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Chapter 3

AN INTRODUCTION OF UPCOMING RADIO RESOURCE MANAGEMENT TECHNIQUES FOR 5G NETWORKS

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ABSTRACT

5G networks are the next generation of mobile internet connectivity, that are able to offer vastly increased speeds, more reliable connections, minimal latency and more supported devices. 5G networks are expected to supercharge Internet of Things (IoT) technology, so as to provide the infrastructure needed in order to support and transfer large data amounts that will enable a smarter and more connected world. To this direction, 5G incorporates many technologies and mechanisms that aid towards the overall goal, such as Multiple-Input and Multiple-Output (MIMO),

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Downlink (DL) and Uplink (UL) Decoupling (DUDe) and Machine Learning (ML). These technologies can significantly help towards more efficient resource allocation inside the next generation networks, offering increased spectral efficiency and data rates, better signal coverage, reduced latencies and many more. In this chapter, we will provide insights over the aforementioned technologies through firstly a literature review and later on by analyzing their architecture and their models. We will explain how these technologies can be taken advantage of in order to support the 5G networks and why they are core components of future networks, as it is expected that also 5G and Beyond networks will capitalize on them.

Keywords: DUDe, MIMO, ML, 5G, resource allocation

INTRODUCTION

Internet of Things (IoT) refers to a system of interconnected devices that possesses the ability to send and receive data over the same shared network (Neto et al, 2018). Based on this architecture, many advanced applications have been created (e.g., smart houses, smart buildings, etc.). IoT applications are utilized in today's industry and the majority of them focus on long-range communication, while at the same time, increasing the data throughput and minimizing power consumption. Big Data (BD) derives by IoT sensors and devices and is transferred to servers, commonly located in Cloud Data Centers worldwide. As a result, the demands for communication and infrastructure keep rising daily. Studies reveal that at least 25 billion devices will be online by 2022 (excluding laptops, tablets and smartphones). This also increases the amount of data that is currently being stored. All this information has to be monitored and analyzed, to extract information from the available dataset and improve without any manual interventions, making the IoT devices smarter and more efficient.

To face these challenges, many models have been designed focusing on making everything inside an IoT network more Cloud independent. This is where 5th Generation (5G) networks come into play, offering massive connectivity and/or massive Machine-Type Communication (mMTC). Massive access alongside with Machine Learning (ML) aims to realize effective and secure communications for many distributions to IoT devices via 5G and Beyond networks. Key features include low power, massive connectivity, while ML must cope with an increased complexity to reduce the number of measurements and facilitating robust decisions and promote self-organizing networks and robust predictions. These characteristics are constantly proven to be promising for 5G networks (Polese et al., 2018). At the same time, Heterogeneous Networks (HetNets) will extend the existing macrocell infrastructures, by installing small cells in specific locations inside the macrocell (e.g., in areas near the macro cell borders) to provide improved coverage and throughput for all devices near cell borders, where interference levels significantly rise. In HetNets, Base Stations (BSs) are brought closer and closer to users by densifying small BSs, which results in higher spectral efficiency and energy efficiency for cellular systems (Liu, Li, Luo, & Jiang, 2018). At the same time, the use of ML and Artificial Intelligence (AI) is deemed necessary for 5G networks, as their application to cellular networks is a subject that has recently gained significant interest (Zantalis, Koulouras, Karabetsos, & Kandris, 2019).

HetNets will change the existing topology towards a user-centric approach. As a result, one of the most significant challenges will be the problem of associating users with a BS. To avoid the issues that the coupled access brings in user assignments to BSs, 5G networks offer the approach of decoupled access, which separates the network in two separate sub-networks, namely Downlink (DL) and Uplink (UL). As a result, UL performance is improved in HetNets. This technique is called DL and UL Decoupling (DUDe) and is considered one of the most promising features of upcoming 5G networks. At the same time, Multiple Input Multiple Output (MIMO) is also considered a major key to unlock the optimal User Experience (UX). At their core, MIMO systems require a combination of antenna expansion and complex algorithms and have been around in previous generations of networks, enabling the usage of multiple antennas thus improving user connectivity, coverage, data rates and overall experience (Shukair, 2019). Meanwhile, ML can be used in order to boost network performance of MIMO and/or DUDe techniques and to achieve the full potential of 5G networks. ML can be used in order to discover patterns in very large user dataset that can help us have a clearer picture regarding resource usage. As a result, better predictions are being made and decision-making times are reduced. ML can be used alongside MIMO and DUDe to help carriers determine the position and the techniques that should be used to achieve efficient resource deployment in order to avoid demand crunches and disruptions of service/connection.

In this chapter, we will provide insights over the aforementioned technologies by firstly analyzing DUDe and MIMO technologies, their underlying architectures, system models, characteristics, advantages and disadvantages, services and applications. Then, we will explain how these mechanisms and technologies can be fully taken advantage of with the introduction of ML techniques in order to support the 5G networks and why they are such core components of future networks. After this comparison on the integration of the DUDe, MIMO and ML mechanisms, we will offer insights for the upcoming 5G and Beyond networks, which are also expected to capitalize on these techniques and extend them as far as possible, offering increased gains.

The remaining part of this paper is structured as follows: In the next section, there is an analysis of the theoretical background regarding both the technologies of DUDe and MIMO that offer better radio resource management. In Section ‘Machine Learning and DUDe/MIMO in 5G Networks,’ we present how ML can be integrated. In Section ‘5G and Beyond Networks,’ we provide insights on the future generations of 5G networks and how we can take advantage of their features to improve various aspects inside the networks. The last Section offers the conclusions of this work.

RESOURCE ALLOCATION IN 5G NETWORKS

DUDe

Introduction

In terms of the potential benefits that can be gained by decoupling a dense heterogeneous mobile phone network, the traditional approach has recently undergone scrutiny. Other BSs can have highly variable transmit power and deployment topologies. The claims in favor of maintaining the status quo of the coupling vary. Physical, forwarding, and logical channels are easy to design and operate from a pure network design perspective. This specifically includes authorization (ACK / NAK) synchronization, approval and handover procedures, DL/UL radio resource management and power control standby. Removing both links also requires strong synchronization with the BS and a data connection (e.g., via fiber optics). From an implementation and topology perspective, until a few years ago, mobile phone systems were designed and implemented assuming a homogeneous network in which macrocells transmit at about the same power. From a traffic perspective, voice-centric 2nd Generation (2G) and early 3rd Generation (3G) systems have about the same bidirectional load. Also, 3.5G (e.g., HSPA) and 4th Generation (4G) systems are dominated by DL traffic, which justifies the use of DL-centric over UL or isolated connection procedures.

However, coupling association is a special case of more general join strategy, with no join restrictions. Therefore, it is clear that a properly designed DUDe-based partnership policy can outperform combined partnerships.

Architectural Characteristics

DUDe allows the User's Equipment (UE) to connect to a different BS for each DL and UL address. In a network using DUDe technology, two lists (one for DL addresses and one for UL addresses) composed of BSs that can be used for association are created for each UE. Each list is sorted according to indicators such as Signal to Interference Ratio plus Noise

(SINR) or Path Loss (PL). After preparing the list, each UE tries to connect to the preferred BS. If the BS can provide the requested Resource Block (RB), a connection between the two is established. If there are not enough RBs, the UE tries to connect to the next preferred BS. The above process is carried out in both directions until each UE is connected to a BS. The main concept of DUDe is that it treats DL and UL addresses as two different tasks, leading to faster associations and a better user experience.

Excellent connectivity and cooperation between different BSs are required in order to implement a decoupled cell association in a real network. The main requirements DUDe needs are a low latency connection between base stations for both directions, to allow a fast exchange of control messages. We emphasize that, contrary to the most complicated forms of Coordinated Multipoint (CoMP) (e.g., joint processing) where a high throughput backhaul connection is required to achieve rapid data exchange, DUDe does not impose a tight requirement on the backhaul capacity. Moreover, DUDe allows gains similar to UL joint processing (about 100% edge and average throughput gain), but with lower deployment costs. Compared to MIMO or new spectrum, to increase the throughput, the cost comparison is even more favorable to DUDe.

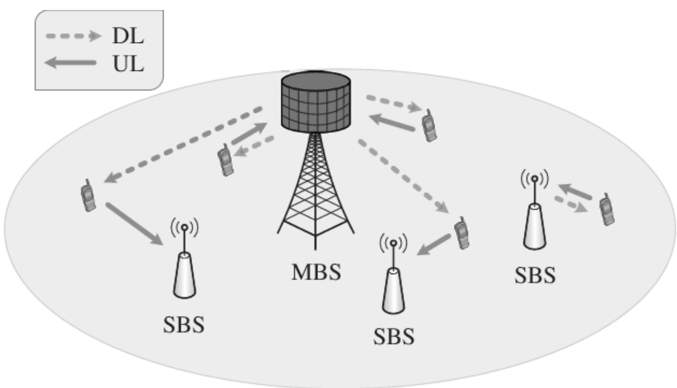

Figure 1. DUDe in action.

Advantages and Disadvantages

DUDe has become an area of interest for many researchers because of its significant advantages. First, DUDe can improve UL Signal-to-Noise Ratio (SNR) and reduce transmit power. In a typical HetNet, the DL coverage area of a low-power BS (also called a 'small cell') is much smaller than that of a macro cell. Unlike the DL, the reverse transmit power is almost the same for all transmitters. Thus, a UE connected to a macro cell in the DL direction can connect to a small cell in the UL, to take advantage of the reduction in path loss (Smiljkovikj, Popovski & Gavrilovska, 2015). This is because the closer the BS connection is, the higher the SNR improves the environment (less interference), so this advantage is important for the UE transmitting power. Another big advantage of DUDe is the different load balancing on the UL and DL. Certain BSs may have different loads for DL and UL directions. That is, it is not suitable to connect the same set of UEs to the same BS in both directions. This means that some of these UEs will need to use detached access (DUDe). DUDe also facilitates UE connectivity to rarely used small cells and as a result, improves the distribution of these cells between micro and macro cells (Boccardi, Andrews, Elshaer, Dohler, Parkvall, Popovski & Singh, 2016).

Furthermore, DUDe is cheaper to implement than other technologies. The only requirements for building a network using DUDe are to provide a low-latency connection (between the BSs) and to allow high-speed control messages between the DL BS and the UL BS. Unlike other technologies, DUDe does not require large link capacity for high-speed data exchange. Based on the above, we can derive that DUDe provides the same UL speed as other technologies, but the implementation cost is low. In a typical HetNet scenario, the macro cell DL coverage is much greater than that of a low-power base station. The difference in range is mainly due to the difference in the DL transmit power and the difference in the height of the base station and the antenna gain. In contrast, in the UL, the maximum transmit power of all transmitters is approximately equal. Thus, devices connected to macro cells in the DL can be associated with smaller cells in the UL to take advantage of the reduction in path loss. There are two positive effects. For UEs transmitting at full power, the closer to the BS the UE is, the more power the BS provides. Also, if the SNR of the target is fixed, the reduced line losses can reduce the power-controlled transmit power instead. UL interference caused by DUDe multi-function effects can also be reduced. First, as an obvious consequence of the reduction in transmit power, interference from the UL to other base stations is reduced by approximately 23 dB accordingly. This is especially important for low SINR UEs in the UL. This is because the low SINR of a high-density network reduces the interference by 3dB and the data rate is about 2x. Then DUDe minimizes interference between UE and BS, to provide the ability to select connections individually. UL interference in a given spectral band is a combination of signal transmissions to multiple UEs in different cells (probably sectors of the same cell) that are received by a given BS (e.g., BS0). The interference generated by each of these UEs will depend on its position relative to the BS it requires, the amount of power control, its distance from BS0, and the UL precoding weight. In contrast, the DL interference of a particular UE depends on the transmit power of the BS, the DL beamforming weight, and the distance to the various BSs. More importantly, near-independent scheduling on DL and UL are improved, and random interferences due to the load are reduced.

For all these reasons, the average interference level of DL and UL resources can vary significantly. Therefore, one can expect that the decoupling association, which allows the UE (or the network) to independently find the optimal interference environment on the two links, outperforms the coupling association, which has to “split the difference.” Third, DUDe is also great for Device-to-Device (D2D) communication. By saving UL transmit power and reducing interference, DUDe creates a more friendly environment for D2D receivers and makes D2D transmission easier.

As expected, increasing the required received power and reducing interference results in higher SINR, higher Spectral Efficiency (SE) and higher data rates. However, there are other factors that complicate the effect of DUDe on UL speed. For example, consider a Long-Term Evolution (LTE) HetNet, which has a small cell range extension. This is achieved by sending the UE to a small cell, which means that even if the received power is less than the power of the macro cell BS (less than the skew value), it is associated with the small cell BS. On average, the best DL polarization is about 510 dB, but in some cases up to 1820 dB can be used through interference suppression or avoidance. DL polarization can also generate better bidirectional relationships, even when it comes to coupling.

The UL load on the specified BS may differ from the DL load on the same BS. This means that at least some UEs should use isolated access, as connecting UEs in the same group to the same BS on the UL and DL is not the best choice. Also, since DUDe is not limited by interference like DL, only UL can push more UEs than low utilization small cells. This leads to better UE allocation between macro cells and small cells, resulting in more efficient resource utilization and higher UL speeds.

Achieving a mobile phone connection that is separate from the actual network requires proper connection and cooperation with another BS. The main requirement of DUDe is a low latency connection between the DL and UL BSs so that control messages can be exchanged quickly. Unlike more complex shaped CoMPs (e.g., coprocessing) that require a BS and a high performance backhaul connection to enable rapid data interchange, DUDe has stringent backhaul capacity requirements. In short, DUDe allows the same benefits as joint UL processing, but at a lower implementation cost. Compared to the case of using MIMO or new spectrum to improve performance, the cost comparison favors DUDe. The current trend of using partially or fully centralized Radio Access Networks (RANs) is the driving force behind DL and UL decoupling as signals are routed to central processing units on low-latency connections. Specifically, it refers to a local implementation (for example indoors) in which the transmission points providing services in a short distance, such as partial concentration, are all connected to the same baseband central processing unit. A fully centralized one, usually called CloudRAN, extends this method to a wider area. In this region, multiple radio frequency units are connected to the same baseband central processing unit. Given this continuing trend, DUDe incremental costs are considered negligible.

Services and Applications

The importance of DUDe is expected to grow significantly in the coming years, as 5G will feature hyper-dense deployments aiming to meet the higher rate demands. One could argue that at extremely high densities of cells, DUDe will lead to lower gains since nearly all the devices will try to connect to the nearest small cell for both UL and DL. However, this will only be true if we assume that all the small cells will have the same deployment characteristics, power and traffic. This hypothesis is unrealistic, as future cellular deployments will be characterized by a mixture of user and operator deployed cells, with different power levels, using frequencies from below one GHz to tens of GHz, providing services for various types of traffic and natively supporting device-to-device communications.

MIMO

Functionality

Because MIMO uses several antennas at the transmitter and receiver to provide a variety of signal channels for data transmission, it is an effective radio antenna technology. Each antenna is assigned to a distinct signal path, allowing for the usage of several signal paths. While still conforming to Shannon's rule, MIMO wireless technology can dramatically increase a channel's capacity. The throughput of the channel can be increased linearly as the number of receive and transmit antennas is increased with each pair of antennas added to the system. As a result, in recent years, MIMO wireless technology has become one of the most important wireless technologies. As spectral bandwidth becomes a more valuable commodity for radio communications systems, strategies are needed to make better use of the available bandwidth. One of these ways is MIMO wireless technology. One of the basic concepts of MIMO wireless systems is space-time signal processing, in which time (the natural dimension of digital communication data) is supplemented by the spatial dimension inherited by the usage of multiple spatially distributed antennas.

As a result, MIMO wireless systems can be thought of as a natural progression of smart antennas, which have been used to improve wireless networks for many years. It's positioned between a transmitter and a receiver, and the signal can go in either direction. If the antennas are moved by a small distance, the paths used will change. The variety of paths conceivable is affected by the number of items that appear to the side or even in the straight path between the transmitter and receiver. Many channels were formerly employed only to cause interference. MIMO can be used to take advantage of these additional paths. They can be used to improve the SNR or increase the link data capacity, giving the radio link more robustness. Massive MIMO is a new technology that scales up MIMO and provides significant energy economy, spectrum efficiency, resilience, and reliability benefits. It allows for low-cost hardware to be used on both the BS and the mobile unit. At the BS, the expensive and powerful but power-inefficient gear is replaced by a large array of low-cost, low-power components that work in unison. The term "massive" refers to the utilization of antenna arrays with a few hundred antennas supporting tens of thousands of terminals at the same time-frequency resource via spatial multiplexing (Larsson, Edfors, Tufvesson & Marzetta, 2014).

Precoding, Spatial Multiplexing (SM), and diversity coding are the three basic categories of MIMO. In the strictest sense, precoding is multi-stream beamforming. In a broader sense, it refers to all spatial processing that takes place at the transmitter. The identical signal is broadcasted from each of the transmit antennas with suitable phase and gain weighting in (single stream) beamforming, maximizing the signal power at the receiver input. The advantages of beamforming are that it improves the received signal's gain by combining signals from several antennas constructively and reduces multipath fading. Beamforming produces a well-defined directed pattern in line-of-sight propagation. However, in cellular networks, which are primarily characterized by multipath propagation, traditional beams are not a fair analogue. Because transmit beamforming cannot concurrently maximize the signal strength at all of the receive antennas when the receiver has multiple antennas, precoding with several streams is typically advantageous. When there is no channel information at the transmitter, diversity coding techniques are used. In diversity approaches, a single stream is delivered (as opposed to several streams in spatial multiplexing), but the signal is coded using space-time coding techniques. With full or near orthogonal coding, the signal is emitted from each of the transmit antennas. To improve signal diversity, diversity coding takes advantage of the independent fading of various antenna links. There is no beamforming or array gain from diversity coding since there is no channel knowledge. When the receiver has some channel knowledge, diversity coding can be used with spatial multiplexing. MIMO antenna configuration is required for spatial multiplexing. A high-rate signal is split into many lower-rate streams in spatial multiplexing, and each stream is transmitted from a different transmit antenna in the same frequency channel. If these signals have sufficiently diverse spatial signatures when they arrive at the receiving antenna array and the receiver has precise Channel State Information (CSI), it can separate these streams into (nearly) parallel channels. Spatial multiplexing is an extremely effective method for boosting channel capacity at greater SNR. The number of antennas at the transmitter or receiver determines the maximum number of spatial streams. Spatial multiplexing can be utilized without CSI at the transmitter, but if CSI is present, it can be paired with precoding. CSI is necessary at the transmitter when spatial multiplexing is employed for simultaneous transmission to numerous receivers, commonly known as space-division multiple access or multi-user MIMO. Good separability is achieved by arranging receivers with diverse spatial signatures.

Architectural Characteristics

MIMO is a method of doubling the capacity of the radio link by using multiple transmit and receive antennas to utilize multipath propagation. MIMO has become a key component of wireless communication technologies such as the Institutes of Electrical and Electronics Engineers (IEEE) 802.11n Wireless Fidelity (WiFi), IEEE 802.11ac (WiFi), High Speed Packet Access + (HSPA+) (3G), Worldwide Interoperability for Microwave Access (WiMAX), and Long-Term Evolution (LTE). As part of the ITU G.hn standard and the HomePlug AV2 specification, MIMO has recently been applied to power line communications in three-wire configurations. In modern usage, 'MIMO' refers to a viable technology for sending and receiving multiple data signals simultaneously over the same radio channel using multipath radio waves. This "multipath" phenomenon is interesting, but the increase in data capacity is due to the adoption of orthogonal frequency division multiplexing to encode channels. MIMO is fundamentally different from smart antenna technologies such as beamforming and diversity, which were developed to improve the performance of a single data stream. Many modern communication standards have integrated multiple antenna technologies, especially in the consumer arena, because of the significant advantages they offer over classes of systems that use a single antenna transceiver. This uses SISO (Single-In Single-Out) systems with a single antenna at both ends of the link and diversity coupling at the receiving end, but still in contrast to Single-Input Multiple-Output (SIMO) systems that transmit over a single antenna. Signal degrees of freedom are introduced by some antennas of broadcasters and receivers that are not in the SISO system.

MIMO technology has become standardized and is currently widely used in wireless local area networks, 3G mobile phone networks, and 4G mobile phone networks. Airgo Networks was founded (Raleigh & Jones, 2001) to create MIMO Orthogonal Frequency Division Multiplexing (OFDM) chipsets for wireless Local Area Networks (LANs). In late 2003, the Institute of Electrical and Electronics Engineers (IEEE) established a working group to develop a wireless LAN standard with user data throughput of at least 100 Mbit/s. By allowing data to be transmitted along multiple signal paths at the same time, the antennas at each end of the communication circuit are fused together to reduce errors, increase data rates, and increase radio transmission capacity. Creating multiple versions of the same signal improves the SNR and error rate by giving the data more chances to reach the receiving antenna without being affected by fading. MIMO provides more reliable connections and reduces congestion by increasing the capacity of Radio Frequency (RF) networks. The form is divided into multiple antenna types (Multiple-Input Single-Output

(MISO), SIMO, SISO, Bell Labs Layered Space Weather (BLAST), Single Antenna Selective Control Speed (SPARC), Daily Line Speed Control (PARC)) and multi-user types (multi-user MIMO (MU-MIMO), cooperative MIMO (CO-MIMO), macro diversity MIMO, MIMO routing, massive MIMO). By providing a large number of antennas for the base station, the spectrum and energy efficiency of the BS can be greatly improved. (Lu, Li, Swindlehurst, Ashikhmin & Zhang, 2014).

To communicate in a MIMO system, we can visualize it as a matrix being sent, rather than a single vector. Thus, it allows the propagation of a parallel stream of data to multiple receivers. The system encodes the data that needs to be sent, and the stream is transmitted using numerous (M) transmitters. MIMO systems have several hundred antennas that transmit to many wireless terminals at the same time. Through the use of beamforming, they manage to serve multiple users uninterrupted. Furthermore, beamforming increases SNR and at the same times reduces latency (Gupta & Jha, 2015). In (Hassan & Fernando, 2017), they list five main components: Pilot Transmitter, Encoder, Decoder & Detection, Beamforming, