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6G Massive Radio Access Networks: Key Applications, Requirements and Challenges

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ABSTRACT Driven by the emerging use cases in massive access future networks, technological advancements and evolutions are needed for wireless communications beyond the fifth-generation (5G) networks. In particular, we envisage that the upcoming sixth-generation (6G) networks with numerous devices will demand extremely high-performance interconnections, even under strenuous scenarios such as diverse mobility, extreme density, and dynamic environments. To cater to such a demand, an investigation of flexible and sustainable radio access network (RAN) techniques to support highly diverse requirements and massive connectivity is of utmost importance. To this end, this paper first presents the key driving applications for 6G, including smart cities and factories, unmanned aerial vehicles, and multi-dimensional sensing services, which necessitate the transformation of existing RAN techniques to achieve the key performance indicators required for 6G networks. In particular, we investigate the flexibility, massive interconnectivity, and energy efficiency aspects of 6G RANs and provide an in-depth discussion on the potential key enabling technologies. Last but not least, we present an artificial-intelligence-assisted network architecture for flexible 6G massive RANs with energy harvesting.

INDEX TERMS 6G, energy efficiency, flexibility, massive access, massive interconnectivity.

I. INTRODUCTION

Driven by the rapid growth of mobile traffic, the fifth-generation (5G) wireless communications have been extensively researched and developed to meet the key performance requirements for enhanced mobile broadband (eMBB), ultra-reliable and low-latency communications (URLLC), and massive machine-type communications (mMTC) [1]. As a result, 5G networks has been successfully deployed in some nations and will soon be widespread by the end of 2020. However, as mobile traffic continues to grow and new use cases are rapidly emerging, 5G will eventually encounter technical limitations in supporting *massive interconnectivity with highly diverse and demanding service and computing requirements*. Such massive interconnectivity not only demands extremely huge bandwidth, but also incurs very high network energy consumption. This fosters the need for new paradigms for the next-generation wireless communications – the sixth-generation (6G).

Both academia and industry have begun to investigate the visions, requirements, scenarios, key technologies, and system architectures for 6G networks. More recently, the International Telecommunication Union and Telecommunication Standardization Sector (ITU-T), has formed a study group, namely Focus Group Technologies for Network 2030 (FG NET-2030), to identify and study issues, challenges, scenarios, and fundamental technologies required for 5G and

TABLE 1. Summary on 6G Key Driving Factors and 5G limitations [2], [5], [9], [16], [17], [22]

Key Drivers	Example Applications	Requirements	5G Limitations
5D Services and Communications	Holographic communications, XR, wireless brain-computer interaction	• Ultra-low latency • Ultra-high bandwidth • Ultra-high reliability	• A mixed use case of eMBB and URLLC is not defined for 5G • Scarce bandwidth
Super-Smart City	Smart vehicles, autonomous driving, smart manufacturing, smart robots, smart tourism, intelligent factories, industrial IoT, massive IoT, drone swarms	• Ultra-low latency • Ultra-high bandwidth • ultra-low latency • Ultra-high reliability • Extremely high data density • Ultra-high computation • Extremely high connection density	• A mixed use case of eMBB, URLLC and mMTC is not defined for 5G • Scarce bandwidth • High energy consumption with massive devices • High interference due to massive interconnections • Insufficient computing capacity • Lacks ubiquitous interconnectivities
UAV-Based Communications	Video monitoring with UAVs, flying UAV base stations, Drone delivery, UAV surveillance	• Ultra-low latency • Ultra-high reliability • Ultra-high bandwidth • Ultra-high computation	• A mixed use case of eMBB and URLLC is not defined for 5G • High energy consumption
Non-Terrestrial Communications	Undersea communications, space travel, water-air communications HAP communications	• Ultra-high mobility • Ultra-long distance	• 5G non-terrestrial network (NTN) use case is defined but limited to airborne and space-borne communications • High energy consumption

beyond. Clearly, the aforementioned initiatives indicate a dire need to begin intensive research for 6G wireless communications. This measure is critical in preparation for the unprecedented demands for ubiquitous high-speed connectivity in ultra-dense future networks.

Recently, several seminal works on 6G have articulated a broad view on the visions, requirements, and enabling technologies for 6G [2]–[21]. Despite each of these articles have pointed useful insights toward 6G, several critical aspects on *6G radio access networks (RANs)*, namely *flexibility, massive interconnectivity, and energy efficiency* which are vital to development of 6G are not well-explored. Importantly, flexibility provides the latitude for 6G RANs to reconfigure diverse network functions and resources to cater to use cases with different requirements including quality of service (QoS), end-to-end latency, reliability and user/device density. Meanwhile, the support for massive interconnectivity enables spectral-efficient data exchanges among massive numbers of devices ranging from low-power Internet of Things (IoT) devices to high-power autonomous vehicles in ultra-dense scenarios. On the other hand, high energy efficiency techniques facilitates efficient utilization of energy, prolongs battery lifetime of wireless devices and enables cost-efficient network operation. To sum up, these key requirements indeed play a vital role in the design of future 6G ultra-dense massive RANs.

In this paper, we focus on the key aspects, namely flexibility, massive interconnectivity and energy efficiency in the design of 6G massive RANs. The main novelty and contributions of this paper can be summarized as follows:

1) We provide a number of key driving applications and services for 6G wireless communications, namely five-dimensional (5D) services and communications, super-smart city, unmanned aerial vehicle (UAV)-based communications and non-terrestrial communications.
2) The key aspects and requirements for RANs to support the 6G-driving applications are described. These aspects and requirements are RAN flexibility, support for massive interconnectivity and RAN energy efficiency.
3) A number of key enabling technologies for 6G Massive RANs and their potentials toward enabling RAN flexibility, massive inter-connectivity and energy-efficient communications are also revealed. Besides that, technical challenges for the implementation of these key technologies are also highlighted.
4) Potential artificial intelligence (AI) applications on 6G massive RANs for tackling the technical challenges of implementing the key enabling technologies are proposed.

The remainder of this paper is organized as follows. Section II provides a comprehensive overview on the advanced 6G use cases including super-smart city, services and communications with 5D senses and UAV, as well as non-terrestrial based communications. Then, Section III presents an in-depth discussion on the key aspects and requirements, i.e., flexibility, massive interconnectivity and energy efficiency, followed by the key enabling technologies for realizing each of these requirements in Section IV. Next, we present an AI-assisted network architecture for flexible 6G massive RANs with energy harvesting in Section V. Finally, the article is concluded with several remarks in Section VI.

II. KEY DRIVING APPLICATIONS FOR 6G-RAN

In this section, we describe several emerging applications and use cases that will be driving the development of 6G. These applications and use cases can be broadly classified under 5D services and communications, super-smart city, UAV-based communications, non-terrestrial communications, which are summarized in Table 1 [2], [5], [9], [16], [17], [22]. Also, the key features for 6G required to support these use cases are shown in Table 2 [2], [5], [9], [16], [17], [22].

