communication system will reduce the E2E latency and increase the robustness of data transmission, based on creating a private connection to dedicated URLLC.

Designing short packet transmission or efficient low-latency transmission over 0.1ms to support URLLC depends on the control signaling and scheduling information for a large portion of the transmit latency and redesign of the physical layer. A guarantee of high reliability depends on redesigning the physical layer and enabling technologies, including packet and frame structure, as shown in Fig. 2. The physical layer latency τ_l for URLLC NR in [66], [82], [83] can be divided into five components, as shown in Fig.2.

$$\tau_l = \tau_t + \tau_{prop} + \tau_{proc} + \tau_{ret} + \tau_{sig}. \quad (1)$$

where τ_l represent the physical layer latency, τ_t is the time to transmit latency, τ_{prop} is signal propagation time, τ_{proc} is the time to achieve precoding and decoding, τ_{ret} is the time is taken by retransmission, and τ_{sig} represent pre- processing time. The average latency of URLLC in 5G is more flexible in terms of packet transmission time τ_t to provide a 99.99% reliability and latency within 1ms in 5G, or less than $<$ 1ms in 6G. E2E delivery of data with reliability and minimum latency include aspects of URLLC and cloud-computing intelligence, which in turn improve the quality of the packet arrival rate for all MUs.

The application of URLLC is the key ingredient and is essential in efficiently processing the IoT devices based on generating short data packets in irregular and unpredictable behaviors [23], [24], [84]. The expected QoS requirements for URLLC are shown in Table 4.

TABLE 4. Requirements of QoS for URLLC [23], [85].

Industry	Error Rate/Reliability	Latency (ms)
Feasible Reality/ Augmented	$10^{-3} - 10^{-5}$	5–10
Self-sufficiencies / directed vehicle	$\geq 10^{-3}$	5–10
Mechanized Industry	$10^{-5} - 10^{-9}$	1
IoT	10^{-5}	1

A. URLLC EQUIRMENTS

Most challenges are caused by conflicting latency, reliability and co-existence with other services simultaneously, which affect the physical layer design of the URLLC. The URLLC requirements can be classified into two sections, which are as follows:

1) LOW LATENCY

From (1) the physical layer latency τ_l for URLLC must not be over 0.5ms. This depends on the time required for transmitting the packet by applying the new frame structure of the physical layer to support URLLC. In addition, the latency requirement of URLLC cannot be achieved when the time-to-transmit latency τ_t is fixed to 1ms. However, the processing time for channel estimation τ_{proc} is equal to latency because the data must be transmitted again with a small code rate. To meet the requirement of low latency, the data transmitted to the user without waiting for the full retransmission. The new frame structure of the time-to-transmit latency τ_t in 5G must be short block-length channel codes by avoiding scheduled delays, depending on the network management for random and dynamic interference models. The diversity of various traffic characteristics and the QoS of URLLC services need to take into consideration the physical layer for URLLC. The scheduling granted to the users is enhanced and allows more accurate modulation and coding selection based on the joined resource allocation framework and the physical layer control channel.

2) ULTRA- HIGH RELIABILITY

In the 5G system, the reliability requirement is 10^{-5}. This is achieved by channel coding and improving the channel estimation accuracy, since the channel coding gain is small for short packets. Improving the reliability in terms of latency depends on recourses such as retransmission, parity, packet design, and other error control mechanisms causing increased latency [66], [82]–[84]. Enhancing automated factories and control are based on obtaining ultra-high reliability in terms of successful packet rate delivery to $1 - 10^{-5}$. The error probability in the one-shot transmission is:

$$\mathcal{P}_e = 1 - (1 - \mathcal{P}_c)(1 - \mathcal{P}_d), \quad (2)$$

where $\mathcal{P}_e$ represents the error probability of transmission, $\mathcal{P}_c$ represents the error probability of the physical downlink control channel (PDCCH), and $\mathcal{P}_d$ represents the error probability of the physical downlink shared channel (PDSCH). From (2), the aim is to achieve a new application of URLLC that can support the reliability requirements such as the probability of packet loss between $10^{-5} \sim 10^{-7}$ and error probability of PDSCH and PDCCH less than 10^{-6}. The sophisticated value depends on the design of control and data channel, whereas when the complication of the channel is reduced by one retransmission [51], [84], [86], [87], the successful probability is:

$$\mathcal{P} = \mathcal{P}_c\mathcal{P}_{d1} + (1 - \mathcal{P}_c)\mathcal{P}_c\mathcal{P}_{d1}\mathcal{P}_{DTX} + \mathcal{P}_c(1 - \mathcal{P}_{d1}) \times \mathcal{P}_N\mathcal{P}_c\mathcal{P}_{d2}. \quad (3)$$

where $\mathcal{P}_{d1}$ represents the successful probability of a single PDSCH, $\mathcal{P}_{d2}$ the successful probability of retransmitted PDSCH, $\mathcal{P}_{DTX}$ the successful probability of discontinuous transmission (DTX) or negative acknowledgment (NAK) detection if no acknowledgment (ACK) ACK/NAK is sent by the UE, and $\mathcal{P}_N$ the successful probability of DTX or ACK guarantees high reliability of data packet delivery if NAK is sent by the user. The long length of time of the training sample is not adequate if the packet arrival rate of a device is low, which requires the application of AI in URLLC to transmit more packets in the real-time network to improve the multi-level architecture for the data-driven network [18], [33]. The secure URLLC in 6G could potentially advance the mMTC, and it is more flexible in terms of requiring reliability greater than 99.99%, and latency less than 1ms. Increasing the throughput and reliability is difficult in the case of transmitting a long packet in URLLC. It is also difficult due to the stringent delay requirements, especially when the number of URLLC devices is exceedingly large. In contrast, the long packet must be transmitted directly, with minimal delay. On the other hand, URLLC easily provides a high achievable data rate when transmitting a short packet [84], [86], since several techniques are employed to ensure reliability and low latency use more resources and enhance

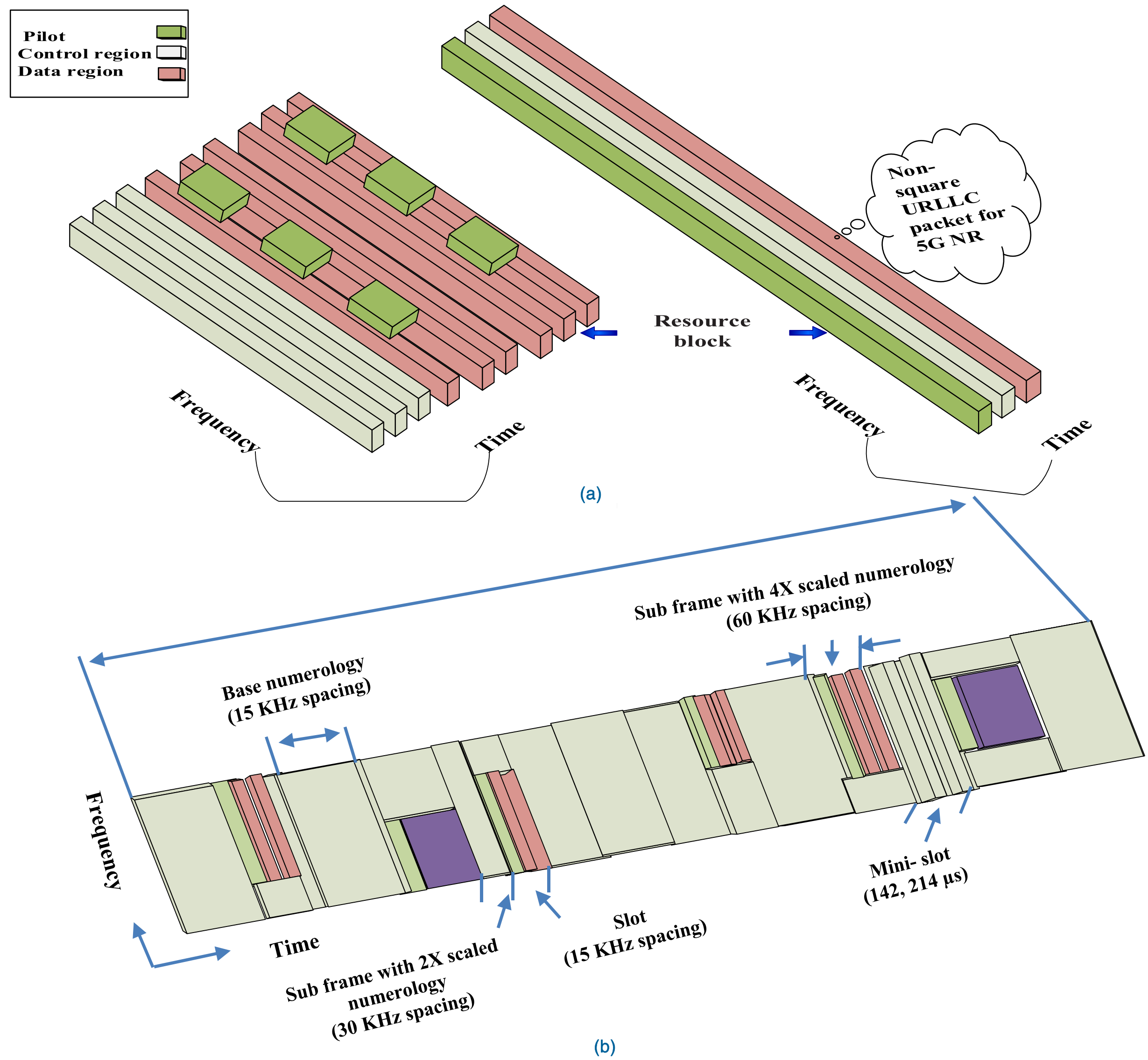


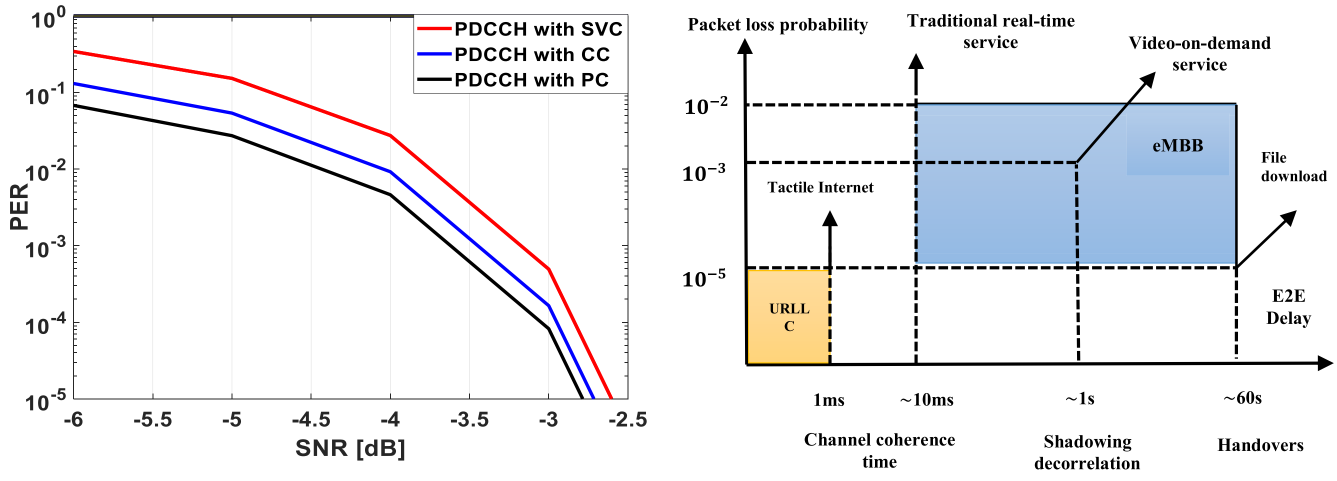
FIGURE 3. Frame structure and packet of URLLC: a) packet structure for URLLC; b) frame structure for URLLC.

reliability without violation, and the data rate requirement is not overly strict. Moreover, designing the physical layer for URLLC is increasingly complicated using interaction with throughput, latency, and reliability. The high reliability in URLLC depends on exploring the link between the multi-level architecture for DL. In addition, developing a multi-level architecture for URLLC can improve prediction within the network and enables real-time between high-speed train connectivity and smart industry applications [87]. Additionally, well-designed models for using DL in URLLC and theoretical methods in wireless networking are useful for a variety of other applications [33].

