NOMA DESIGN IN THE SIXTH GENERATION: A NEW FRONTIER

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Abstract**—** The communication industry is making rapid strides toward the implementation of 5G and beyond 5G (B5G) wireless technology. New applications are being developed in order to fulfil the ever-increasing demand for faster data rates as well as increased service quality (Quality Of Service). These new applications require wireless connectivity that possesses a massive increase in data rates, a significant decrease in latency, and widespread public acceptance for a large number of devices. The non-orthogonal multiple access (NOMA) protocol, which is a key component of the family of protocols known as the next-generation multiple access (NGMA), has recently come to be acknowledged as a viable multiple access option for sixth-generation (6G) networks. In this article, we will discuss the different 6G dimensions that are available. The primary objective of this paper is to present fundamental ideas on multiple access that are necessary for B5G communication, to discuss recent research developments on significant technologies, and to provide research and development guidelines for NOMA in mobile communication systems that go beyond 5G communication networks.

Keywords**—** 6G, Artificial Intelligence (AI), Intelligent Reflecting Surfaces (IRS), Machine learning, non-orthogonal multiple access (NOMA), successive interference cancellation (SIC).

I. INTRODUCTION

Mobile data traffic, in particular mobile video traffic and small-size Internet of Things packets, has expanded at a breakneck speed as a direct result of the proliferation of smartphones, tablets, and a wide range of other innovative applications. It is essential to boost network capacity in order to meet the increased data traffic caused by these applications and services.

The most recent global analysis from Visual Network Index predicts that by 2022, the volume of mobile data traffic will be seven times more than it was in 2017. In addition to the growing demand for data, new bandwidth-hungry applications such as space-air-ground-integrated-networks (SAGINs), virtual reality (VR), and augmented reality (AR), as well as others that require stringent quality-of-service (QoS), pose new challenges for next-generation wireless networks. issues that arise for wireless networks of the future generation [5].

NOMA is a promising technology for improving spectral efficiency and overcoming massive connectivity challenges. It does this by accommodating multiple users within the same orthogonal resource block by multiplexing at different power levels. The technology was recently proposed for the 3rd generation partnership projects long-term evolution advanced

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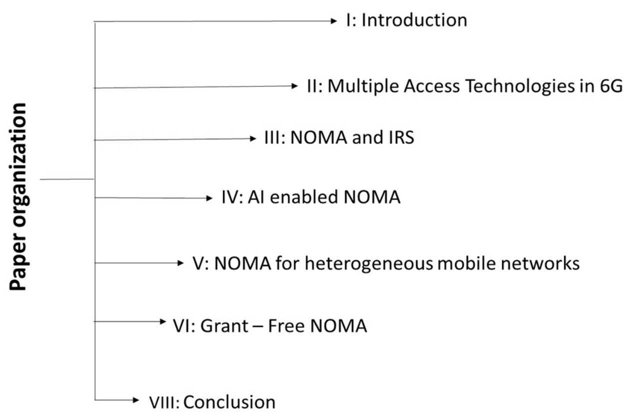
(3GPP-LTE-A). When this is done, it is possible to obtain significant spectrum efficiency benefits in comparison to the conventional orthogonal multiple access (OMA) methods. Since the potential of 5G networks has gained widespread attention, it is only logical for research to investigate these networks.

This article's primary objective is to provide fundamental ideas and theories and to analyse recent research accomplishments in significant technological areas relevant to massive NOMA in mobile communication systems that go beyond 5G and 6G.
The whole of the essay is structured like what you just read.



In the second part of this chapter, many access mechanisms for 6G and how they vary from 5G are investigated. In Section III, we go into further depth on the relationship that exists between NOMA and the IRS. In the fourth segment, artificial intelligence-enhanced NOMA is investigated. In conclusion, NOMA for heterogeneous mobile networks is covered in part V, and Grant-Free NOMA for massive connectivity in IoT networks is covered in section VI.

II. HOW WOULD 6G DIFFER FROM PREVIOUS GENERATIONS IN TERMS OF MULTIPLE ACCESS?

To address the issues that have been raised with sixth-generation (6G) networks, it will be necessary to make technical breakthroughs that go beyond those of the fifth-generation (5G) networks that are already in use. The following are the performance targets that are projected to be met by 6G: 1) an increase in connectivity density that is ten times higher than that of 5G; 2) a peak data rate that is one terabit per second; 3) an increase in energy efficiency that is one hundred times higher than that of 5G; 4) a reduction in air interface latency that is 0.1 milliseconds; and 5) an increase in reliability that is 99.99999 percent higher than that of 5G. In order to do this, 6G will need to make use of exceptionally effective protocols for next-generation multiple access (NGMA) [2].
Because it gives an additional degree of flexibility in the power domain, non-orthogonal multiple access, also known as NOMA, has garnered a lot of interest from academics as well as corporations. Decoding different signals contained within the same orthogonal (time/frequency) resource block is accomplished by NOMA via the use of superposition coding at the transmitters and successive interference cancellation (SIC) at the receivers (ORB). Previous study has focused on static devices and the data rates that broadband users experience.

This is despite the fact that NOMA has been the subject of substantial research in 5G and beyond networks [4]. This ignores some significant problems that are associated with NGMA, such as the effect that mobility has and the compromises that have to be made in the architecture between connectivity, dependability, and latency.

A. ***In NOMA, SIC Is Being Reconsidered***

The SIC process is a significant component that is used by a variety of NOMA implementations. Consider the example of power-domain uplink NOMA, in which the channel state information (CSI) is used as a basis for defining SIC decoding order. This means that users are differentiated based on the channel circumstances in which they transmit and receive signals. Examine a concrete scenario with a powerful user and a less capable user [2], without sacrificing the overarching point. The CSI-based SIC will begin decoding the signal from the powerful user first. In the event that the first stage of SIC is successful, the base station (BS) will proceed to decode the signal sent by the weak user. The CSI-based SIC is a user-friendly decoding method that is able to investigate the dynamic channel conditions of the users effectively. Another use of SIC is one that is based on the quality of service requirements of the consumers, such as cognitive radio's inspiration for NOMA. Take for illustration purposes a scenario with two users. Assume that the primary user is a sensor that is part of the Internet of Things (IoT), and that the secondary user is someone who uses broadband. Since the data rate that is available during the initial stage of the SIC process might be very low owing to considerable co-channel interference, the QoS-based SIC detects the primary user first. As a result, it is necessary to first decode the signal of the sensor that is going to be delivered at a low data rate.

There have been a number of different efforts made to develop efficient strategies for allocating resources that would improve the overall performance of such networks. For example, they have an issue with power allocation and the precoding design in which they deploy single carrier multiple-input multiple-output (MIMO) NOMA systems. The authors propose an optimum resource allocation in order to optimise the system throughput for full-duplex (FD) and NOMA systems, respectively [20]. However, due to the fact that the base station (BS) only has a single antenna, it is not possible to fully use the degrees of flexibility offered by the network. The research presented in [10] examines the use of beamforming design for MISO-NOMA systems with the goal of maximising the system's performance while minimising its costs. In specifically, the authors of [5] propose a reliable beamforming design for the MISO-NOMA mechanism in order to maximise the amount of data that may be sent. In [2], suggestions are made on beamforming architecture and subcarrier allocation with the purpose of maximising the overall data rate. Both optimal and sub-optimal methods are discussed in this work. In [20], a design for beamforming is shown that aims to maximise the least EE while maintaining a proportional level of justice. This is done in order to strike a balance between the EE of the system and the equality that exists amongst users. The majority of previous research focused on fixed SIC ordering, in which the order of decoding at each receiver was chosen based on the channel gains. [10] The users are grouped in SIC, and each individual user has the ability to prevent interference caused by other users according to the ordering system.

Even while the most majority of publications on SIC ordering arrange customers according to their channels, this is not a practical situation and cannot be guaranteed either. In addition, it should be stressed that ranking individuals for SIC based on the channel gains is neither an ideal nor a feasible strategy at all, particularly in MAS owing to the absence of the complete CSI [20]. This is because rating people for SIC based on the channel gains is not even possible. It is recommended that the ordering of SICs be dependant on the circumstances of the network, channel gain, and available resources in order to circumvent this challenge. The authors in [2] discuss a solution to this problem for the case of a BS with a single antenna and perfect CSI. When taking into account single-antenna BS and also having a flawless CSI channel, it is not practicable and it is not acceptable for future networks to implement it.

In QoS-based NOMA for Downlink Transmission, considerable waiting durations and high outage probability are caused by several SIC rounds. In the case of downlink NOMA in 6G, the primary challenge is to overcome high latency and poor dependability as a result of SIC. This is particularly true for the scenario involving many users. In addition to utilising the hybrid SIC in order to improve the spectral efficiency, QoS-based NOMA necessitates the definition of the concepts of QoS-based user clustering (Q-UC) and QoS-based power allocation (Q-PA) in terms of connection. Both of these concepts are required for the implementation of QoS-based NOMA. For the Q-UC, the following are two essential questions that need to be answered: 1) In a NOMA cluster, is it preferable to group users with the same or different QoS requirements? 2) How can users who are particularly sensitive to latency and reliability avoid SIC? [2]

III. Network interaction between NOMA and intelligent reflecting surfaces (IRS)

Large intelligent surfaces, also known as LIS, and intelligent reflecting surfaces, also known as IRS, are the two categories that make up intelligent surfaces (IRS). It is believed that both of these technologies might be candidates for the 6G standard. The concept that in very large MIMO systems, antenna arrays provide the function of the LIS. In contrast to the beamforming method, which requires the use of a very high number of antennas, the multi-antenna method does not. Due to the fact that the LIS generates electromagnetic activity, it is able to focus the signals. Due to the fact that the LIS takes into account the topography of the area and places relatively few restrictions on the distribution of antennas, it is able to avert unfavourable outcomes and mitigate the effects of antenna correlations. However, as a result of the surfaces' The LIS is an active property that consumes a significant amount of power, resources are inefficient with regard to power [30].

Variations in the quality of the wireless channel often have an effect on the signals that are received. The intelligent reflecting surface, also known as an IRS, is a relatively new emerging spectrum and energy-efficient technology that has the potential to help reduce the radio signal degradation that occurs as a result of the congestion that is present in the surrounding area. The integral reflector system (IRS) is constructed out of ingenious reflecting array components that are able to absorb energy and modify the phase of light rays. Controlling oneself is the means through which this is done. reflecting photons in an appropriate manner and, as a result, reconfiguring communication via the use of wireless methods. Despite the many advantages of SE, there is still a question over user fairness. In spite of the fact that it has a higher system throughput and an improved system throughput, NOMA still has a great number of significant drawbacks. One of the problems is a lower received power, and another is strong interference inside the cell. Against orthogonal multiple access systems, the intrinsic interplay between NOMA and IRS has been a focus of intense research in recent times [4]. This is because it is a potential solution to the difficulties described above.

IRS may reduce the amount of hardware complexity at both the receiver and the broadcaster by reducing the number of antennas that are deployed. This results in shorter radio frequency (RF) chains at both the receiver and the transmitter. The conventional relay system may be replaced with IRS if desired. Because of its benefits in terms of power, spectral efficiency, and decrease in the amount of hardware required The non-line-of-sight (NLOS) and deep-fade communication environments are both suitable for the use of complexity IRS. The signal-to-noise ratio (SNR) at the receiver may be increased by adhering to the following principle: controlling the phases of the incoming beam in an optimal manner at numerous IRS components in order to provide acceptable beamforming at the receiver Noise and other variables that degrade signal quality The Internal Revenue Service is untouched by any interference. The Internal Revenue Service has every quality necessary to become a viable business. This technology is used in the B5G and 6G communication networks [33].

IV. ARTIFICIAL INTELLIGENCE-ENABLED NOMA FOR B5G COMMUNICATION

In recent months, there has been a lot of attention directed toward various uses of artificial intelligence (AI) and machine learning (ML) in wireless communications. Artificial intelligence (AI) has made significant strides in the fields of voice recognition, image identification, and natural language processing, which demonstrates the huge potential AI offers for finding solutions to issues. The modelling process is difficult. AI techniques have become a critical enabler as well as a broad variety of demands across a wide range of application conditions [17]. This is because AI approaches are helping to address the rising demand for wireless communications.

AI technologies, in particular machine learning (ML), offer the capability to effectively address unstructured and intractable issues by combining a vast volume of data that must be handled within the confines of B5G [18]. This is made possible by combining the data in such a way that it can learn from its own experience.

Artificial intelligence (AI) introduces intelligence and automation to wireless networks by modelling the processes that occur in the human brain as well as the intelligent behaviours that humans do. For instance, it is anticipated that 6G AI will be able to give full automation, and as a result, it will become one of the 6G technologies that will be very important and highly valued in the future. It is believed that AI may also be used as a tool for modern data analysis in the context of systems for wireless communication. Machine learning models are supposed to generate accurate decisions on their own automatically by learning from large amounts of data. As a consequence of this, artificial intelligence technologies such as machine learning and learning are anticipated to play a significant part in networks. This is due to the fact that networks are too complicated and dynamic to be researched due to the presence of people. Particularly relevant to scenarios are laborious processes such integrated optimization in network design and resource allocation management, in addition to resource allocation [30].

It is essential for fifth-generation (5G) wireless communication systems to support a wide range of frequency bands, including those operating at sub-6 GHz, millimeter-wave (mm-Wave), and terahertz. Channel modelling has become much more difficult as a result of the introduction of THz as well as optical bands. For the purpose of addressing the B5G channel Both the existing channel models and the modelling requirements have been upgraded to accommodate a much increased level of processing power complexity [19].

Analyzing the enormous amounts of data produced by large antenna arrays, especially enormous MIMO arrays, is a task that lends itself very well to the use of machine learning methods. Because parametric models are often unavailable, standard estimate and detection algorithms are often rendered ineffective as a consequence. Deep learning in particular is an example of an algorithmic approach. There is a possibility that image processing networks and methodologies, together with video analytics, will deliver the most promising outcomes route [18].

Data-driven localization is going to become more crucial as the amount of data generated by sensing and communication in B5G systems continues to expand, both in terms of volume and variety. The use of data to drive localization is an effective strategy for location-based placement. Using machine learning algorithms to learn from raw sensing devices and users as well as data interchange. It has been determined that the data-driven localization strategies will not be successful. not only be capable of self-adaptation to real-time dynamic transmission obstructions, but also change over time by learning from data on a continuous source. this is in addition to the ability to self-adapt to real-time dynamic transmission impediments. When using a wireless connection, the order in which the channels are used might be changed on a regular basis. and improved as a consequence of automatic learning based on massive amounts of crowdsourced data collected from a big number of individuals using mobile devices. Making advantage of the specific example given As a consequence of the results of the localization process, users will reap the benefits of enhanced location-based services [19].

The advancement of machine learning technology has led to a rapid acceleration in the development of wireless communication technologies. Massive volumes of traffic including a number of different sorts of traffic It is anticipated that the requirements for the quality of service (QoS) would be stringent. The management of this will be handled through wireless communication networks. Take, for instance, wireless communication of the fifth generation. Increased bandwidth is one of the primary benefits that 5G networks are expected to provide. "electronic mobile broadband" is the abbreviation for "eMBB." (2) ultra-reliable low-latency communications with high per-user data rates (uRLLC), also known as a system that guarantees huge dependability within a constrained delay Machine-type communications are denoted by the abbreviation mMTC. [17-19] Enables the deployment of Internet of Things (IoT) devices on a massive scale so that they may acquire access to the network.

The data that is stored in wireless systems such as CSI is getting more varied and difficult to understand [12]. It is possible to get improved performance by training this data in an efficient manner. NOMA is a charitable organisation that works to make people's lives better. A great number of research on the use of DL have been carried out over the course of the last several years. Several other kinds of learning algorithms are used in a number of different criteria, and their results demonstrate greater performance when compared to those of regular systems [12]. In NOMA, DL has been put to use in a wide range of different applications. DL has the potential to be very successful for very complex data processing and the acquisition of faultless CSI [21]. Deep learning may also be used in NOMA for various objectives, including the allocation of resources, the decoding of signals, the construction of signal constellations, and so on.

Existing machine learning algorithms concentrate their attention mostly on computer vision, natural language processing, and robotics, making use of advanced graphics processing units (GPU) or robotics. Real-time computing is computing that operates utilising a central processing unit (CPU) to get the desired results. Nevertheless, communication is a necessary component. Systems often include a significant number of devices with limited resource capacities. For example, embedded systems and the internet of things. (Internet of Things) systems, as a direct consequence of this, machine learning strategies Complex communication is something that should not only be learned, but something that should also be practiced. Networks, clients, and statistical models are the foundation for them, and they are supported not just by computers and technology but also by humans. With a restricted amount of storage space, embedded devices, and computing power, in addition to constrained energy resources The process of development is challenging but ultimately very satisfying. There is a need for lightweight machine learning methods, in particular deep learning for embedded system models. [18-19].

V. NOMA AND HETEROGENEOUS MOBILE NETWORKS

The most important need for 5G is to satisfy the pressing needs of particular use cases and mission-critical applications in vertical industries. Then there is the question of how to improve network capacity in order to achieve high-bandwidth mobile connections for anything, anytime, and anywhere. Additionally, there is the question of how to enable sensory integration, holographic transmission, and other advanced technologies, which has emerged as the new vision for the growth of mobile communication networks [32]. In conventional networks, routing and traffic engineering are often implemented as parts of specialised hardware that runs on a particular operating system. These kinds of networks are known as "traditional." On the other hand, a structure that is so inflexible would not be able to meet the ever-changing resource requirements of contemporary data centres, cloud computing, and the usual heterogeneous network environment. In addition, it is challenging to upgrade to new creative functions while maintaining flexibility. Combining notarization with cutting-edge technologies like SDN, NFV, network slicing, and MEC allows for the transformation of traditional hardware- and software-based network infrastructures into fifth-generation network infrastructures. These infrastructures are now known as 5G. The security risk associated with virtualization is brought to light by the SBA of the 5G core network. Despite the fact that SDN presents a risk to network security and privacy protection, it also makes it possible to maintain consistent security throughout the whole network [38].

The use of artificial intelligence technologies, in particular machine learning and big data analytics, has seen widespread use in the context of improving heterogeneous network settings [35]. On the other hand, the very complicated nature of AI technology makes its implementation in wireless networks problematic [37]. As the peak rate of the network continues to climb, the processing capacity of the components of the 6G network will expand significantly. This will encourage the deep integration of AI into the architecture of the 6G network's security [36], notably for encoding, authentication, and detection.

VI. Grant-Free NOMA in IoT Networks WITH massive connectivity

Access schemes that are grant-based (GB) and grant-free (GF) are the two categories that may be used to classify NOMA transmissions. Unlike Access to the GF has been established, in addition to the more conventional procedures for accessing the GB. to realise as an essential component of the media access management strategy Massive connections, low latency, and the elimination of signalling overhead [40, 41], which are all essential for URLL Internet of Things networks. When thinking about GF NOMA (via RA) uplink (UL), it is important to remember that power control (which includes a range of different approaches) is one of the factors to take into consideration. It is very crucial to have a substantial influence on the performance of NOMA. It causes problems due to the fact that it is carried out in a distributive manner. Every node in the network is aware of the identities of the other nodes that are broadcasting as well as the locations of those identities.

It is possible to divide grant-free NOMA schemes into four primary categories: (1) those that are based on MA signatures, (2) those that compute-and-forward (CoF), (3) those that compressive sensing (CS), and (4) those that are based on machine learning (ML). The selection of the MA signature may be done either by having MTCD pick at random or by having MTCD's signature be pre-configured or pre-determined. Both of these options are discussed more below. The use of these MA signatures enables the authorization of a variety of grant-free NOMA transmissions. Spreading, scrambling, and interleaving, in addition to other crucial MA signatures [41]. A novel method for grant-free NOMA based on the CoF approach that employs codes with a linear structure is presented in [43]. This method is in addition to the conventional MA signatures that are used. Due to the linear nature of the codebook, it is guaranteed that every integer combination of code words will also be a coded word. The destination choose which linear equation to get, hence [43] is left up to interpretation. Machine learning is a faster, more accurate, and more resilient solution to NP-hard optimization problems than traditional techniques. Traditional approaches also take longer. Instead of relying on models and equations to determine the best course of action, ML algorithms look for patterns in the data in order to come to a conclusion. Virtually optimal choices. The robustness of various machine learning approaches [41-43]. As a result of the need for transmission methods that are spectrum-efficient, non-orthogonal multiple access, also known as NOMA, has developed as an essential enabler for Internet of Things networks. On the other hand, grant-free random-access (RA) algorithms show a significant deal of potential for both increased spectral efficiency and increased security. An extensive connection is desirable since it reduces both the cost of signalling and the latency in packet delivery [40].

VII. CONCLUSION

Within the scope of this study, we emphasise the relevance of NOMA when applied to communication at higher speeds than 5G. A discussion is had on the various multiple access strategies for 6G. The dependability of NOMA in B5G communication is improved by integrating it with a variety of technologies like as artificial intelligence and machine learning, among other technologies. In addition, we talk about NOMA for networks that are diverse and the interplay between NOMA and IRS in network settings. In addition, we think that 6G will pave the way for a great many new contemporary developments that will be to the world's advantage.

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