A. 5D SERVICES AND COMMUNICATIONS

Services and communications based on 5D (i.e., sight, hearing, smell, touch and taste) such as extended reality (XR), holographic communications, and wireless brain-computer interaction are envisioned as 6G killer applications. Many of these applications will incorporate high-precision tactile

TABLE 2. Comparison Between the Key Performance Indicator of 5G and 6G [2], [5], [9], [16], [17]

Cellular Network	Data Rate	Bandwidth (MHz)	Latency (ms)	Reliability (%)	Spectral Efficiency	Energy Efficiency	Connection Density (devices/km^2)	Traffic Capacity	Mobility (km/h)	Network Trait
5G	1 Gb/s	100	1	99.999	3× over 4G	10-100× over 4G	10^6	10 Mb/s/m^2 (Areal)	500	Transmission-centric
6G	1 Tb/s	≥ 300	0.001 - 0.1	99.99999	10-100× over 5G	10-100× over 5G	$\geq 10^7$	1-10 Gb/s/m^3 (Volumetric)	1000	Transmission- and computing-centric

and haptic features to provide a close-to-reality experience to users [2]. To realize these applications, 6G technologies need to offer extremely high throughput requirements, which is in the order of Gbps to Tbps, and guarantee a latency of $1 - 10\mu$s. Such use cases entail the joint fulfillment of eMBB and URLLC, which have only been considered independently for 5G networks.

B. SUPER-SMART CITY

Emerging smart city and industry applications such as smart vehicles, autonomous driving, delivery drones, smart manufacturing, and smart robots generally require precision control, strict guarantee of ultra-low latency (typically below 1 ms) and reliability of 99.9999% [7]. These applications are well-investigated in 5G under the URLLC use case. On the other hand, industrial and massive IoT are well-explored under the 5G mMTC use case, which in general corresponds to low-power applications. However, in the era of 6G, it is foreseen that all the aforementioned applications will be widespread. Extreme network densification give rise to a large number of wirelessly connected sensors, cameras, caches, computing elements, and controllers (ranging from low-power ones to high-power ones) concentrated within every small area. Consequently, a huge volume of data will be generated and will need to be transmitted across the 6G network. Furthermore, given the advancement in the area of XR (e.g., augmented reality), it will be introduced into smart factory for remote control and inspection, which will require a large bandwidth. Besides, future smart applications will be empowered by AI, which consist of computational-intensive operations. Furthermore, energy consumption will be enormous with the massive amounts of communications, processing, and sensing [23], [24]. Hence, a new use case category on massive autonomous systems - concerning latency, reliability, bandwidth, data density, connection density, computational load and energy efficiency - need to be defined for 6G, and both mMTC and URLLC would just be special use cases under this new category. Besides that, intercity travel with high-speed transportation such as high-speed trains will become more prevalent across the nation, and this will foster the need for extremely high reliable connectivity [25].

C. UAV-BASED COMMUNICATIONS

Various UAV applications including delivery of supplies, surveillance, communications, rescue, and public safety have been investigated under 5G use cases [26]. However, UAVs have found another important use whereby UAVs can be used as *flying base stations* (BSs) or *flying relay nodes* to extend connectivity in hotspot areas, disaster-struck regions and rural areas [27], [28]. This application requires the UAVs to process and transmit data quickly while maintaining ideal positioning in the 3D space to provide optimal communication coverage. Nevertheless, executing such tasks successfully involves extreme precision control, strict end-to-end latency and reliability guarantee, and high computational power, which poses substantial burden on power-limited UAVs. Moreover, interference between flying BSs and fixed BSs will become a major issue due to varying position and mobility of the UAVs. Currently, the development of UAV-mounted base stations have been considered as one of the study items in 3GPP Release 17, but this technology may only be fully functional in the 6G era.

D. NON-TERRESTRIAL COMMUNICATIONS

Although 5G has defined several non-terrestrial network (NTN) scenarios such as satellite-terrestrial communications [29], these scenarios are limited to airborne and space-borne communications [30]. Next-generation mobile networks are envisioned to span all sorts of non-terrestrial domains including sea and underwater which are yet to be studied under the 5G standardization [2], [3]. Relevant 6G NTN scenarios include communications between users on the ground, airplanes, satellites, ships, and even undersea submarines. These scenarios will be useful for use cases such as monitoring marine lifes, underwater oil exploration and tracking of airplanes. Although guaranteeing performance under such challenging and dynamic environments is difficult, 6G networks is expected to deliver excellent performance. Recent development in wireless communications have made communications between airplanes and undersea submarines feasible [31]. Nevertheless, several issues are still open and required to be addressed. For instance, 6G needs to support a mobility of up to 1000 km/h for air or space-borne communications, communications through the water-air barrier and energy-efficient long-distance communications.

III. KEY ASPECTS AND REQUIREMENTS FOR 6G RAN

In the future, 6G is envisaged to support even more diverse use cases with various requirements, not only limited to 5G eMBB, URLLC, and mMTC use cases. As such, 6G RANs need to be extremely flexible in customizing their resources for the various use cases. Specifically, some of the 6G use

TABLE 3. Appropriate OFDM Numerology for Different 6G Use Cases

Example 6G Use Case	Numerology Parameter (n)
5D Services and Communications	High
Super-Smart City	Low-to-High
UAV Communications	Low-to-High
Non-Terrestrial Communications	Low-to-Medium

cases such as smart city and industry are anticipated to involve complex computation and massive interconnectivity. Furthermore, standalone wireless devices operating on limited-size batteries (e.g., UAV-based communication and non-terrestrial communications) are expected to be self-sustainable. To maintain uninterrupted operations, the research community has also put additional emphasis on improving energy efficiency. In this section, we explore and analyze three key requirements for 6G RANs, namely *flexibility, massive interconnectivity, and energy efficiency*.

A. FLEXIBILITY

In the future, 6G is envisaged to support even more diverse use cases with various requirements, not only limited to 5G eMBB, URLLC, and mMTC use cases. Here, we discuss several aspects crucial for RAN flexibility, namely frame structure, cell size, bandwidth scaling, network function placements and resource management.

Frame Structure: Scalable orthogonal division frequency multiplexing (OFDM) numerology has been proposed for 5G to make the transmission frame structure flexible [32]. By parameterizing the OFDM-based subframes, the subcarrier spacing of resource blocks (RBs) can be scaled according to 15×2^n kHz, where n is the integer-valued numerology parameter. The subcarrier spacing can be chosen according to performance (e.g., latency, reliability, throughput, etc.) requirements of the specific application. For instance, wider subcarrier spacings are suitable for low-latency and high-reliability critical applications such as autonomous driving and UAVs, whereas narrower subcarrier spacing is suitable for low data rate or machine-type communications such as narrowband IoT applications. In addition, a wider subcarrier spacing is essential for applications operating at higher frequency bands, such as millimeter wave (mmWave) and Tera-Hertz (THz) frequency bands, to alleviate the Doppler spreads for high-mobility scenarios. Clearly, the scalable OFDM numerology will be the underlying foundation for flexible 6G RANs [6], and more numerologies will need to be available to cater for even more diverse applications in the 6G era. See Table 3.

Cell Sizing: Cell sizing has been traditionally manipulated to achieve RAN flexibility for addressing coverage holes and load balancing problems. It is mainly performed by scaling the transmit power and cell range biasing. In ultra-dense networks, adaptive cell sizing can help cater to different user densities and heterogeneous traffic demands in different geographical areas. For instance, in areas with high user densities, the coverage of the nearby small cells can be expanded by increasing their transmit power, or cell range bias (e.g., via signal-to-interference-plus-noise ratio [SINR] biasing). Looking into the rapid network densification, cell sizing will undoubtedly play a central role in supporting massive access, however other factors such as computing and transmission capacity of the cells will still need to be taken into account.

Bandwidth: In ultra-dense networks, the accessible bandwidth of each cell can be scaled and allocated to meet the variation in traffic demands or the number of users in proximity. For instance, the bandwidth of under-utilized cells can be "borrowed" by other congested cells to enhance the capacity. More importantly, it is vital to support high-bandwidth applications such as holographic communications and XR. Although the proliferation of carrier aggregation, mmWave and THz communications can provide huge amounts of bandwidth for 6G, efficient bandwidth allocation will still be needed to support 6G massive access use cases with highly diverse requirements.

Customization of Network Resources and Placement of Network Functions: In next-generation RANs, network functions and processing tasks will be distributed in cloud and edge servers. Such a distributed paradigm allows functional splits between RAN functions so that some of the RAN functions are centralized in the cloud while others are located at the radio frontend and edge server. By leveraging network function virtualization (NFV) and software-defined networking (SDN), logical RAN functions (e.g., scheduling, baseband processing) can be flexibly virtualized, scaled, and placed at the cloud and edge based on service types, QoS requirements, or transport network requirements [33]. For instance, more storage and computing resources can be allocated for logical RAN functions in the control plane (CP) than in the user plane (UP) for IoT applications, because these applications often generate small data packets with a multitude of connections [33]. Moreover, the computational capacity of baseband processors can be scaled according to the QoS requirements, such as minimum data-rate requirements [34]. RAN functions that handle strict real-time (RT) requirements such as scheduling can be placed at the edge to minimize latency and improve reliability. Besides, for more latency- and reliability-critical applications that heavily involve a number of CP functions, these functions may be moved to the edge. With the emerging numerous diverse 6G use cases, flexible customization of network resources and network functions is absolutely important to ensure efficient resource utilization, while meeting the requirements of the use cases.

Dynamic Radio Resource Management (RRM): Most of the RRM functions are featured to be dynamic and adaptive. These features indicate that the radio resources can flexibly be allocated according to the traffic demands, channel conditions, and users' QoS requirements such that the network performance can be optimized. Typical flexible RRM functions are RB scheduling and power allocation, which are often jointly considered for optimal resource allocation algorithm design. Essentially, such design achieves the targeted data rate by allocating sufficient transmit power to the RBs selected for transmission. Given the importance to support high-throughput massive access, a flexible power allocation mechanism for BSs, which are equipped with advanced signal processing and antenna technologies, is required to facilitate advanced techniques such as the coordinated multipoint transmission in multiple-input-multiple-output (MIMO) systems. Besides, link adaptation is regarded as a flexible RRM function, whereby adaptive modulation and coding scheme (MCS) is applied to improve the data rate and reliability of the transmissions.

B. MASSIVE INTERCONNECTIVITY

Unlike the 5G mMTC use case, emerging 6G smart city and industrial IoT applications involve vast amounts of communications, data exchange, sensing, storage, controls, and computing in supporting the upcoming massive interconnectivity in dense 6G networks. Indeed, supporting such connectivity requires sufficient capacity and efficient spectrum usage.

Network densification is a viable way to support massive interconnectivity. By densely deploying low-power BSs, network capacity increases and more users/devices can be supported. The capacity can be further enhanced by exploiting the spectrum beyond sub-6 GHz bands such as mmWave and THz, which provide a substantial amount of bandwidth, and with appropriate access mechanisms, the network can effectively provide support for data-intensive use cases such as: (i) the delivery of large-size sensory data in vehicular communications, (ii) very-low latency and data-rate intensive sensory data delivery in XR, holographic communications and UAV applications in smart city, and (iii) connected autonomous robotics in Industry 4.0. However, network densification alone cannot keep up with the rapid growth in the number of wireless devices. In addition, inter-cell interference can severely limit the achievable capacity when BSs are in proximity. Although exploiting the mmWave or THz band potentially provides extremely-high data rates and capacity, it suffers from high channel attenuation and is susceptible to blockages. Another approach for supporting massive access is to reshape the traffic data arrival distribution into random access attempt distribution which can reduce burstiness of data arrivals [35]. However, this may only be suitable for low-rate MTC devices.

Therefore, it is hard to guarantee reliable communications and is problematic, because enabling future super-smart city and industry indeed require ultra-high reliable communications providing data rates of up to 1 Tbps under dynamic and dense scenarios.

C. ENERGY EFFICIENCY

With the rise of cloud/edge/fog computing, 6G RANs can be envisioned as *massive-access massive-computing* networks. Key technologies for massive access such as mMIMO and NOMA incur a substantial amount of energy to improve the signal strength for enhancing the achievable throughput. Meanwhile, dense deployment of edge/cloud servers, use of advanced signal processing techniques and massive data processing will significantly increase the network power consumption. Moreover, due to the advent of Industry 4.0, industrial IoT applications have gradually become prominent and the number of IoT devices will rapidly increase, resulting in even higher power consumption from the industry [36]. Traditionally, the energy efficiency of wireless networks is enhanced by means of improving the design of hardware equipment, physical-layer functions [37], high-level network protocols [38]–[40], cellular network architectures [41], [42] and other aspects which are detailed in [43]. However, these directions are not adequate to reduce the power consumption of the future massive-access massive computing 6G networks. That said, the design of sustainable 6G wireless communications are of paramount importance, and this is aligned with the United Nation's call to achieve the sustainable development goals (SDGs) by year 2030 [44], [45].

IV. KEY ENABLING TECHNOLOGIES FOR 6G MASSIVE RANS

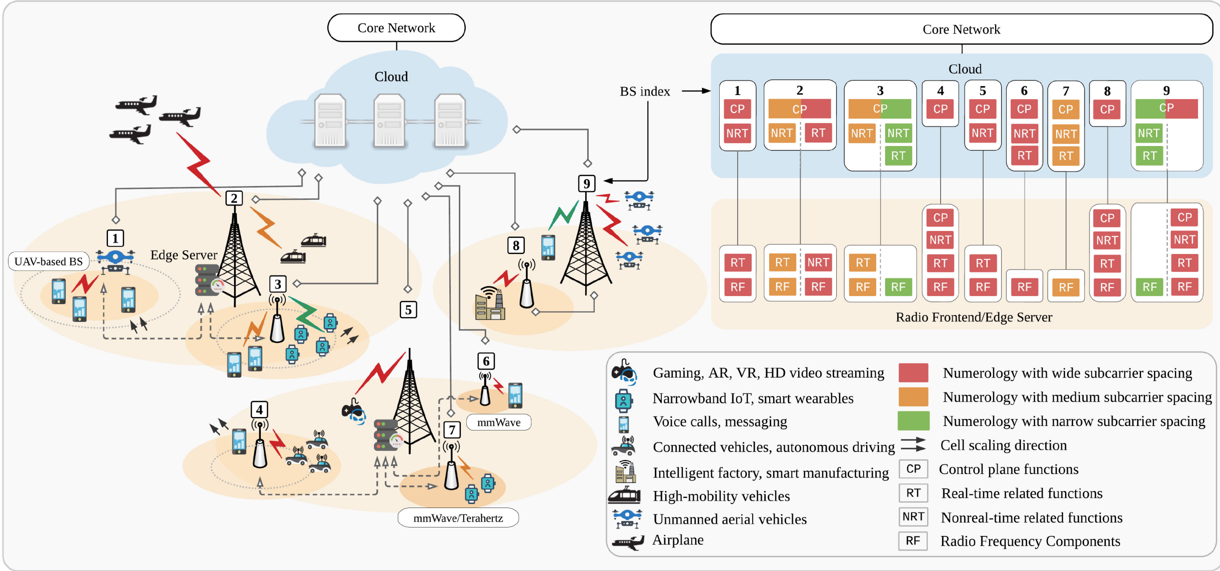
In this section, we present several potential key enabling technologies for 6G to enable flexibility, massive interconnectivity and energy-efficient communications.

A. NETWORK SLICING FOR 6G FLEXIBLE MASSIVE RANS

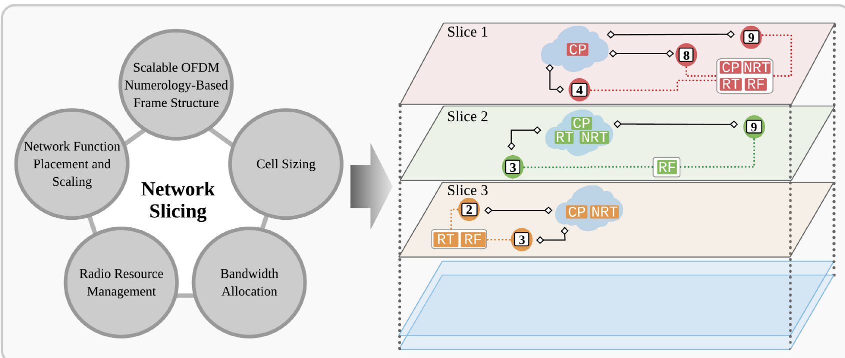
6G needs to be fully flexible, that is, the ability to adaptively customize the RAN configurations, functions, and resources to accommodate the highly diverse 6G use cases. That said, 6G networks need to integrate all the flexibility aspects, as mentioned in Section III-A. Here, we deem that network slicing is a promising technology for such integration.

With the advancement in NFV and SDN, network slicing [46] becomes a promising technique for achieving full RAN flexibility. Traditionally, in the context of 5G RAN, network slicing focuses on the process of virtualizing multiple logical networks (i.e., *network slices*) containing all essential logical RAN functions and resources, which are customized to a specific use case. We envision that 6G RAN slicing will realize fully flexible RANs whereby slices will be instantiated with flexible selection of OFDM numerology, placement and scaling of RAN functions, cell size and bandwidth of the involved cells, and radio resource allocation strategy to meet the requirements of various 6G use cases. The applicability of network slicing for 6G use cases is demonstrated in Fig. 1.

In Fig. 1, an example future 6G scenario is shown, where several network slices instantiated for different types of services, taking into account the adaptation of frame structure, cell size, bandwidth, network functions and radio resource management in the instantiation. For example, slice 1 is instantiated for latency-critical applications (e.g., UAVs and autonomous driving). The CP and non-RT related RAN functions are placed at the cloud, while the RT-related RAN functions are placed at the radio frontend/edge server, where an OFDM numerology with wide subcarrier spacings is selected. In this slice, the cell size is enlarged for BS 4 to support the connected vehicles, and a larger bandwidth is allocated for BS



(a) (Left) Flexible RAN architecture with scalable OFDM numerologies and cell sizes. (Top-right) The corresponding flexible placement of logical RAN functions at the cloud and radio frontend



(b) RAN slices with flexible radio access settings

FIGURE 1. Our vision for 6G flexible RAN architecture, placement of logical RAN functions, and network slicing.

9, which is serving an intelligent factory, to support smart services such as AR-based remote diagnostics. In addition, slice 1 adopts a more latency- and reliability-aware radio resource allocation mechanism. In another example, slice 2 deals with low-rate communications such as narrowband IoT services. Thus, most of the RAN functions are located at the cloud, and less bandwidth is allocated. In the same slice, the cell size of BS 3 is enlarged to support more IoT devices. Slice 3 is instantiated for applications with medium QoS requirements and for cells with a small coverage.

Despite the applicability of network slicing for 6G, it is very challenging to take into account numerous parameters, aspects and constraints in the slicing process and to be fully flexible in managing network resources and functions in rapidly changing and dynamic environments. Although many related network slicing studies have been conducted for 5G, such network slicing technologies are still far from being fully flexible and capable of processing large numbers of parameters and constraints (e.g., service types, QoS requirements, channel conditions, carrier frequencies, user locations, availability of cloud and edge resources, transmit power budget, RB availability, statistical multiplexing gain of the central cloud, and transport network requirements [33]). For complicated use cases such as UAV navigation and autonomous driving, additional control parameters (e.g., 3D positioning, coordination) have to be considered to adapt to the network dynamics and meet the performance requirements.

B. HYBRID MASSIVE MIMO FOR MASSIVE INTERCONNECTIVITY

BSs with a large number of independently-controlled antennas, i.e., massive multi-input-multi-output (mMIMO), multiplexes multiple data streams in the time-frequency domain. As a result, many users can be served simultaneously, even in high-density networks. This technology is beneficial for industrial IoT applications where many devices will be concentrated in the factory. In [47], it has been shown that mMIMO with 400 antennas can cater to about 8000 industrial IoT devices with low delay, moderate rate requirements - a compelling case where the number of antennas is smaller than the

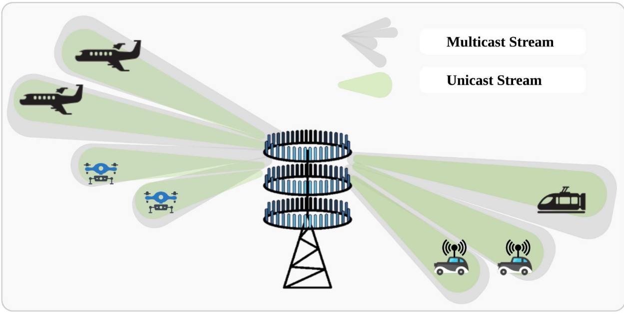


FIGURE 2. BS cooperation with mMIMO-NOMA for massive connectivity with diverse applications' requirements with superposition of unicast and multicast transmissions.

number of devices. Furthermore, by applying practical hybrid-precoding techniques such as that in [48], a system with low-cost hardware, low complexity, and low-power consumption can be achieved. A hybrid-precoder technique is imperative, especially for systems operating at high frequencies as it is technically prohibitive to equip every radiating element of a large antenna array with individual radio frequency chain, which is required for a fully-digital precoder. Furthermore, a fully-digital precoder results in extremely high power consumption at the power amplifier and DACs/ADCs at higher frequencies (e.g., mmWave, Terahertz), especially when the bandwidth is increased. As bandwidth increases, the need to process billions of samples per second in parallel results in high power consumption. While beneficial, due to the limited number of radio frequency chains, designing a hybrid precoder that performs close to that of a digital precoder is very challenging. Essentially, given the limitation, researchers consistently search for the ideal optimization techniques that yield optimal performance for various network scenarios. Other technologies such as that proposed in [49] potentially enhances the performance of mMIMO-based 6G systems.

C. ADVANCED MULTIPLE ACCESS TECHNIQUES FOR MASSIVE INTERCONNECTIVITY

Recently, non-orthogonal multiple access (NOMA) has shown to promote spectral efficiency. By cooperating mMIMO and NOMA, the network capacity can thus be further boosted, and interference between users in the spatial and power domains can be efficiently mitigated. For instance, by applying successive interference cancellation (SIC) at each receiver, a receiver sequentially decodes the received signal while treating the other signals as noise. A variant of NOMA, namely layered division multiplexing (LDM), enables the transmission of unicast and multicast services at the same time-frequency RBs. This feature allows LDM to achieve a much higher multiplexing gain than orthogonal multiple access techniques and thus possess high potential in accommodating massive connectivity of future networks. Fig. 2 illustrates an example network scenario on how a NOMA-based mMIMO system supports massive connectivity with various application requirements.

Apart from NOMA, rate splitting multiple access (RSMA) is less mature but has been recently shown as a promising multiple access technique supporting access for massive connectivity [50] in dense network scenarios. Although RSMA was initially developed for interference cancellation between two single-antenna users, recent development also shows that it supports multi-user multi-antenna non-orthogonal transmissions. In contrast to space division multiple access (SDMA) and NOMA techniques that either treats the interfering signals as noise or decodes the interference, RSMA partially decodes the interference and partially treats the interference as noise. On the one hand, RSMA reduces to SDMA if the channel strengths among the users are similar and exhibit sufficient orthogonality to each other. On the other hand, RSMA reduces to NOMA if the channel strengths are sufficiently diverse and aligned with each other. Having said that, RSMA has shown to be more general, robust, and powerful multiple access techniques than NOMA and SDMA. Furthermore, RSMA offers a lower computational complexity for the transmit scheduler and the receivers. As a result, RSMA can efficiently cope with the high throughput, heterogeneous services, and massive connectivity requirement of future dense wireless networks. Unfortunately, designing RSMA algorithms for systems operating at mmWave or Terahertz frequency resulting in optimal performance is challenging. This issue is mainly due to limitations such as the limited number of radio frequency chains and complex optimization techniques.

D. INTELLIGENT REFLECTING METASURFACE FOR ENERGY-EFFICIENT MASSIVE ACCESS

In the past few years, the advancement in the area of metamaterials revolutionizes wireless communications where the resultant meta-surface can alter the propagation characteristic of wireless signals. Such meta-surface is commonly known as intelligent reflecting surface (IRS), large intelligent surface (LIS), software-defined surface (SDS), or reconfigurable intelligent surface (RIS). In particular, IRS consists of a large array of passive antenna elements (also known as meta-atoms or unit-cells) whose amplitude and phase shifts can be reconfigured. By properly tuning the phase shift of each element, the reflected path of the signals impinging on the surface can be altered to maximize the received signal power. Precisely, the desired signals are added constructively while the interfering signals are added destructively. Preliminary research indicates that precise and narrow beams can be achieved using a large number of passive scattering elements on the IRS, promoting much higher spectral and energy efficiency. As a result, a large number of antennas or radio-frequency chains are no longer necessary at the transmitter and receiver. Furthermore, the reconfiguration of the IRS elements does not require complex decoding, encoding, and radio-frequency processing operations. Therefore, the complexity, power consumption, and hardware cost of the system can be substantially reduced. The aforementioned properties are particularly appealing for densely deployed massive IoT devices. Besides that, IRS is shown to be able to enhance secure wireless communications [51].

By incorporating IRS into the exiting wireless ecosystem, several problems can be encountered. As more and more wireless applications rely on the large bandwidth available at millimeter-wave frequencies or higher (transmission at such frequency is highly susceptible to blockages), IRS can be deployed as a passive relay to overcome blockages, thus maximizes the network capacity. IRS can also be leverage to encounter physical-layer security issues, in which the joint precoding/beamforming signals from the transmitter and the IRS are destructively added at the illegitimate users or eavesdropper. Besides, IRS can assist UAV communications (by deploying IRS on the building to enhance communication quality between UAVs and ground users), wireless power transfer (by exploiting the beamforming at the IRS to enhance the received signal strength of an information receiver while guaranteeing the energy harvesting requirements of the energy receiver), as well as mobile edge computing (by using IRS beamforming to assist the offloading process and enhance the channel conditions).

In the past few years, the advancement made by physicists in the area of meta-materials resulting in meta-surface, which revolutionizes wireless communications; IRS consists of a large number of passive antenna elements with tunable amplitude and phase shifts. Specifically, by properly tuning the phase shift of each element, the reflected path of the impinging signals can be altered to maximize the received signal. Precisely, the desired signals are added constructively while the interfering signals are added destructively. Preliminary research indicates that, by using a large number of passive scattering elements on the IRS, precise and narrow beams can be achieved at the receiver end, promoting much higher spectral efficiency, especially for densely deployed massive IoT devices. Moreover, a massive number of antennas may no longer be necessary at the transmitter, thus substantially reduces the complexity and hardware cost encountered in existing mMIMO implementation. While hardware complexity at the transmitter may be reduced, new complexity issues surface due to the large number of passive antenna elements on the IRSs which only have limited signal processing capabilities. Furthermore, many research questions remain open. These questions are: *(i)* how to allocate resources among the mobile users, given a large IRS or multiple IRSs? *(ii)* how to control each radiating element? and *(iii)* how to accurately estimate the channel between IRS and transmitter and mobile users?

E. ENERGY HARVESTING (EH) FOR ENERGY-EFFICIENT MASSIVE ACCESS

EH is a promising alternative for energy-efficient massive radio access where the energy from ambient environments can supply continuous power to RAN nodes. For example, as depicted in Fig. 3, terrestrial and drone communications can be supported by solar energy. Vibration and kinetic energies can power human body wearables. Industrial IoT can be powered by thermal energy produced from the industrial manufacturing

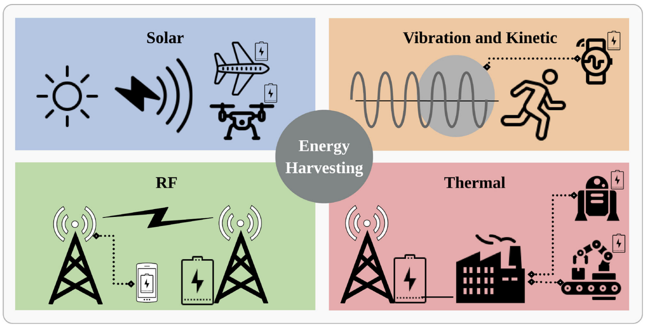


FIGURE 3. Energy harvesting scenarios in future wireless networks.

and production process; and ground BSs can be powered by RF energy emitted from other BSs. In particular, interference energy harvesting is most useful in ultra-dense networks with massive numbers of network nodes. Besides, artificial noises and jamming signals can also be potential energy sources. Such sources have been considered for wireless EH [52].

RF interference is potentially a more prominent energy source, compared to other energy sources. This is because RF energy is increasingly becoming ubiquitous in the frequency band such as the 2.4 GHz and 5.8 GHz bands for WiFi, the cellular telecommunication band from 700 MHz to 2.7 GHz, and the 2.40 to 2.48 GHz band for Bluetooth, as a result of the ever-growing number of RF devices operating in these bands [53]. This is particularly crucial for supporting massive IoT interconnectivity and reducing battery power consumption. Nonetheless, it is vital that an energy harvester such as rectenna[1] to be capable of harvesting energy from those RF bands mentioned earlier. Recent breakthroughs in flexible electronics have allowed rectennas to cover the WiFi and cellular bands for RF energy harvesting, which potentially be the key energy harvesting technology for 6G. However, the design of energy-harvesting rectennas is a daunting task as it needs to accommodate unknown polarization of electromagnetic waves. Besides that, broadband or multiband energy-harvesting antennas have a tradeoff issue between efficiency and bandwidth [53].

Simultaneous wireless information and power transfer (SWIPT) is another promising technology that can allow both information and energy to be extracted from the same received RF signals. This technology, coupled with the use of multi-antenna beamforming, will highly improve the SWIPT efficiency without increasing the bandwidth or transmit power; which greatly benefits the implementation of multi-antenna massive access technologies such as mMIMO. Nevertheless, optimization for beamforming-assisted SWIPT requires a highly sophisticated algorithm due to the fact that the beamforming problem is often non-convex [52], which is not easily solved with standard optimization techniques.

[1] A rectenna is a rectifying antenna which can convert electromagnetic radiation into a direct-current (DC) power.

F. IRS-BASED ENERGY COOPERATION FOR ENERGY-EFFICIENT COMMUNICATIONS

EH-enabled RAN nodes can cooperate among each other by intelligently sharing their harvested energy. Some RAN nodes may request more energy from others due to the need to satisfy the traffic demands or have low harvested energy levels, despite the potential energy transfer loss in the wireless channel. Promising technologies for energy cooperation include antenna beamforming and IRS whereby energy can be relayed to intended directions. In fact, several new studies have recently demonstrated the feasibility and applicability of IRS for energy-harvesting SWIPT communications [54], [55]. However, development of optimal energy-harvesting algorithms remain a major challenge as the IRS-based energy harvesting problems in the studies are non-convex and their proposed algorithms are suboptimal, and thus there is much room for further energy-harvesting performance enhancements.

G. QUANTUM COMPUTING FOR ENERGY-EFFICIENCY

Quantum computing provides significant enhancement for the computing capability due to the use of *qubits* which can hold more information compared to the conventional binary bits. Theoretically, quantum computers can save more energy as they can process more data, and they have the potential to execute complex AI-based network operations for 6G. Recent research on quantum computing has shown that substantial reduction of many orders of magnitude in energy consumption has been achieved by quantum computers over classical supercomputers [56]. Given the powerful features of quantum computing, its application areas have been identified by the industry, which include physical-layer processing in the RAN user plane (e.g., quantum Fourier transform, prediction of the quality of experience for video streaming (e.g., quantum support vector machine), database search, etc. An extensive survey on quantum computing algorithms for wireless communications can be found in [57]. Nevertheless, implementation of quantum computing for wireless communications faces a number of challenges such as the design of quantum error correction codes, development of reliable quantum memory, development of quantum programming languages, the architectural design for a quantum computing-based wireless network architecture, etc [58].

H. ADVANCED RANDOM ACCESS PROTOCOLS FOR MASSIVE INTERCONNECTIVITY

Random access protocols have been considered for supporting delay-tolerant mMTC applications [59]. With the rapidly rising demand for such applications and the increasing number of the corresponding devices, random access protocols would be necessary to handle the massive interconnectivity and access collision avoidance between the devices. Tree-based random access protocols, such as that proposed in [60], are especially promising to handle massive access and interconnectivity while effectively resolving access collisions.

V. ARTIFICIAL INTELLIGENCE FOR 6G MASSIVE RANS

In the previous section, we elaborated several promising technologies that can potentially be used to tackle specific issues in meeting a particular performance requirement of 6G massive radio access. While promising, there remain challenges that are needed to be overcome in order to implement these technologies. Artificial intelligence has demonstrated impressive achievements in processing large numbers of parameters, data and requirements, under diverse constraints and restrictions, such as those for IoT [61], [62]. In view of this, we propose to equip AI into 6G massive RANs via the cloud and edge servers to enable full flexibility, massive computations and connectivity as well as energy harvesting. We envision an AI-assisted 6G Massive RAN architecture incorporating flexible network slicing, BS cooperation, IRS and mMIMO-NOMA technologies shown in Fig. 4. Particular AI techniques that receive much interest are deep learning (DL), reinforcement learning (RL) and deep reinforcement learning (DRL) [63], where DL runs a neural network with many layers of artificial neurons that will allow to find the relationship between the input and the output; RL deploys an agent in search of a policy that will obtain an optimal action for each possible state of the system or environment, based on a long-term reward function whose value is approximated by a deep neural network; and DRL is a form of RL which exploits deep neural networks to approximate the long-term reward function (cf. Fig. 5).

A. AI-ASSISTED FLEXIBLE RAN SLICING FOR 6G

Flexible 6G RAN slicing can be realized by introducing AI at the cloud and edge servers. The centralized AI at the cloud server can act as the “global brain” to solve problems with higher complexity involving all BSs, such as placement of logical RAN functions at the cloud and OFDM numerology selection, whereas the edge AI can act as a “local brain” to solve more straightforward localized problems for individual BSs such as resource scheduling among users and cell size expansion. The centralized AI can also interact with the edge AI to jointly instantiate and orchestrate network slice functions and operations. The AI techniques can be implemented under an SDN framework, where the control for execution of AI techniques can be managed by a centralized SDN controller. Besides that, SDN allows for collection and observation of relevant input data (e.g., channel conditions, service types, QoS requirements, resource availability) required for the execution of the AI techniques [71], [72], thus enabling a data-driven self-adaptable RAN slicing mechanism. This is in fact inline with the emerging concept of self-driving adaptable and autonomous networks [73], which is envisioned for 6G.

DRL has shown a lot of promise for executing RAN slicing. Recently, several studies have demonstrated the feasibility of DRL for RAN slicing in 5G mobile networks [64]–[70]. Table 4 shows the features of several state-of-the-art DRL-based network slicing schemes. For 6G networks, these DRL techniques need to be further extended by incorporating the types of applications and latency requirements as part of the

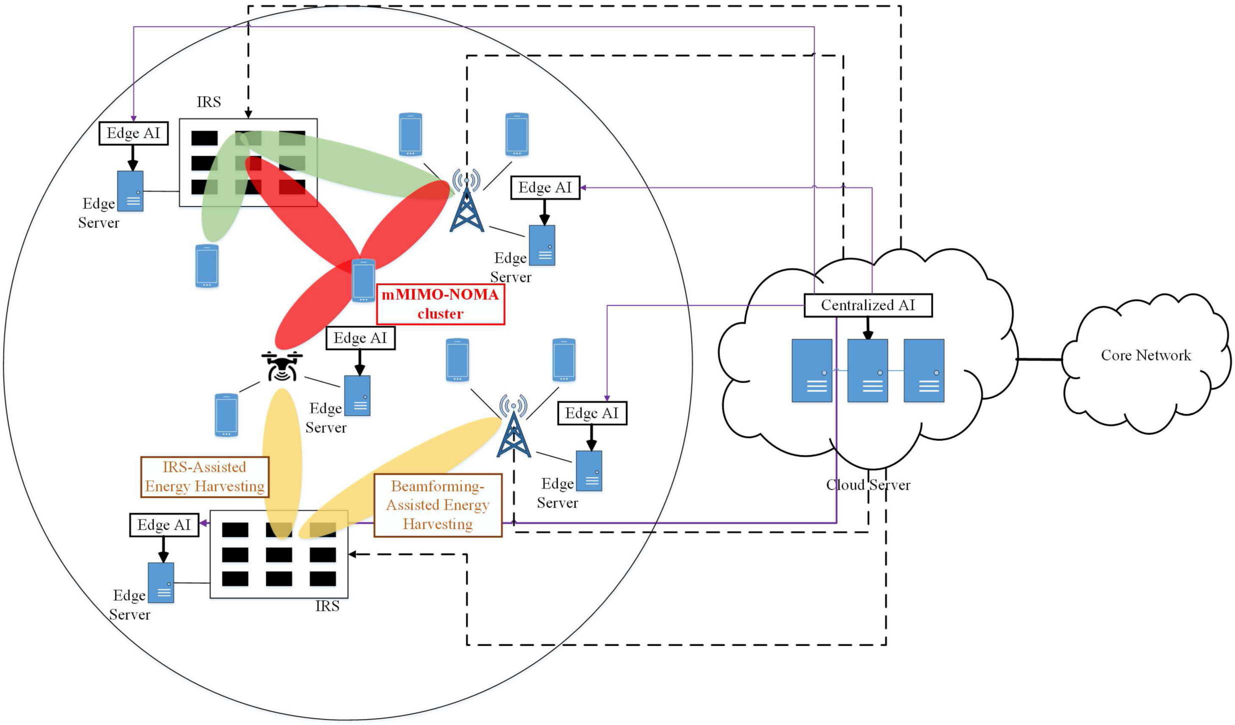


FIGURE 4. Cloud and edge AI-assisted 6G RAN architecture equipped with network slicing, IRS and mMIMO-NOMA technologies.

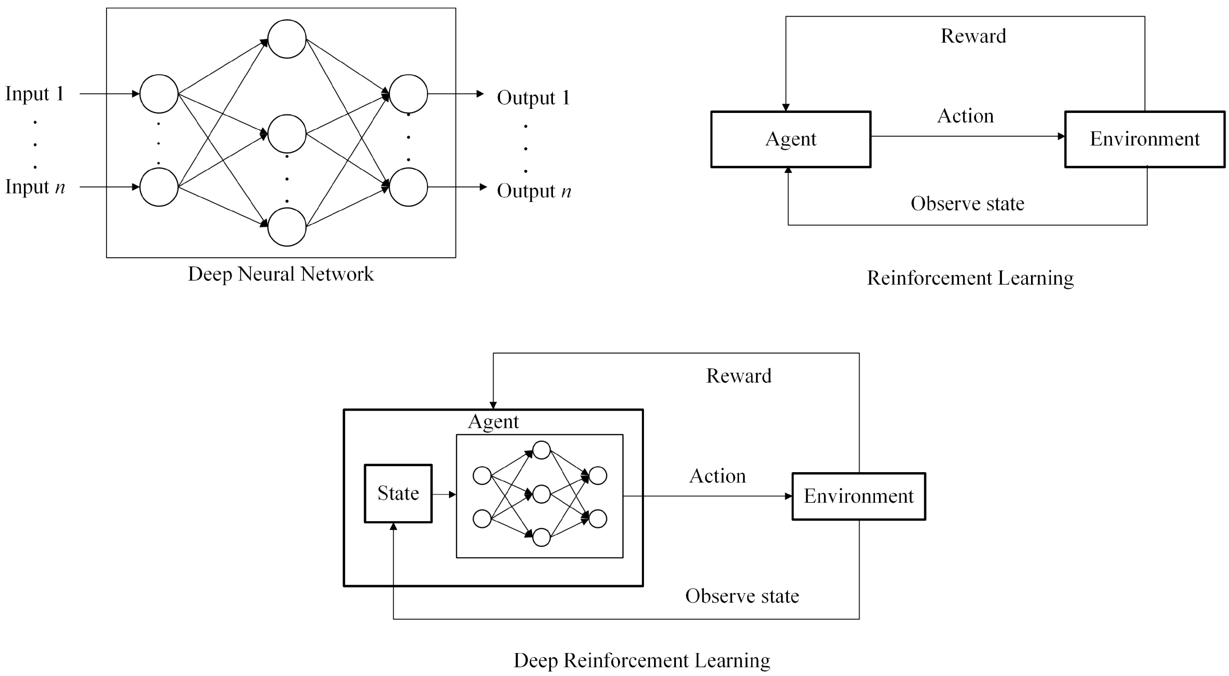


FIGURE 5. Potential AI techniques for 6G.

state parameters, the OFDM numerology selection as part of the actions, and energy efficiency and massive access quality as part of the long-term reward function. On the other hand, most of the studies mentioned in Table 4 are only suitable for implementation at the cloud. In fact, slicing of some resources and functions can be localized to individual 6G access points or base stations, by considering a localized long-term reward function. One important study has demonstrated the use of edge computing for radio and computational resource slicing [74]. As such, it is highly promising to apply DRL at the edge server for better resource slicing at the access points or base stations. Having said that, decentralized multi-agent

TABLE 4. Comparison Between DRL Techniques for RAN Slicing in Different Studies in Terms of Design of the States, the Actions and the Long-Term Reward Function of the DRL Techniques

Reference	State	Action	Reward Function
[64]	Processing, storage and bandwidth resource utilization	Selection of nodes (with fixed amounts of processing and storage capacities) and links (with a fixed amount of bandwidth)	Combination of resource consumption and end-to-end link delay
[65]	Location of mobile user, amount of computation tasks, queue occupancy	Channel selection, amount of tasks to be transferred to edge servers, number of data packets to be removed from the user queue	Combination of delay satisfaction, packet drops, computational and transmission energy consumption
[66]	Probability of users' successful access to core network and RAN	Bandwidth resource scaling	Total access rate of the RAN
[67]	Network slice requirement satisfaction, radio resource usage	Increment or decrement of the number of radio resources	Combination of network slice requirement satisfaction and radio resource usage
[68], [69]	Number of arrived packets in each slice within a specific time window	Bandwidth allocation to each slice	Combination of spectral efficiency and quality of experience
[70]	Queue length, resource availability	Slice allocation	Combination of slice request fulfilment and service delay

TABLE 5. Comparison Between Multi-Agent DRL Techniques for Energy-Harvesting in Different Studies in Terms of Design of the States, the Actions and the Long-Term Reward Function

Reference	Agent	State	Action	Reward function
[75]	Base station	Data rate, harvested power, distance between base stations and users	Power control	Combination of data rate, QoS requirement fulfilment and harvested energy fulfilment
[76]	MTC device	buffer state, battery state	Power allocation	Combination of delay and battery depreciation
[77]	Energy-harvesting node	Energy harvested, battery state and channel state	Power control	Sum-throughput

DRL may be more suitable to be implemented at the edge server. Some study has shown the applicability of decentralized multi-agent DRL for power control of each base station in cognitive radio networks.

B. AI-ASSISTED BS COOPERATION WITH IRS-BASED MMIMO-NOMA

BS cooperation with mMIMO-NOMA involves selection of cooperating BSs, beam-steering of each cooperating BS, analog precoding at the IRS, and the number of data signals in each frequency sub-band. Besides, each cooperating BS needs to jointly allocate power fractions for the selected data signals to achieve the target objective (e.g., maximum throughput, the fulfilment of minimum user rate). This can be modeled as an optimization problem. However, due to the non-convexity of the problems and the interdependence of the design parameters, obtaining the optimal solution would be highly complex and time consuming. Hence, a low complexity, efficient, and intelligent solution is urgently needed to cope with continuous network densification in 6G networks. By leveraging AI at both the cloud and edge, the cloud AI can determine the cooperative BS and the IRS selection whereas the edge AI can solve the power allocation problem for the users/devices in each mMIMO-NOMA cluster (i.e., a group of users served by a set of cooperating BSs using IRS-based mMIMO-NOMA). Currently, DL and DRL show a lot of promise for this problem. Recently, the studies in [78], [79] have developed DL-based precoding schemes for MIMO-NOMA systems and shown that these schemes are able to optimize energy efficiency, data rates and bit error rates. In these studies, deep neural networks are used and sophisticated training algorithms are designed to allow the neural networks to approximate the solution to the formulated precoding problem. Another related study has demonstrated the use of DRL for IRS-based multi-input single-output (MISO) systems in maximizing received signal quality (i.e., signal-to-noise ratio (SNR)), by treating the signal quality as the long-term reward function and the phase shifts of the IRS as the actions [80].

C. EDGE AI FOR ENERGY HARVESTING AND COOPERATION

Edge AI can be applied to allow each EH-enabled RAN node to learn and perform the best action (e.g., transmit power level) so as not to degrade the received signal quality of the nodes in proximity, while allowing other EH-enabled nodes to harvest energy. However, this requires the implementation of distributed AI techniques. Several related works have demonstrated the use of decentralized multi-agent DRL techniques for power allocation in energy-harvesting mobile networks, as shown in Table 5. In these works, the proposed DRL techniques are designed in such a way that it operates collectively by a group of entities with each running the learning mechanism independently. As such, this is suitable and highly promising for the implementation of edge AI for energy harvesting.

Edge AI also potentially facilitates IRS-assisted beamforming-based energy cooperation for quickly determining the direction of the intended EH-enabled node to where energy will be relayed. Nonetheless, the application of AI techniques for IRS-assisted energy cooperation would need to additionally encompass the design parameters of IRS, which could be more challenging than conventional energy cooperation. Currently, the application of AI in this problem is lacking and in need for attention.

VI. CONCLUSION

It is envisioned that the next-generation wireless network will bring forth a whole new level of experiences and applications, from enabling multi-sense communications to super-smart cities and communications beyond terrestrial domains such as space and underseas. With these emerging use cases and applications, flexibility, the ability to support massive applications and energy efficiency become the key aspects and requirements for the development for future wireless communications. We have discussed in the article several key technologies that undoubtedly have a huge role toward realizing the futuristic 6G networks. On top of that, we point out that AI will be crucial to effectively implementing the key technologies and intelligently optimize the 6G performance under vastly dynamic conditions and environments.

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