B. FRAME AND PACKET STRUCTURES FOR URLLC

Among the main goals in 5G and 6G is designing a joined frame structure to ensure a wide range frequency band. From (1), the issue in URLLC packet design needs improvement by decreasing the processing latency τ_{proc} and the time-to-transmit latency τ_t. To reduce the processing latency τ_{proc}, the flexible structure should be grouped mutually to create a pipelined processing of pilot of acquired channel information, data detection, and scheduling information, as shown in Fig. 3(a). The processing latency τ_{proc} contains the processing of the channel achievement, control channel, and data detection.

Improving the flexible frame structure for the URLLC depends on reducing the time-to-transmit latency τ_t, which is able to support future mission-critical treatments, self-driving cars, and remote control devices. The author in [83] proposed a flexible frame structure to reduce the transmission delay and transmitter and receiver processing delay. A frequency band above 6GHz is estimated to



(a) (b)

FIGURE 4. a) Performance latency and reliability for URLLC scheduling; b) Latency and reliability requirements of URLLC and eMBB.

reduce the path loss at the base station based on set users.

The retransmission is applied to improve packet success probability by controlling the subcarrier. The cell reduction could be smaller based on controlling the subcarrier spacing for the channel delay, which will be small, as shown in Fig.3(b). Using the mini-slot level (142, 241μs) shown in Fig.3(b), the time to transmit latency τ_t decreases. Therefore, controlling the symbol period and number of symbols inside the packet τ_t more than 1ms depends on instant scheduling for data transmission to advance a flexible frame structure. From Fig.3(b), 2x and 4x represent the base numerology for sub-frame and slot in time to transmit latency τ_t.

Fig. 4(a) shows the packet error rate (PER) versus signal-noise ratio (SNR). The performance latency and reliability depend on the sparse vector coding technique (SVC) to reduce the error rate by managing the interference more than the convolution code (CC) and polar code (PC). The reduced error rate depends on controlling the symbol period and number of symbols within the packet τ_t over 1ms. Moreover, the reliability improved in URLLC with $\mathcal{P}_c$, $\mathcal{P}_{d1}$, $\mathcal{P}_{d2}$, $\mathcal{P}_{DTX}$ and $\mathcal{P}_N$ by decoding PDCCH and PDSCH in the beginning transmission, as shown in (3). This is done by enabling the location of a user and receive ACK/NACK for PDSCH from the user. The URLLC is relatively easy to maintain at the link level in the managed environments, and it is implemented at the network level. Meanwhile, it is particularly not easy to maintain over a wide area and in remote scenarios [64], [65].

This is primarily due to the intermediate nodes suffering from latency in their application over wide areas. The 6G communication network eMBB with URLLC, by replacing the eMBB in 5G bases, and by providing a more efficient and improved cellular communication system in terms of security, privacy, interference, handover as well as huge data transmission and processing as shown in Fig. 4(b).

IV. EMERGING TECHNOLOGIES

A. NEW SERVICES OF 6G

The potential key technologies required for achieving the aforementioned 6G networks would involve the features shown in Fig. 5. The new services offered by 6G are organized into four types of new technologies of examining nature,namely, holographic radio, advanced wireless channel coding, massive IoT integrated and haptic communication, and tactile internet. In addition, 6G is achieved by concentrating on the important technologies that are considered too immature for 5G, and need new KPIs, as displayed in Table 5. Based on AI-driven studies on the holographic radio, advanced wireless channel coding, and massive IoT, integrated and haptic communication for virtual augmented reality enables new services in 6G networks.

1) HOLOGRAPHIC RADIO

Holographic radio is a technology that improves the efficiency of spatial multiplexing, decreases the hardware costs, and achieves a holographic imaging level of 6G wireless networks. URLLC, which includes holographic calling, is an advancement of transmitting holographic videos that require a high spectrum bandwidth available in THz bands in 6G. The holographic data and video use a high bandwidth and require transmission over reliable network links. In addition, the holography calling consists of massive holographic input and output and 3D spectral holography that is able to use exceedingly intelligent surfaces by controlling the entire physical space and the full closed-loop during spatial-spectral holography. Support holographic and great precision transmissions require applying two drivers for 6G networks for the mobile internet and the IoE. Due to the lack of a fundamental breakthrough, the physical layer has not yet been developed. A major conceptual breakthrough has recently allowed for increasing popularity in holographic communication,

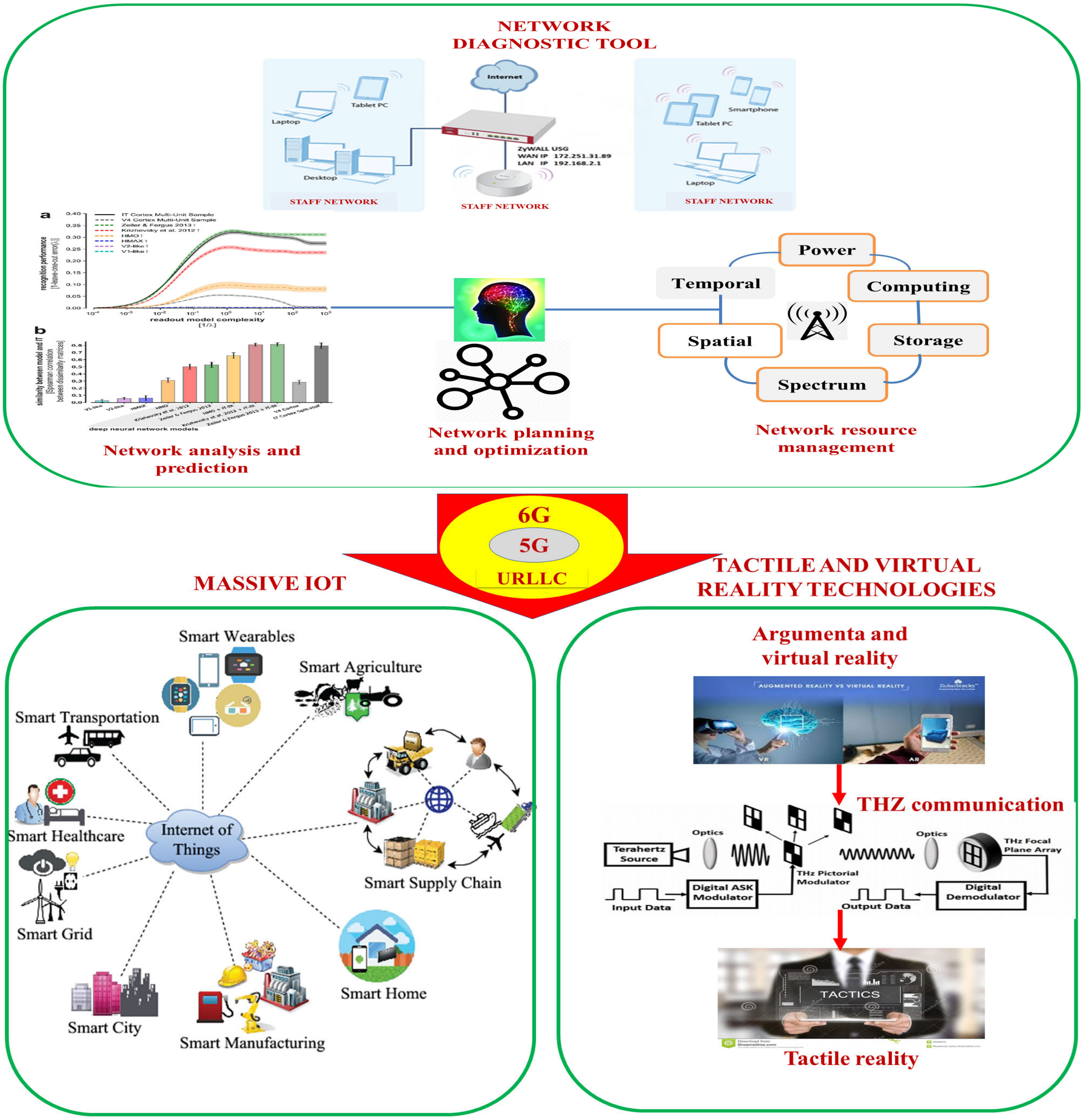


FIGURE 5. AI-driven for achieving the aforementioned 6G networks.

which enables the creation of a low-cost transformative wireless communication network. In addition, holographic communication can manipulate data transmissions by reducing the electron magnetic or dielectric scattering particles that affect electromagnetic waves at any time. This manipulation aims to reduce low-cost and low-power consumption by generating the desired THz wave. However, the challenges related to spatial-spectral efficiency in 6G networks need frequency spectrum bands to transfer the data-traffic volume of holographic videos. Meanwhile, the data-transfer traffic volume of holographic videos needs a spectrum bandwidth that is currently inaccessible in the mm-wave spectrum [114]–[117].

Achieving the greatest transparency and highest data traffic depends on a junction with high bandwidth between the network links. On the other hand, the high bandwidth enables the attainment of data rates of terabit-per-second across the MUs, with low bit error rates in the order of 10^{-5} in a low-mobility environment. The interfaces during inline play-back of holographic videos are established by applying a requirement of high data bandwidth from 100 Gbps $\sim$ 1 Tbps through a limited network that involves a high bandwidth.

TABLE 5. KPI comparison between 5G and 6G wireless communication systems [1], [12], [13, [60], [93].

KPI	2020 5G	2030 6G
Bandwidth	0.25-1 GHz	Up to 3THz
Traffic Capacity	1Gbps	100Gbps
Peak Data Rate in Downlink	20Gbps	>1Tbps
Peak Data Rate in uplink	10Gpbs	>1Tbps
User Experience	50bps	10Gbps
End to End Latency	1ms	<1ms
Mobility Support	Up to 500km/hr	Up to 1000km/hr
Processing Delay	50ns	10ns
Spectral and Energy Efficiency Gains	10x in bps/Hz/m^2	1000x in bps/Hz/m^3
Frequency Range	3-300GHz	10THz
Reliability	99.999%	99.99999%
Connection Density	10^6devices/km^2	10^8devices/km^2
AI	Partial	Fully
Area Traffic Capacity	10Mb/s/m^2	≥ 1 Gb/s/m^2
Jitter	Not Specified	1 µsec
Authentication and Access Control	Meter-level	Centimeter-level
Mobility	Up to 500km/h	Up to 1000km/h
Dynamic Spectrum Sharing	Sub-GHz and 1–6 GHz.	Terahertz channel estimation

Ultra-high-resolution spatial multiplexing improves the efficiency of spatial multiplexing and advanced breakthrough technologies in holographic radios for 6G [91], [92]. In addition, through improving, receiving, and determining the continuous waveform based on the expected values, the holographic record sensor for aperture antenna arrays is to maximize low costs and lower power consumption for radio frequency chains when the number of antennas is infinite. The large bandwidths (∼40GHz) for coupled antenna arrays form a continuous aperture of the optimal antenna array to achieve a nearly infinite number.

2) WIRELESS CHANNEL MODELING FOR 6G

Novel channel estimation techniques for directional transmissions are a key component of actualizing the 6G communications system at mm-waves and THz frequencies. Supporting accurate predictions of channels in URLLC depends on the essential predictive leveraging of the new developments in ML. Control systems will be used in the wireless channel dynamics of 6G to support communication for the learning data samples, so that URLLC can treat the repeated packet errors or disruptions caused by losses, as shown in Section III. Under the control system posed by a URLLC network, perfect reliability is enacted when the transmission rate is lower than the channel capacity. 5G systems offer a high data rate (20Gb/s) based on the medium selection regarding the propagation channel of the electromagnetic waves by selecting an optimal antenna from a large number of connected devices [94]. Providing high connectivity for a device anytime and anywhere cannot be achieved in 5G. This task requires the new technologies applied in 6G. Therefore, 6G systems are in need of new channel estimation techniques to provide high connectivity. The suitable immersion into a distance depends on using holographic communication to guarantee the performance of the high interaction [95]–[97]. Increasing the big data rate exponentially is based on enabling full channel state information (CSI), where channel modeling is comprehensively discovered through transmitting information between transmitting and receiving antennas [98]. Moreover, the application of ML for synergetic transmission and interference controlling allows for the prediction, enhancement, and management of CSI, which will appreciably decrease the pilot overhead for achieving CSI [99].

The optimization and enactment analysis of a channel model provides a big data rate during the transmitting of a signal based on the proposed distribution of the channel. This distribution uses DL techniques for reproductive models as intelligent frames for exhibiting the geometric distribution of channel measurements [100], [101]. In addition, improving the beams and the proposed propagation channels is based on applying time-varying CSI by applying configurable intelligent antennas and train DNNs for transmission prediction [102]. AI uses the long block-length codes for channel decoding based on using the tanner graph learned for DNNs, to ensure the accuracy of the CSI and develop the conjunction with conventional training data and performance gains [103]–[105].

3) MASSIVE IOT CELLULAR TECHNOLOGY

The IoT is a great enabling device. It senses several devices, data storage, and data processing capacities that are interconnected with AI. Combining AI with the IoT is able to provide better visibility and regulation for the wide array of devices associated with the internet. Applying substantial IoT in 6G cellular networks is needed to perform various highly-demanding functions such as diminishing latency-sensitive, ubiquitous connectivity, performing extensive big data analytics, achieving a great level of low device complexity, and reducing energy consumption in multiple mobiles with a wider coverage [106]. Real-time IoT is able to work through the integration of the tactile internet to provide big data sets for mission-critical IoT devices with reliability and low-latency requirements [107]–[109]. Furthermore, supporting intelligent processing data before transmission is able to provide better services to users by supporting extensive quantities of IoT devices through wireless power transfers, which augments the battery-power life of mobile devices.

The latest massive cellular technologies like IoT, which are driving growth in narrowband IoT (NB-IoT) and long-term evaluation-machine (LTE-M) for multiple mobile IoT communications, provide highly efficient connectivity that is needed to support 6G networks [110]. The NB-IoT increases multicast transmission and capacity and supports random access for non-anchor carriers to improve the accuracy of the position of users. Delivering perfect computation and efficient transmission for a massive IoT makes 6G capable of supporting big data in real-time processing. The efficiency of wireless power provides big data that depends on applying a massive number of IoT instances to increase the performance of sustainable 6G cellular networks [111]. The IoT adopts big data analytics that depends on the distributed DL framework. In addition, the proposed taxonomy of the ML algorithm for IoT varies in terms of location and time in massive IoT, depending on intelligent processing for big data [112]. Smart manufacturing, smart objects, humans, and physical environments are enhanced in 6G through the use of DL, where it has a vital role in designing smart IoT [113], [114].

4) HAPTIC COMMUNICATION AND TACTILE INTERNET

Haptic communication is among the most interesting immersive aspects of 6G, which will become a driver for economic growth when the low-latency network is able to provide enough haptic traces in real-time. The big data of wireless communications continue to rise and generally operate when the latency becomes low enough to support haptic communication for virtual augmented reality objects, which can be applied to many situations in our lives. The haptic communication in massive URLLC is able to provide high-quality video and audio traffic within conventional multimedia services in real-time. The typical massive URLLC services will vary in terms of haptic information such as packet size, video, and audio. The QoS must be delivered within a sub-millisecond E2E latency. The holographic communication of a virtual vision in 6G enables the control of the physical communication in nearly-actual sights of environments in the tactile internet, in real-time [115], [116]. The tactile internet is the next evolution that will enable the control of IoT in real-time. In addition, it will combine ultra-low latency with extremely high availability, reliability, and security. It will also add a new dimension to human-to-machine interaction by enabling tactile and haptic features.

Improving multi-access MEC will lead to solving problems in haptic communication by extensively predicting its propagation under the influence of widespread multi-access edge computing delays. The AI allows humans and machines to cooperate within their environment to recognize remote commission locations in real-time, at a 1-ms granularity [117]. Humans are not able to distinguish different latencies within the URLLC system in extended reality [118]. The AI-enhanced multi-access edge computing proximity (Mobile Edge-Cloud) can keep humans largely out of the loop (tactile internet) and provide predictable data traffic by proposing the knowledge and identity of the changing haptic trace [119]. Through applying DL in the mULLRC, the tactile internet can predict the mobility of the tactile device based on using the fully connected DNNs that are trained from the training samples [120]. Additionally, it controls the machine operation in real-time and improves the interconnection of smart devices.

This high accessibility in the tactile internet could potentially enhance 6G cellular networks' ability to provide a big data rate and a low round-trip latency through effective enabling interaction between environments [121], [122]. Enabling the democratization of skills for the tactile internet's long-term future provides suitable haptic equipment for the edge-cloud and edge-AI capabilities of communications networks. Furthermore, current virtual and augmented reality (VAR) applications provide the tactile internet with high ultra-responsive connectivity in 6G [123].

V. ML ENABLED INTELLIGENT 6G NETWORKS

This section discusses the hypotheses of the possible achievements of 6G wireless networks if they were enabled through alternate AI in URLLC. This enables AI for URLLC to improve the learning efficiency for MU and MEC. Overcoming the challenge of providing 6G requires providing a comprehensive survey on various ML techniques that can realistically support communication networking and envision the ways of applying AI to create a 6G wireless network.

ML techniques offer new abilities for modeling and analyzing mobile wireless communication systems. ML and AI are revolutionary innovations that improve system-level solutions in 6G networks and the IoT. The flexible requirements for E2E delay and reliability depend on the integration of DL in URLLC. Developments in 6G focus on ubiquitous wireless intelligence, a multi-level architecture that empowers device intelligence and improves their process based on training DNNs and evaluating the latency and reliability in URLLC. Designing new techniques of future wireless communication networks can be improved by in-depth discussions on connecting DL with AI. Using the DL with AI, enabling edge intelligence, the intelligence of context-aware smart services, cloud intelligence, and knowledge gained from research depend on using the prediction of the probability of error [124]–[127]. The powerful hardware and software are highly important to enable ML in mobile communication based on using support training and reducing interference in complex designs by training and inference processes that use large quantities of matrix multiplications such as parallel computing, optimization algorithms, and distributed ML.

The majority of surveys are concerned with implementing intelligence for ML techniques in wireless communication [128]–[133]. On the other hand, improving throughput in mobile communication is based on exploiting the power of the graphics processing unit (GPUs). The GPU is a highly inefficient method of providing low latency, high memory bandwidth, high-performance video games, and graphics. New techniques such as compute unified device architecture (CUDA) and CUDA deep neural networks (CUDNN) [134], [135] were developed by NVIDIA to reduce the complex hardware and permit users to adapt their usage for exact purposes.

ML techniques are used to support a high level of intelligence by assisting a large quantity of data generated to achieve self-sustenance for connected devices in wireless cellular networks such as sensors in autonomous vehicles. This AI is expected to play a key role in the edge of the network, based on predictions provided by the smart radio mobile and self-optimization for practical network learning. The design plan is for an intelligent radio that is able to independently access the obtainable spectrum through the support of learning. Meanwhile, ML equips systems with the ability to learn automatically, and it supports high data rates in 6G. It is able to provide a high degree of correlation, depending on the input vectors and the probability of the arrangement. Also, this technique is able to be deployed for modeling several technical problems inherent in next-generation 6G. This is important since there is no exact mathematical model that provides high training efficiency of the data rate that is currently being investigated, which slows the varying time of the system model. The challenges appear at the transfer data rate in the transceiver system, which requires working with high THz frequencies to achieve high-speed data rates. Moreover, the THz wireless bandwidth provides a terabit-per-second data rate at a high THz band. The high propagation loss is caused by the relatively long distance for data transfer. The smart device connected to 6G is able to develop self-sustaining and adaptive networks based on the deployment of ML.

The high quality of data not only comes from the mathematical model, but also depends on the management of preceding transmission data. The growth of fully data-driven networks depends on the exact ML approach, such as DL algorithms that activate the learning process and guarantee the accuracy of large data sets corresponding to an increase of available data [31], [32], [39]. The developed data-driven approach depends on the application of DL to the physical layer, which increases the massive quantity of data in wireless communication systems and reduces the power consumption by analyzing the data detection, localization, and channel estimation, as demonstrated by [35], [42], [136], [137]. Furthermore, developed data-driven networks depend on the management of the physical layer by the employment of DL to achieve radio-resource allocation at the physical layer, with the smallest possible complexity [37], [41]. The supervised DL and the deep-RL in URLLC improve the data-driven network based on an advanced multi-level design that supports device and cloud intelligence. The data-driven network must complete an adequate training phase and an accurate number of training sessions to guarantee the reliability required for real-time processing. Meanwhile, every DL is consistent in the number of resources it consumes and gives a predictable output [34]. The DL algorithms allow the DL to perform in the cloud/edge intelligence locally, which provides high-data videos that are more driven and intelligent to augment the reality of the devices and network data usage.

The trade-off between high accuracy and low latency depends on improving the compromises made between videos and prediction abilities by increasing the reality for DL, such as in shopping malls. Obtaining more intelligent videos by enabling DL, namely, ones that choose remote implementation, requires implementing the optimal tradeoff between network utilization and prediction quality [36], [43], [45], [138], [46]. Therefore, increasing the amount of exploding mobile traffic depends on the gap between the efficient employment of DL architecture in the mobile networks domain by managing the increased amount of big data and algorithm-driven treatments. The high data traffic in mobile networks is improved by using traditional deep-RL. These developments can solve problems that mobile networks face by reinforcing the training demonstration that uses an alternative learning model to inform the agent what should be implemented under specific interpretations during the training [47], [139]–[141], [50].

The conventional mathematical model is classified based on operating the network in a truly autonomous fashion and structure for ML algorithms and the conforming functions corresponding to the classification of supervised, unsupervised, and reinforcement learning [142]. However, adopting heterogeneous hardware in ML requires the development of transfer learning for the communication system by determining the demonstrated effectiveness in producing purposeful intelligent communications. The new challenges in 6G wireless communication for ML in mobile devices that need to be addressed by processing data locally and high storage power are related to securing efficient distributed training for computation complexity. Meanwhile, the ML is used to develop big data analytics and professional estimation of different layers of wireless networks [14]. The big data obtained by investigating ML strategies that are able to evaluate and discipline techniques include supervised, unsupervised, and reinforcement learning.

In this section, the ML is introduced in the context of widely used mobile and wireless communication networks.

A. SUPERVISED LEARNING

Supervised learning has adopted the motivation of several conditions in wireless networks, based on the labeled training data availability and real-time processing potential. This technique also applies an ultra-wideband in real-time to discover problems based on predictions for the multiclass hypothesis. In addition, to improve general capability, predicting path loss, low error on the training set, channel estimation, and robustness of the response to channel distortions in the physical layer of development, networks rely on supervised learning. The self-sustaining and proactive wireless networks respond more robustly to channel distortions and efficient approaches to the physical layer. These are efficient advances for the physical layer in MIMO system approval for making real-time network decisions and achieving a big data rate when their capacity is proportional to the complexity based on training data under channel non-linearity [143]–[145].

The wireless networks need to use a higher number of training samples to select the optimal state decision based on the historical data of traffic packs and using the supervised learning for URLLC. Conversely, supervised learning for URLLC makes traffic and mobility predictions based on information sharing to approve real-time network decisions through estimating the time-sequence models of the channel such as Markov chain models, which cannot provide sufficiently accurate traffic packs for URLLC to support 6G networks. Therefore, providing sufficiently accurate traffic packs for URLLC depends upon improving the precision of accuracy data in the supervised learning environment to avoid leaving a large number of training samples unlabeled. This must be avoided in order to achieve the long-term dependency of data and guarantee the QoS requirements of URLLC. Large interference and huge communication collisions are created at the beginning of each prediction and failure in detecting probability due to the long training of prediction errors that were incurred through using supervised DL in URLLC. Through the use of SON, the high traffic demands improved and achieved high reliability and low latency by avoiding scheduled delays, depending on using the network management for random and dynamic interference models.

Supervised learning is used for self-optimization, intelligently extracting valuable information from massive data, and increasing capabilities to sufficiently lower the costs and elevate the data rates. However, the effect on reliability depends on a variety of factors, namely, whether the enablers of URLLC are able to mitigate the interference caused by users in neighboring channels, the use of a large number of training sessions, or collisions with other users due to uncoordinated channel access. The importance aware scheduling decisions for efficient edge learning is based on multiple beams via multiple RF (MBMRF), achievement channel diversity and data diversity, and data sample signal is defined as follows:

$$v_{k,n} = \frac{1}{\sqrt{\mathcal{P}}} \Re\left(\frac{\hbar y}{\|\hbar_k\|^2}\right), \tag{4}$$

where the y is the received signal, $\hbar$ is the Gaussian random variable $\hbar_k \sim \mathcal{CN}(0, 1)$ and $\mathcal{P}$ is the transmitting power. The noise ratio for the real of the combined signal for processing data for ML at transmitted data, video is given as follows:

$$SNR_k = \frac{2\mathcal{P}}{\sigma^2} |\hbar_k|^2, \tag{5}$$

where σ represents the noise in the real dimension with variance. The optimized data importance is difficult due to a shortage of tractable mapping from noisy data importance. The data importance learning is typically measured by its uncertainty, as viewed by the model for efficient edge learning based on MBMRF. The training of MBMRF at the edge intelligent devices for the $k\,th$ local dataset of the edge intelligent devices and SNR.

Nevertheless, in a mobile cellular network, ML provides adaptability to the accurate path-loss estimation and high throughput, depending on the use of the predicted performance learning-based dynamic frequency and the bandwidth allocation. A predictive estimate of the path-loss for every user is provided based on the applied vector regression to provide a QoS accordingly [146]–[149]. The channel-learning

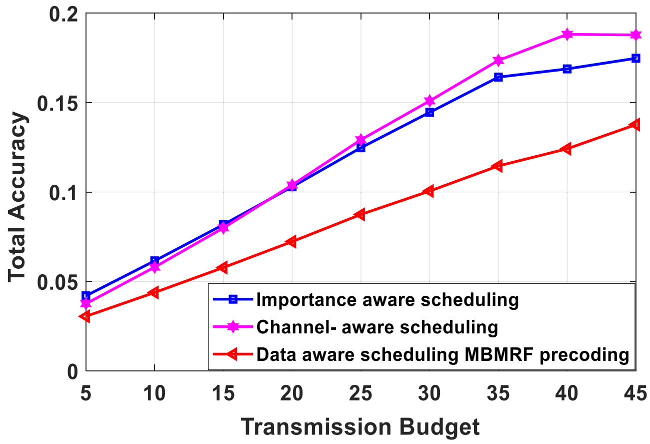


FIGURE 6. Edge Learning performance for importance-aware scheduling [150], [151].

framework in wireless communication performs the requirements of URLLC with a target (block error rate BLER) through accurate location information of CSI. The exploited location information depends on channel learning, which builds a supervised learning framework in multi-tier networks, [150], [151] as shown in Fig.6. In addition, aware importance scheduling reduces the effect of channel fading and noise on the predictable received data sample, where the SNR_k and $v_{k,n}$ are SNR and the nth of a data sample of the $k\,th$ users. The importance aware from multi- level edge devices is expressed as follows:

$$k = arg \max_k \left(1/SNR_k\right) + v_{k,n}. \tag{6}$$

The localization information for a channel is generally expensive and utilizes the angle-of-arrival (AoA) and time-of-arrival (ToA) due to multi-path propagation as well as a small bandwidth. Software-defined networking (SDN) in the ML mechanism is used to provide 10 gigabits in a modern broadband hybrid optical wireless network and multiple long term evolution (LTE) radio communication by controlling the proper pattern based on the traffic dynamics in the whole hybrid network [152], [153].

B. UNSUPERVISED LEARNING

Unsupervised learning for URLLC is used to solve non-deterministic learning problems and create decisions in real-time. In addition, it is used to process the training data based on the labeled training-data set and also assist in achieving the desired output. Achieving high availability with a small loss of bandwidth efficiency is attained through the QoS requirement of URLLC, by learning the hidden function with unsupervised DL to optimize and train DNN. The transmit data packets of users depend on authenticating a packet from a specific signal strength or channel estimation by using conventional statistics such as the widespread likelihood ratio analysis in the physical layer protocol. The unsupervised DL for URLLC guarantees the QoS requirements on the E2E latency and reliability for every user in terms of the delay and total packet loss probability [77], [78], [154]. However, the flexible transmission time interval is required for the channel-estimation support vector in ML to detect the data rate for linear scales and reduce the delay and packet loss rate of URLLC. The training data uses the learning process to improve the transfer of information through convolutional neural networks on very big datasets. Enabling URLLC improves the channel quality based on applying a low complexity learning-based heuristic process that keeps a vector machine for user connection. In addition, the efficacy of unsupervised learning techniques which function to repeatedly regulate the number of retransmissions and improve the BLER, depends upon an analysis of dynamic parameter prediction, traffic control, improvement in the capacity, adjusting the position of the cellular cells, and mitigating the inter-cell interference in the ML algorithm [155]–[158].

The ML for artificial neural network (ANNs) is able to perform tasks in a multi-level architecture as $A : z \in Z \subseteq X^n \to b \in B \subseteq X^n$, where z is the data vector, b is the output produced by the ML algorithm, and A is the performance function to maximize the performance metrics; In $z \in X^n$, Z and B represent the set of z and b. By utilizing the best activation function, $a_{n,l}$ to $s_{n,l}$ obtains fully joined layers that are essential for ANNs to be able to reduce the computing delay and select the activation function of the hidden layers [159]. The processing achieved in every neuron, n, for layer $l - th$ in the network is then implemented to search for the optimal decision. The output is the neuron, $z_l(n) = a_{n,l}(s_{n,l})$, where the intermediate-term, $s_{n,l} = \beta^T_{n,l} z_{l-1} \Omega_{n,l} + \rho_{n,l}$, is used to improve the training process in an unsupervised learning environment by selecting the optimal training for DL to learn the complex interference in order to reduce loss and acquire the desired input-output. The $a_{n,l}$ is called activation function of neuron n in layer l. The architecture employed in the DNNs consists of three hidden layers, as shown in Fig. 7(a), where the training process optimizes the ANNs by applying the active function for weight, $\beta^T_{n,l}$, $\Omega_{n,l}$, and bias $\rho_{n,l}$ terms.

To decrease the loss acquired in the actual output, $z^T_{n,l}$, the amount of data required is significantly decreased. $\rho_{n,l} \in X^n$ represents the bias term of neuron n in layer l, while $\beta^T_{n,l}$ represents the weight of the connection between the $k - th$ neuron in layer $l - 1$ and the $n - th$ neuron in layer l, and $\Omega_{n,l}$ represents the iterative updating for each iteration onto one layer of the ANNs and computes $\Omega_{n,l}$ at the output of $k - th$ to form a hidden layer used in the production of the final output of the neuron $z_l(n)$. Based on the experimental results, the neuron of layer n_0 has the dimensional input vector, z_0, and is served to the network through the n_0 neurons of the input layer, which passes across the hidden layer, $l - 1$. Achieving an increased capacity and a more achievable big data rate requires utilizing the input data and training process in an unsupervised learning setting of the DL-dataset size by developing data-driven resource management, with an affinity to the propagation channel, as shown in Fig.7 (b).

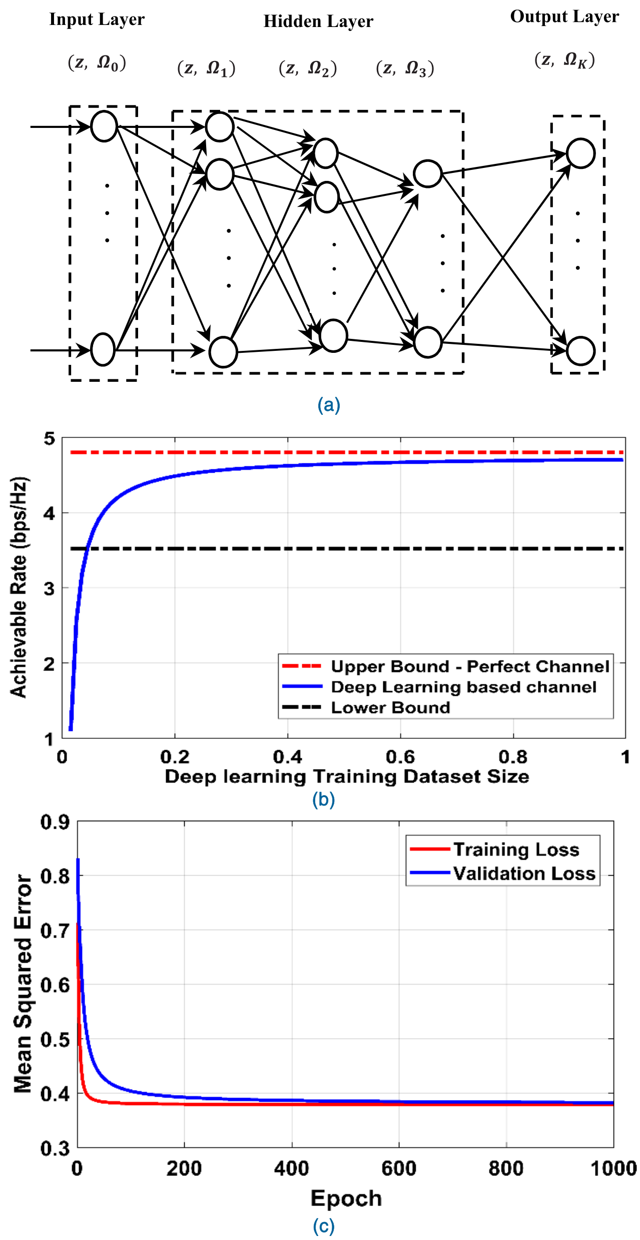


FIGURE 7. (a) DNNs architectures for Joint layer l – th, (b) Achievable rate vs. the DL training dataset size, and (c) Training loss and validation losses versus training epoch number in URRLC.

The channel that is perfectly aware of interference for DNNs can learn to mitigate complex interference based on affinity propagation clustering in the unsupervised learning methods. The DL utilizes THz communication to maintain the perfect channel quality estimation and high prediction accuracy based on the time-varying channels such as a drone small cell (DSC) in real-time operational data. The perfect channel quality estimation and the high prediction accuracy reduce the loss acquired in the actual output $z^T_{n,l}$ by decreasing the amount of data required to reach the required performance level.

For the physical layer, the unsupervised DL develops an E2E optimization transmitter for a single process in a communication system by reducing the bit error rate and efficiently mitigating interference by using strategically designed neural networks. The domain-relevant performance metrics are enhanced by using the quantitative metrics for a shared radio communications signal to achieve both data bits and accurate channel estimation through the current unsupervised learning algorithm [88], [72], [129], [189], [190]. The improvement of the total cell throughput depends on enabling the hidden structure of unlabeled data, while the reduction of energy consumption depends on applying the unsupervised learning algorithm to ultra-dense small cells. The challenges depend on the integrated communication in high and large antenna arrays in a massive multiple-input multiple-output (MIMO) system that creates complexities in hardware implementation design when upgrading from 5G to 6G [163]. In addition, the unsupervised learning of the physical layer improves routing and guarantees message authenticity, traffic control, parameter prediction, complex networks, and mobility management.

The proposed ANN implement with $l = 5$ hidden layers and having 128, 64, 32, 16, 8 neurons, respectively. To avoid any redundancy, the two hidden nodes join to the same input layer with the same activation function and should have various initial parameters. The activation functions of the hidden layers include the rectified linear unit (ReLU), which is proposed to improve neural networks during the training process. The unsupervised DL for URLLC achieves the desired performance on the E2E latency and reliability by decreasing errors quickly and moving towards a very small value based on the average training loss and validation loss for the ANN, as shown in Fig. 7(c).

The hidden layers alternate the ReLU function and exponential linear unit activation (ELU) functions to improve the accuracy and decrease the number of needed neurons. The initial hidden layer has an ELU activation, the extra hidden layers alternate ReLU and ELU activation functions. The output layer uses a linear activation function, which produces low training error and decreases the output error [159].

C. DEEP REINFORCEMENT LEARNING

Deep-RL is proposed to support model-free URLLC and a highly dynamic transmission in smart cities and reservation of reliable wireless connectivity for air networks based on the resource allocation in 6G networks [164]. In the last few years, improvements to games, robotics, and natural language processing have been studied based on developing DL or DNNs in reinforcement learning. The multi-level architecture has improved through the decrease in treating time and delay-prevention that has occurred through enabling deep-RL in URLLC. The proposed deep-RL features are a new model-free design for resource management that guarantees the balance of long-term reliability and low latency without explicit prior assumptions on every user who is under data rate constraints [165].

The improved high-traffic demand and the achievement of the QoS in 6G depend jointly on optimized bandwidth allocation and overlapping positions of URLLC users by using deep-RL for joint scheduling of eMBB and URLLC [166]. The deep-RL in URLLC enables a feedback loop among the decision producer and the physical system by generalizing the arithmetical structure of the information from the desired input to the preferred transmitted output. This decision procedure allows the feedback loop to maximize the packet scheduling and traffic prediction among the Monte Carlo Method algorithm and Q-learning techniques. These techniques developed for network management include Q-learning and Markov choice development in the application layer by selecting the optimal active caching, data rate allocation, and error prediction. The deep-RL and URLLC jointly enable the autonomous building of symbols, protection, channel tracking, beamforming, energy harvesting, and the multi-routing of the complex network layer to provide a more reliable peak data rate and a low-interface latency.

Table 6 summarizes various ML algorithms with big data in mobile and wireless communication networks.

The vast amount of automotive technologies deployed in 6G wireless communication networks help to improve the reliability of broadcasting and the big data rate between the ground-based controller and the system communication such as drone racing [167]–[169]. Moreover, achieving maximum energy efficiency in wireless communication networks depends on the good decisions of DNN by using an emerging deep-RL algorithm together with URLLC to serve unmanned aerial vehicles [204], [170]. The performance channel metric covers a wide of factors that influence a channel condition and nodal mobility in wireless networks so that it is not necessary to rely on every individual factor. The deep-RL algorithms with URLLC apply the learning-based dynamic channel selection to achieve context awareness and intelligence [171]. The strong interference and large transmission collision are reduced through the application of a prediction error in deep-RL with URLLC. Therefore, reducing the unlabeled training samples achieves a high QoS by proposing an approximating feedback decision. This algorithm applies Q-learning to determine the state and action of [172] Q-value in deep-RL with URLLC for immediate reward and to discount the reward from the output of the DNN [205]. However, the efficient handover management, high capacity, and guaranteed high QoS in heterogeneous networks that using The Q-learning algorithm for reinforcement learning achieved [173] related to load balancing [174]–[177], mobility management [178]–[181], user association [182]–[184], and resource allocation [177], [185], [160], [186]–[190], [191].

D. DEEP LEARNING PLATFORM FOR MOBILE NETWORKING WITH URLLC

In this section, the main key underpinning of DL network control and deliberation is presented. The possible explanations of mobile networking problems are mainly unexplored. Successfully processing big data that stems from several

TABLE 6. Summary of ML with big data in the mobile and wireless communication networks.

ML Technique	Learning Model	Mobile and Wireless Communication
Supervised Learning	❖ SON	➢ Optimizes the location of network management and maximizing the capacity by using the SON for URLLC[132] .
	❖ Linear reversion	➢ Enables Energy harvesting and energy prediction modeling used to adapt energy harvesting availability by equipping the harvesting node in real-time power as in [190].
	❖ Supervised Classifier	➢ Enables autonomous network management aware of quality of experience through using ML for SDN and network function virtualization (NFV) techniques in order to improve a prediction of the network demand and autonomous network sensitivity in [187].
	❖ Support Vector Machines	➢ Uses ML techniques to predict propagation path loss in wireless networks [152].
	❖ Quantum ML	➢ Uses the Quantum Computing ML to increase performance through enabling technologies at the network-edge, air interface, and on the user's end based on user-demand self-reconfiguration in 6G as in [14].
Unsupervised Learning	❖ Latent function with unsupervised DL	➢ Reduces problems regarding the QoS constraint of URLLC aimed to demonstrate how a variable optimization problem through applying the framework of learning in the latent perform with unsupervised DL to achieve the high availability with a small loss of the bandwidth [78].
	❖ K-means clustering	➢ A tremendous capacity for every user in mobile network data through neural-network prediction to utilize ML in unsupervised learning as in [192].
	❖ k-means technology	➢ Low latency data access and big store data blocks depend on the use of DL technology in data center networks (DCNs) as in [193].
	❖ Unsupervised Clustering.	➢ The unsupervised soft-clustering ML algorithm is used to decide which low-power node is upgraded to a high-power mode in order to reduce latency and the power node in wireless cellular networks [194].
	❖ Self-organizing Map	➢ Increasing the capacity and improving user experience in small cells depends on using the unsupervised self-organizing map, which provides an intelligent solution for both coverage planning and performance optimization as in [195].
Reinforcement Learning	❖ Framework Dynamically predicts	➢ The tradeoff between the E2E reliability, latency and data rate, which guarantees long term reliability and latency for every user based on a collected dataset for training the DNN under URLLC [75].
	❖ Markov Decision Process	➢ Enables vertical handoff decisions that depend on various parameters such as minimum bandwidth, delay, and low battery of the mobile terminal in heterogeneous wireless networks [178].
	❖ Q-learning	➢ Maximizes the data rate through local data in cell associations between a small number of base stations and users. Q-learning enables users to predict their return function using a neural network [196].
	❖ Deep Q-network	➢ Increases the SNIR and the efficacy of the secondary user by utilizing the benefits provided by the spread spectrum and user mobility to select the optimal anti-jamming communication policy through Q-learning [197].
	❖ Deep-RL	➢ Optimizing the cooperative coded caching by applying joint optimum caching and estimating the allocation problem to reduce the system cost based on the deep Q-learning algorithm [198].

sources depends on using a DL system with URLLC, which enables the real-time connection in 6G networks. URLLC improves network management based on using reaction analysis and the correlated prediction [87], [191], [199]–[202]. The URLLC design focuses on enabling precise predictions of channels and the high speed of traffic data, which is essentially predictive, and controlling the new development in DL. Furthermore, the high prediction accuracy in DL with predictive URLLC diminishes the discrepancy between the practical and predicted losses of the training data using time-varying channels [203]. Also, the low-latency and reliable ML supports the data-driven network in the edge intelligence by decreasing latency and the rate of transmitting device-generated data to the cloud. Creating intelligent decisions without any human interference allows for accurate predictions in a DNN. Therefore, achieving substantial improvements in the efficiency of wireless systems depends on utilizing DL in the decision-making process on the basis of this information and its approval of risk analysis or prediction.

The strong function mechanism in DL adapts to the high traffic in the real-time data network by using a routing protocol. It also employs an empowering intelligent resource to adopt mobile computing and achieve network intelligence [204]. In this case, it is used to solve the control problem in mobile networks by acquiring the nearby systematic applications of advanced ML techniques and unsupervised DL with predictive URLLC [36], [205].

The expert's cost functions with inverse reinforcement learning utilize the initializing policy with behavioral cloning to improve the learning speed for expert data [206]. The DL platform for mobile networking with URLLC provides the optimal action for the multi-agent reinforcement of DL depend on the data correlates provided by an agent (a learning machine) continuously with the environment. Meanwhile, in mobile networking, using DL with URLLC reduces the problem of teaching without the demand for explicit programming. Moreover, designing it will be improved through the use of generic imitation learning methods [207]. The details of the inclusion of DL in future wireless communication and how it can improve the performance in areas of computer designs discussed in [206]–[211]. Furthermore, in [212], a study is conducted to show what treatments involving the IoT have gained from using DL algorithms. IoTs have been shown to improve on big data and streaming data through using the DNN architectures [212].

New static tools such as android apps and a smartphone app-based in the wild were improved by optimizing DL models. The allocated DL was implemented as an iterative map reduce, computing on many spark workers to improve the learning time of deep models and used to increase massive streaming data in mobile devices such as smartphones and IoTs [211]. Providing more intelligence with a more powerful backend, such as video quality, low battery consumption, and high-data usage depends on implementing DL. These achievements increasingly assure positive results in 6G wireless mobile. Achieving a variety of domains with low-dimensional state spaces requires developing a novel AI agent by using the deep convolutional neural network, namely, a deep Q-network [213]–[215].

The main objective of this article is to present an up-to-date analysis of URLLC while stressing the importance of the technical challenges and solutions posed by the generation partnership project (3GPP). We first describe the multi-level architecture for URLLC and DL that enables a data-driven service requirement as illustrated in Fig.8, and then discuss the performance of 6G networks for device intelligence and enabling technologies.

VI. MULTI-LEVEL ARCHITECTURE FOR URLLC IN DL

In this section, we address the problem in section (V) by proposing a multi-level architecture that enables a data-driven network for URLLC. Developing a multi-level architecture enables device intelligence, edge intelligence, and cloud intelligence for URLLC to be the best realized in MU and MEC. The URLLC is a new application in 6G communication systems and will be the key enabler for mission-critical IoTs. Achieving a data-driven DL for URLLC in future 6G networks is very challenging, whereas facilitating mission-critical IoTs with severe requirements on E2E is a more readily achievable way to decrease delays and increase reliability as is studied in [216], [211]. The data-driven DL has the ability to learn a training data set and the need to obtain the optimal varied range of policies in wireless communication. Moreover, the reliability requirement depends on either a wide range of policies or the packet loss probability of $(10^{-5} \sim 10^{-7})$, achieved through using the long training. However, securing a sufficient data-driven DL only becomes possible when the packet arrival rate of a device is high. The latter is achieved by a long duration of a large number of training samples to send more than 10^7 packets [33], [32], [216]. Meanwhile, improving multi-access edge computing and data analytics at the edge of cellular networks in 6G requires an effective intermediate layer that provides fast and localized data processing capabilities.

The E2E delay and reliability requirements are the challenges in 6G and are achieved through deploying the massive URLLC. However, the E2E delay is much greater than the transmission delays due to interference; this issue is solved by using a large number of training samples and ultimately improve a multi-level architecture for data-driven DL. In practice, supporting the integrated data transmission (throughput) in cellular networks depends on two advantages in 6G IoT. The first is IoT data transmissions of "massive IoT" in cellular networks that are designed to meet integrated data transmission requirements such as long-range applications, transmission reliability, spectrum resources, and strength over long distances. The second one is that the cost of IoT devices is low and that communication protocols use very little power during the integration of radio frequency identification (RFI). RFI is accomplished by eliminating the cross-interference between IoT devices and MUs and enhancing sensing capabilities and intelligence. The whole data-driven

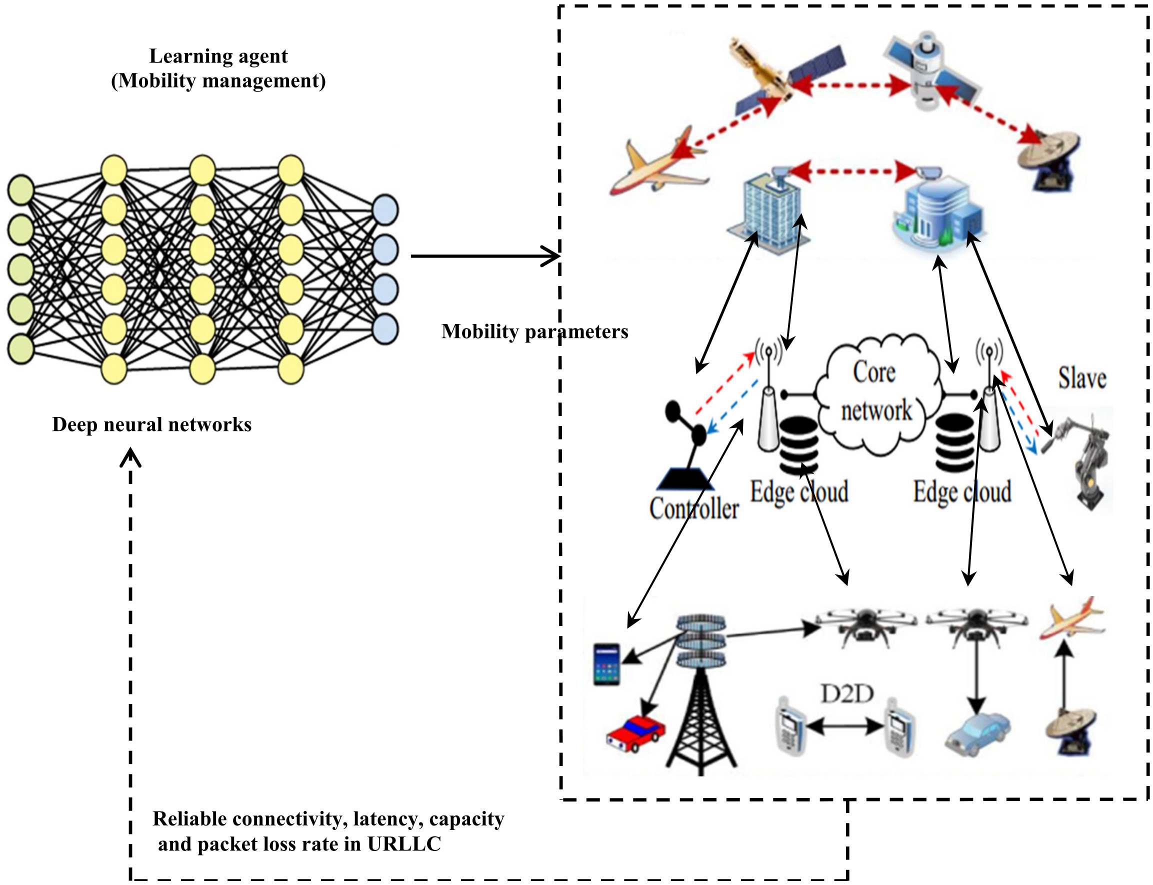


FIGURE 8. ML for enabling mobility management, scalability, and robustness in URLLC.

approaches are developing in 6G by employing a DL and an integrated ANN that uses the accurate mathematical models for the initial network in all phases of network design. Also, data-driven development decreases the amount of live data required to be learned and calculated in implementing data-driven techniques. To address this problem, we propose a multi-level architecture that enables a data-driven DL in the edge and device intelligence for the MU and MEC servers.

A. PERFORM OF 6G NETWORKS

6G networks are data-driven associations supported by meticulously prepared unlimited wireless connectivity. The multi-level architecture that enables a data-driven DL in the edge and device intelligence represents emerging driving applications of 6G. The architecture of DL increases the reliability and reduces the delay of URLLC devices. It also increases the implementation of all involved massive IoT devices. In addition, DL is very challenging for the reliability of data transmitting that granted a total of traffic prediction within the scheduled time duration to satisfy predictions for futures 6G systems. The data-driven DL has the potential to provide ultra-high data rates to end-users and generate a good policy according to the direct cost feedback in wireless networks [217], [218]–[222]. Meanwhile, the reliability requirements and DL in URLLC require a long training phase and an exorbitant number of training samples. The connection capability and suitable delivery of a wide coverage depend on the effective reduction for the signals propagated at these frequencies [223].

The IoT networks with URLLC are able to seamlessly integrate data, processes, and physical devices in 6G. This is because the IoT is often involved in self-organized decision-making to fill the gap between 5G and market demand. Therefore, 6G must reinforce URLLC in most or emergency proceedings with traffic designs and sequential device densities. URLLC is essential to support intelligent services, reconfigure intelligent surfaces, and solve problems in 6G by growth data traffic, increasing battery efficiency, and increasing data-driven DL for ultra-reliable are summarized in [59], [60], [224], [225]. The following is needed to address these challenges 6G.

1) END TO END QUALITY OF SERVICE

The URLLC in 5G systems achieves third generation partnership project (3GPP) levels on latency and reliability to successfully release delay-sensitive information. Meanwhile, end-to-end (E2E) latency and reliability requirements hardly improve in 6G networks, which require adjusting the whole network according to a short channel code design and an optimal policy for short packets that supports deep learning in URLLC. The QoS for E2E must be 10^{-3} and the reliability of packet loss probability should be less than 10^{-5}. To obtain ultra-low latency while providing ultra-high reliability, the transmission delays must be short block-length channel codes, depending on the decoding error probability in the short block-length system.

5G mobile communication systems had already minimized the E2E service latency for edge AI by optimizing nearby edge computing techniques and distributed AI without increasing the complexity [30]. But in 6G, the E2E QoS will be adjusted within the entire network to optimize communication by improving the scheduling scheme for wireless channels, queue states of buffers, and workloads of servers to provide big data-driven DL in URLLC [34]. Therefore, minimizing the E2E QoS in 6G depends on using URLLC under the constraint on packet-loss probability. This transfers short packets enhance offloading probabilities, and updates network architectures such as optimizing scheduling policies and evaluating the implementation of the physical layer [226]. Therefore, AI holds a unique importance in wireless networks [227], especially the latest advances in deep learning, in increasing the data available for every user and the prevalence of smartphone devices. Edge computing offers one promising path to decrease the treating time of the local server of every device and prevent delays using DL in URLLC.

2) ACCESSIBLE AND FLEXIBLE CONTROL PLANE

The control plane latency is caused by the random access to the usual up-a-radio resource control and defines the time needed for the MU to transmit an efficient state from IDLE to the start of a continuous data transfer. The future of 6G networks depends on designing the control plane to distribute and collect multiple signals to the beginning of incessant to lead to big data, and the minimum control latency is 10ms to reach a performance target in 3Gpp. The user plane is the one-way time in 3Gpp for URLLC, and the minimum user plane it is 1 ms. Both the control and user planes are silted in 5G networks. Moreover, big data traffic is spurred by the IoT through fully flexible and better scalability [228].

The DL algorithms for the control plane are fully centralized or distributed through an analysis of the dynamic and immense data comprised of multiple signals. This data is used to increase the better scalability and flexibility in 6G. The full centralization of the control plane in the network increases the flexibility of treatment based on the control plane intrusion detection by managing the scheduling and resource allocation for DL. The control plane uses the learning process and trains the DNNs to guarantee the QoS requirement of URLLC [61]. The short-packet transmission and shorter transmission time interval are very important for URLLC [229], [230]. Several critical elements to 6G radio access networks necessitate fulfilling the service requirements to provide better scalability and flexibility. This is done by designing the network functions for the control plane based on key issues such as fully centralized, partially centralized, or fully distributed [228], [231]. Therefore, DL algorithms are able to be unified and allocated based on network functions.

3) COMPUTING RESOURCES AND MULTI-LEVEL STORAGE

In 6G network transfers, achieving greater data transfers depend upon the full realization of the IoT and DL in big data analytics. Incorporating AI into a future 6G network depends on evaluating storage and computational capacities, which is very important for multi-level storage usage. 6G enables scalable MEC through deploying multi-level storage and computing resources [224]. Edge computing is a very important technique in 6G that guarantees ultra-low latency. Using training data to train DNNs and deploy computing resources at MUs based on proposed dense high-performance servers in a high real-time system [232]. The DL is utilized to learn from great amounts of supervised data to represent big data analytics and exploit the availability of huge amounts of data [233]. The multi-level storage and computing services are achieved by using fog computing, which is able to reduce the latency in URLLC [217], [234], [235], [173]. Guaranteeing a general ability of the trained network necessitates the employment of a large number of training data in DNNs. In addition, high centralized and high-performance computing resources provide high capacity backhaul connectivity, big data, and low latency for URLLC. However, some of the IoT's device data will be handled by edge-computing resources. Training the DNNs depends on the network function, where the IoT device data is deployed by edge-computing resources for MUs and MEC servers by integrated intelligence in the network.

The edge-computing resources and mobile-edge computing must be processed to apply more centralized high-performance computing resources for MUs. In addition, edge computing achieves a high capacity and improves accuracy by utilizing predictive data analysis and ML in real-time for the holistic view of AI. The device mobility and communication latency are difficult on a massive scale of IoTs systems. Edge computing allows a real-time framework for understanding intelligent platform management, which provides a policy for decentralized IoT system control [236].

B. MULTI-LEVEL ARCHITECTURE

From the above feature in section V, it can be seen that a significant improvement in 6G wireless network architecture consists of smart MUs, and MEC at the access point. To guarantee the future functionality of 6G, the multi-level architecture included mobility and traffic prediction for all MUs, a scheduler design at each access point, and user connection. These elements of a multi-access point wireless connections network are considered.

1) USER LEVEL FOR DEVICE INTELLIGENCE

The local prediction information is able to achieve a highly efficient user-level intelligence and generate decisions based on mobile device predictions, such as flexibility and traffic state. Maximizing the number of URLLCs depends on evaluating the reliability of device intelligence. The MU provides good decision-making abilities based on a connected device's network activity by analyzing the probability error prediction and limiting the predicted information in device intelligence at the user level. The efficiency of user-level intelligence depends on the mobility management for device intelligence technology. This technology selects the predicted traffic state by enabling the end-user and then selects the optimal user. The difference between eMBB and ultra-high reliability will no longer work in reality and Brain-Computer Interactions. This is because both reality and Brain-Computer Interactions require not only high reliability and low latency but also an elevated 5G-eMBB of big data rates. Enabling 6G requires applying any desired capability within the rate-reliability latency through applying the new facility such as the mobile broadband URLLC. This URLLC is based on the predicted traffic state and reliability with regard to a packet loss probability between (10^{-5} to 10^{-7}). Furthermore, the prediction error should be extremely low to improve the URLLC [139], [47]. The prediction error probabilities depend on neglecting the hybrid automatic repeat requests, improving mobility predictions in traffic state, and decoding [140]. Deriving the prediction error probability allows for the capability to increase and serve a data-driven DL in an upper bound of URLLC [46].

2) CELL LEVEL FOR EDGE INTELLIGENCE

The AI used for edge intelligence is functionally essential for quickly analyzing large quantities of data. Providing efficient AI for edge-cell levels depends on having a strong demand for integrating edge computing and AI. Therefore, in edge cell-level intelligence, deep-RL achieves higher package reliability with the lesser cost of industrial equipment and optimizes the scheduler at the access point with edge intelligence. However, the cell level for edge intelligence is planned to enable URLLC to enhance scheduling in computing communication by keeping advanced AI in edge intelligence by minimizing E2E delay and achieving high reliability for URLLC. The proposed ML training entails controller switches, multiple training processors at the cell level of edge intelligence to enhance the accounting of transmission overhead and the channel dynamics [30], [161], [237], [238].

The deep-RL enables access points by estimating the decoding error probability in the short block length, the access point able to evaluate the delay, and the reliability of a clear exploit by transmitting a great number of packets through the wireless network. The deep-RL minimizes the average training latency by evaluating the loss and guaranteeing target reliability. To address this, the theoretical formulas are applied to evaluate a clean-slate design in terms of DNN architectures [62], [63] and used practical coding schemes like polar codes to guarantee and reduce transmission error probability with short, block-length channel codes [30], [48], [141], [239]–[241].

3) CLOUD INTELLIGENCE AT NETWORK LEVEL

The could intelligence in DNN improves the estimation channel for large-scale channel gains by guaranteeing a high packet-arrival rate from all MUs to the access point [33]. The intelligence-based cloud computing allows MUs to act as data collectors that always transmit data to cloud servers through the access point with controlled data preprocessing capabilities. Because of difficulties in predicting queuing delays, the DL uses off-line datasets at a central server algorithm through using the mobility management entity for selecting the optimal user association in the large-scale channel gains. This is to guarantee a high packet-arrival rate between the mobile edge and each access point [242], [51], [217], [61]. This scenario requires a decrease in connection with the cloud. Its applicability is controlled by the battery capabilities of edge hardware. To address this, the optimal solution proposed for the training samples through optimization algorithms depends on when channels change and also on training the DNNs for optimization. In addition, based on a highly active network that is entirely updated to the central cloud through real networks, the excessive communication overheads are made adequate.

The predictability in a large, central cloud-only area needs information that is static to prevent big overheads [33], [53], [51]. How the AI training is divided between the edge and the cloud depends on what grants their small power necessities for devices at the edge of the network and intelligent phones. Currently, the cloud-centric architectural model of AI requires end-user devices to transmit data to the cloud while accruing a high cost for data transmission and meets delays in achieving the low latency requirements for URLLC. This requirement possibly reflects the latest information on joined learning and allocated learning for edge devices.

4) INTELLIGENCE SENSE LAYER

Deep learning is used to enhance the stringent requirements of 6G for an intelligence sense layer to provide high security and low latency. The integration of sensing data in physical environments and high capabilities with mobility is the most primeval responsibility in 6G networks. The intelligent-sensing layer was described by independent intelligent sensors and information pertaining to the whole physical network layer. Established routing protocols are mainly based on the sensing layer. Moreover, improvements to the design and flexibility of sensors and innovations in sensing functions depend on dedicated signal processing. Whereas sensing is very important in cellular IoT, the highly accurate sensing for the IoT reduces the latency of big data by transmitting sense information through wireless communication networks. For example, address spectrum shortage problems and spectrum efficiency depend on improving the spectrum sensing technique in the physical network layer for 6G networks. Conversely, the intelligence sense is very important for minimizing the average prediction error and optimizing the sensing decision. This depends on whether the base-learner for stochastic-gradient-descent is deployed, which decreases the operating cost of transmission and data redundancy through arranged fusion accuracy [162], [243]. Moreover, the intelligence sensing layer is able to help in interacting with the physical environment and provide an ultra-reliable transmission between sensors, controllers, and actuators for a high-definition video transmission among a remote monitor, a procedure, and another slice [244].

The sensing in the physical layer is able to sense several physical parameters and provide more integrated services to collect data using sensors for MUs, which are the crucial drivers of the IoTs [245]. Avoiding interference and selecting higher-layer protocols depend on developing a dynamic sensing protocol in cross-layer architecture. The intelligent sensing for both space transmission channel information and interferences requires using intelligent channel sensing. This intelligent channel sensing utilizes the cross-layer cognitive networking algorithm and develops to improve system reliability and reconfigure network protocols at several layers [246]. Furthermore, the lack of data transmission in the routing of mobile intelligent fog computing will be enhancing by employing the routing protocol through the control procedure of the cluster. This is achieved through employing fog nodes onto the sensing layer. The guaranteed optimal clustered routing depends on selecting an optimal number of clusters and the distance of the single-hop by employing fog nodes onto the sensing layer [246], [52].

5) MOBILE DATA MINING AND ANALYTICS LAYER

The analytical layer aims to treat and evaluate the great amounts of data created from a massive number of devices connected to 6G networks. The big data DL aids in data reduction at early stages and analyzes the big data during the preprocessing of sensitive data created from a large number of devices. Achieving the valuable feat of early information detection from large data streams requires using a large number of high-dimensional and sparse data [52], [247]. In addition, the prediction of user mobility, traffic comportment, and channel variants enable flexible network capability distribution at the core of the network through leveraging data mining and big data technology. Data mining and information detection are needed to analyze the collected data and support improved decision-making during the processing of big data.

The improvements in channel modeling were initiated by the big-data DL method, whereas data mining approaches used the mining connection rules to accelerate the development of information detection, to avoid the low-density value of high mobile costs, and to provide efficient transmission in the complex channel [55], [248], [249], [250]. The proposed DL algorithms improved big data by using different methods for huge data reduction approaches [16]–[18], [33], [56]. In the era of huge data, several data analysis systems are facing great challenges as the data capacity increases in 6G networks. The data capacity in ML-based mobile devices for DL is improved by solving the complex problems preventing increasing data capacity. This improvement is generated by simulating neurons and synapses that are able to produce a learned hierarchical approach to current big data samples and avoid the low-density value of big mobile data [57], [251]. Facing the challenges threatening future 6G networks depend on the development of data storage during the preprocessing of sensitive big data from physical environments such as heterogeneous sources, data mining, and analytics.

The quite valuable initial knowledge was obtained by analyzing the collected data regarding information detection while the data-driven DL improves 6G by advanced data analytics. The proposed AI-based enhancements are self-aware, self-adaptive, and use predictive networking to run the network. These advanced methods analyze the collected data and support improved decision-making during the processing of big data, enhancing the system's intelligence [54]. Moreover, the collected data from physical environments are enhanced by decreases in processing time and storage space through features such as channel information being greatly collected and high-dimensional data. This great data collection is enhanced by utilizing self-aware, self-adaptive, and predictive networking algorithms to achieve more in-depth knowledge of the performance of 6G networks. The proposed method incrementally optimizes the swift decision-tree algorithm by a balance of general accuracy, high-prediction accuracy, and tree size. This proposal guarantees the best performance under imperfect data information without reinventing the proverbial wheel [55].

6) INTELLIGENT CONTROL LAYER

Great agents such as devices and base stations are enabled by utilizing a selection of correct actions such as power control, spectrum, and network connection. The power control, spectrum, and network connection all improve based on the intelligent control layer that involves learning and decision-making, and that improves from lower layers. Determining a feedback loop between the decision-maker and the physical system to adopt universal AI services from the core to the end of devices attached to the network requires using a deep-RL [22]. Decision-making in 6G networks improves on the basis of the precoding variables in THz transceiver systems, which allow massive agents to intelligently select the maximum of correct decisions through joining the high-quality service requirements. However, power control access to the physical channel for all upper layers and network connection functions are achieved by utilizing AI techniques for medium-access control (MAC). Meanwhile, every agent has an intelligent brain. The AI in 6G networks achieves optimum network sharing, E2E PHY scheme, edge computing, and heterogeneous networking by using the learning process to increase the performance of every device. Furthermore, intelligent deep-RL algorithms will enable a more reliable and established data rate per application, based on advances in ML, which facilitate the real-time analysis in different layers of the network such as the medium access layer, the physical layer, and the application layer [252].

High levels of feasibility, self-confirmation, self-improvement, and self-regulation are achieved through employing AI learning. The high coverage area, big data rate, and applicability improved in 6G networks by using the MAC layer protocols with IoT [253]. Therefore, MAC allows big data analytics to extract huge patterns for machine-centric communication based on allowing self-organizing processes [254]. The MAC layer protocols with IoT enable access to carrier sense multiple accesses with collision avoidance and access to the physical channel to improve the transmission efficiency for all upper layers and handle the big data rate. Supporting THz band communication depends on using the MAC protocol in multi-band transmission with high flexibility that changes during the aforementioned bands for data transmissions through designing more flexibly integrated networks [255], [256]. The MAC layer proportion trains cellular AI by using the over-air response to inform layer weights based on the backward propagation algorithm to increase the availability of training data. The decreasing training overhead is a critical product for the feasibility of a MAC layer based on AI models [257]. The intelligent MAC protocol improved by using ML, which utilizes classification training for MAC protocol selection. The operation of the proposed non-competitive protocols selected the optimal MAC protocol, which improved big data collection and dense networks [279]–[282].

VII. FUTURE RESEARCH DIRECTIONS

Future research is based on the application scenarios and a multi-level architecture that enables a data-driven DL in AI as well as many supported slices in 6G discussed in the last section. In this section, we present the future research direction for AI technologies that will improve the 6G network performance based on its effective learning capability.

A. COMPUTATION EFFICIENCY

The computation efficiency is a challenging topic for DL, which is capable of gradually achieving promising results in wireless networking. The improved computational complexity in 6G wireless networks based on explicit inductive inference models normally pursue learning algorithms that achieve exact identification. The learning algorithms are essential to be efficient by developing their performance by analyzing the collected data in 6G and evaluating transmission links with every IoT devices designers. The best computation efficiency was deployed by apply DL for URLLC in 6G wireless networking. Furthermore, the computation efficiency for IoT devices trains the necessary DNN treatments in resource-constrained devices such as self-driving cars, drones, and auto-robots by reducing the delay caused by device transmission. DL provides high computation efficiency to design efficient AI by improving research methods with high-performance computing facilities. These improvements include reducing complex computation, network control, network edge, storage, cloud, and end devices of 6G networks. The DNN develops extremely challenging techniques in distributing the neural networks based on proposed new designs ranging from systems for estimation offloading to network architectures [262].

B. HARDWARE COMMUNICATION FOR 6G

The hardware development is a very critical challenge for designing 6G, where the radio access equipment and IoT devices have become a more pervasive method to satisfy the future connectivity requirements. Moreover, involving more hardware and algorithms designed for Non-Line-of Sight and multi-beam acquisition allows 6G wireless networks to operate in THz. The hardware development depends on the low cost of hardware components and achieving a low-cost distributed policy with good antennas and the smallest processing. In addition, the hardware communication for 6G can make improvements through using the massive MIMO techniques that will become more advanced from 5G to 6G and could involve a new complex architecture such as transmission protocol and algorithm design.

Design complexities in hardware for different communication implementation DL and AI were overcome by applying the well-behaved solution in unsupervised and reinforcement learning environments [93], [263]. The radio access moves toward THz bands by reducing the cost of hardware, lowering interference, reducing the power constraints, and increasing the gains for the antenna array, which will considerably affect the transceiver and algorithm design. Advanced hardware-efficient transceivers are applied through increasing the IoT devices' storage, highly accurate sensing at IoT, and civilizing the design flexibility to allow for the development of hardware in 6G networks. From increasing the IoT devices' storage and producing highly accurate sensing in the IoT, the latency will be reduced depending on DNN architectures and developing the complicated transmission protocol for learning algorithm design. In addition, the development of AI learning algorithms in terms of learning is essential to significant research for improving high computational functions such as adapting learning matrix computation and transferring learning for intelligent communications.

C. SCALABILITY AND ROBUSTNESS

The ML techniques are able to provide an adequate capacity for big data by increasing the performance of the infrastructure that supports immense parallelization and improving the scalability of model training through treatments that range from inference algorithms to developed learning [264]. It is even possible to apply the ML techniques in terms of computing for large data sets, where the total data collected from mobile networks is too large to predict productivity. Managing big data require so great capacity for both regulated and unregulated data that exceeds the capacity afforded even by established database and software techniques.

Demonstrating high dynamics in both of the base station's relatives, the high quality of channels, and network topologies depend on overcoming the current limitations of AI learning algorithms. Developing the tremendous robustness and scalability of the learning framework to overcome these limitations depends on supporting the possibly infinite number of interacting entities and high QoS. In addition, enabling the scalable epistemic uncertainty estimation in DL depends on the robustness of the design that's required in real-world vision. It also requires the use of state-of-the-art DNNs. However, the high scalability and robustness depend on providing strong verifiable acuity by designing a dynamic Mix-Train using an accurate prediction from ANNs to guarantee the capacity for big data in 6G. The estimation of necessary scalability is made by subsequently trained robust ANNs, whereas the ANNs enhance the efficiency and decrease the processing delay of the communication [265]. Nevertheless, the proposed compensated learning phase provides a real estimator of neural networks that were able to evaluate the robustness of a neural network without the costly testing and provide robust neural networks.

D. TERAHERTZ COMMUNICATIONS

THz communications are a promising technology that supports ultra-broadband in 6G networks. The THz band from 0.1 THz to 10 THz was identified as a gap band among the microwave and optical spectra. Increasing system capacity and improving spectrum efficiency depends on increasing the system bandwidth to this THz range. This requires decreasing the propagation loss to provide the high data-rate communication for hundreds of Gbps for short-range communications. It also requires increasing the wireless data traffic volume by using several folds in 6G. It is not currently possible to run data-hungry apps that have large quantities of information, such as video transmission, and spectrum bandwidth, in the mm-wave spectrum. Therefore, addressing these challenges requires improvements to spatial-spectral efficiency and a larger radio frequency spectrum, which are only found in the THz and THz sub-bands. The merging of THz communications and sensing equipment for future 6G cellular networks is very important to fulfilling the requirements for a multi-Tb/s data rate. Additionally, the THz band will sustain mm-wave, a quiet frequency, to avoid high path loss. The 6G global networks will be an ultra-dense heterogeneous network, which needs the aid of ultra-high-capacity x-haul.

The large intelligent surfaces enable the super-narrow beams that will diminish the strict propagation loss for THz bands and the collected co-channel inter-cell interference. However, the ML uses THz communication to provide an exact estimation of channel quality and high prediction accuracy based on treat time-varying channels. The treat time-varying channel function as finite-state Markov channels and utilize deep Q networks able to learn and provide the best user selection. Meanwhile, the THz spectrum combined with a DNN provides unprecedented sensitivity for detecting at air interfaces and user-end levels [266]. It is widely recognized that 6G can achieve the hybrid THz/free-space based on the hybrid electronic-photonic transceivers [267]. Enabling the spectrum beyond 140GHz with exacting products in actual short-range communication provides high data rates [268]. Nevertheless, the major challenges that need to be addressed in the coming years depend on improving the sensibility of the THz band, molecular absorption, selection, and reducing the complexity circuits for Analog-to-Digital and Digital-to-Analog conversion and transmission.

E. ENERGY MANAGEMENT

In the future, the most formidable challenge is energy management for 6G networks, which requires managing controlling and decreasing energy consumption. The energy efficiency will matter more in the case of reducing energy consumption per bit (J/bit), where more power will be consumed due to intelligent connectivity for massive data processing and ultra-large antenna processing. Moreover, energy management is designed to maintain the efficient treatment of the harvested energy. The circuit power consumption and transmission stack enhanced in 6G networks based on design energy-awareness in mind provides for energy harvesting circuits and allows devices to be self-powered with high efficiency and less energy [269].

The advanced energy management schemes are very sharp in 6G networks. Furthermore, AI techniques have the potential to help these infrastructures and help devices optimize energy management strategies through intelligent energy consumption management. In addition, neural networks use AI and DL techniques to optimize energy management. Achieving the performance tradeoff of the energy efficiency of THz communications systems depends on selecting the optimal power in massive antenna arrays that need to be carefully treated in the ultra-massive MIMO. However, the current predominant method fulfills the future connectivity requirements depending on deployed energy-harvesting schemes for low-power consumption. Energy harvesting is established to produce the highest reliability for energy management. The reinforcement learning for energy harvesting adapts its energy management policy and power consumption for a time-varying environment to achieve a very low computational output that is suitable for resource-constrained systems in reinforcement management.

Achieving the highest throughput possible and low energy consumption requires using harvested energy prediction schemes that use an improved pro-energy model to develop energy management [270]. Furthermore, the extended Kalman Filtering techniques adopt its energy management method by controlling and decreasing energy consumption, which is achieved by predicting the harvesting power for AI through adaptive security specification in the IoT and 6G networks. Then, it must be addressed that the 6G high-level security necessitates the consumption of more energy. For this reason, the IoT sensing devices are proposed to provide the energy harvesting technique based on the adaptive security technique for IoT devices at transmission signal through THz [138], [271].

F. NOVEL CHANNEL ESTIMATION

The channel estimation for identifying entrance will be an essential module of ultra-high frequencies in 6G. Hence, 6G wireless network systems require improved channel estimation performances. This can be achieved through designing efficient processes for directional connections by using multiple frequency bands and high bandwidth. Producing accurate CSI is challenging due to channel estimation errors and mobility. The ML in DNN improves channel estimation in future 6G networks based on training and inference.

The physical layer employs unsupervised learning to exploit novel channel estimation techniques. This is done to improve the efficiency through the proposed channel-aware feature extraction and interference elimination. The DL-based channel estimation improves the accuracy of the estimation during the training of the neural network, although it must cope with complex channel environments. The equalization modules of the channel in the physical layer that were realized in a single DNN were able to achieve better accuracy of the channel estimation [272]. However, it is difficult to obtain a channel transfer that can deal with the time-varying channel and location. Solving this issue requires auto-encoding an E2E learning system within DNNs to enhance the capacity and accuracy of the estimated channel. Meanwhile, improving intelligence to the physical layer also improves the smart estimation of symbol detection, channel tracking, and mitigation of interference at transmission signal between transmission and receiver [273]. Besides, eliminating the applied priority of signal processing enhances the capacity and improves the accuracy of channel estimation by using ML for the physical layer. The high data rates and low latency for future 6G implemented in real-time are achieved through using the channel model standards for 3GPP ITU to support the modeling of channels up to 100 GHz [274]. The ML and the intelligent channel modeling will be automatically predicted and will allow the channel to more adequately accommodate the big data.

VIII. CONCLUSION

URLLC is an innovative technique that can adequately address the reliability challenge in 6G communications and has a wide array of applications. The applications include tactile internet and intelligent transportation systems based on ML techniques. The main contribution of this research paper is to enhance the data-driven DL in AI based URLLC. This enhancement enables device intelligence, edge intelligence, and cloud intelligence through the use of the training process in unsupervised learning for URLLC. A comprehensive review on advanced URLLC and its enhancements was thoroughly explored in this research paper, and prepare references to discuss certain primary problems that are still unresolved in this research field. After exploring this comprehensive review on advanced URLLC some AI-based solutions are provided to be adopted into different features of 6G networks in deploying and managing multi-level architecture for URLLC in DL. These AI-based solutions are data-driven in the edge intelligence, device intelligence in MU, and cells. In addition, this paper presents the AI technologies that improved the 6G network's performance based on its effective learning capabilities. The learning capabilities such as computation efficiency, hardware communications for 6G, THz communications, energy management, scalability and robustness, and novel channel estimation. The ML in 6G utilizes THz communication to achieve a perfect channel quality estimation and high prediction accuracy based on the treat time-varying channels. In addition, future connectivity requirements in 6G devices depend on deploying energy-harvesting schemes for low-power consumption. Therefore, the high computation efficiency that 6G provides requires the development of efficient AI by increasing research methods through high-performance computing facilities and develops extremely capable methods to distribute the processes of the neural networks.

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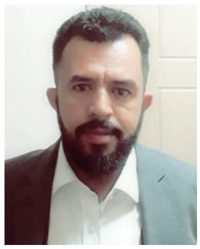
ADEEB SALH (Member, IEEE) received the Bachelor of Electrical and Electronic Engineering from IBB University, IBB, Yemen, in 2007, and the master's and Ph.D. degrees in electrical and electronic engineering from University Tun Hussein Onn Malaysia, Malaysia, in 2015 and 2020, respectively. He is currently a Postdoctoral Researcher with the Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia.

LUKMAN AUDAH (Member, IEEE) received the Bachelor of Engineering degree in telecommunications from Universiti Teknologi Malaysia, in 2005, the M.Sc. degree in communication networks and software and the Ph.D. degree in electronic engineering from the University of Surrey, U.K. He is currently a Senior Lecturer with the Communication Engineering Department, Universiti Tun Hussein Onn Malaysia. His research interests include wireless and mobile communications, internet traffic engineering, network system management, data security, and satellite communications.

NOR SHAHIDA MOHD SHAH (Member, IEEE) received the B.Eng. degree in electrical and electronic from the Tokyo Institute of Technology, Japan, in 2000, the M.Sc. degree in optical communication from the University of Malaya, Malaysia, in 2003, and the Ph.D. degree in electrical, electronics and system engineering from Osaka University, Japan, in 2012. She is currently a Senior Lecturer with Universiti Tun Hussein Onn Malaysia. Her research interest includes optical and wireless communication.

ABDULRAQEB ALHAMMADI (Member, IEEE) received the B.Eng. degree in electronic majoring in telecommunications, the M.S. and Ph.D. degrees in wireless communication from Multimedia University, Malaysia, in 2011, 2015, and 2020, respectively, and the second M.S. degree from the University of Putra Malaysia, in 2019. He served as a Research Assistant/Research Scholar with Multimedia University from 2012 to 2019. He is also the author of more than 30 articles in international journals and conferences. His main research interests include heterogeneous networks, mobility management, D2D communication, cognitive radio networks, localization, and propagation modeling. He is also a member of professional institutes and societies, such as IEICE, IACSIT, and IAENG. He is also a member of program committees at international conferences and workshops. He was a recipient of several awards, including the Excellent Researcher Award 2019, Multimedia University.



QAZWAN ABDULLAH (Member, IEEE) was born in Taiz, Yemen. He received the bachelor's and master's degrees in electrical and electronic engineering from Universiti Tun Hussein Onn Malaysia (UTHM), in 2013 and 2015, respectively. He is currently pursuing the Ph.D. degree. His research interests include control systems, wireless technology, and antenna filter design.

YUN HEE KIM (Senior Member, IEEE) received the B.S.E. *(summa cum laude)*, M.S.E., and Ph.D. degrees from the Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 1995, 1997, and 2000, respectively, all in electrical engineering. Following graduation, she joined the Electronics and Telecommunications Research Institute, Daejeon, for four years. In 2000 and 2011, she was a Visiting Researcher with the University of California at San Diego, La Jolla, CA, USA. She is currently a Full Professor with the Department of Electronics and Radio Engineering, Kyung Hee University, Yongin, South Korea. Her research interests include mobile communications, cooperative communications, and statistical signal processing.

SAMIR AHMED AL-GAILANI received the B.Sc. degree from the Higher Technical Institute, Aden, Yemen, in 1992, and the Ph.D. degree in optoelectronics from Universiti Technologi Malaysia (UTM), in 2014. He started his career as a Senior Lecturer with the Higher Technical Institute. Since then, he has been given various responsibilities, including teaching in high-ranking universities (USM and UTM Malaysia), such as a Postdoctoral Fellow, supervising laboratory sessions, supervising post-graduate students and undergraduate students, an Academic Advisor, the Head of the Laboratory, the Head of the Research Group, the Chairman and a member of different committees, and conducting short courses and training. He has authored nearly more than 30 ISI articles and has an H-index of 9 and total citations of 353. He has presented more than 90 papers in reputed refereed conferences. He also successfully supervised nine postgraduate students. He received the Best Student Award for the Ph.D. degree.

SHIPUN A. HAMZAH received the Bachelor of Electrical Engineering degree from Universiti Teknologi Malaysia, in 1998, the M.Sc. degree in communication and computer from Universiti Kebangsaan Malaysia, in 2000, and the Ph.D. degree in electrical engineering from Universiti Teknologi Malaysia, in 2014. He is currently a Senior Lecturer with the Communication Engineering Department, Universiti Tun Hussein Onn Malaysia. His research interests include active antenna design, harmonic suppression antenna, and energy harvesting.

BASHAR ALI F. ESMAIL (Graduate Student Member, IEEE) received the B.Eng. degree (Hons.) in electrical engineering in telecommunications from Ibb University, Yemen, in 2008, and the M.Eng. degree in electrical engineering from Universiti Tun Hussein Onn Malaysia, in 2016, where he is currently pursuing the Ph.D. degree in electrical engineering with the Faculty of Electrical and Electronic Engineering. He has published many articles in journals and conference papers. His research interest includes design of metamaterials structure, millimeter wave antenna, reconfigurable antenna, and FDMA systems.

AKRAM A. ALMOHAMMEDI (Member, IEEE) received the B.Sc. degree in electronics engineering from Infrastructure University Kuala Lumpur, Malaysia, in 2012, the M.Sc. degree in electrical and electronics engineering majoring in computer and communication system from Universiti Kebangsaan Malaysia, Malaysia, and the Ph.D. degree in wireless communications and networks engineering from University Putra Malaysia (UPM), in 2019. He is currently a Senior Researcher with South Ural State University (SUSU), Russia. His research interests include vehicular ad-hoc networks, the Internet of Things, fog computing, steganography, and wireless sensor networks.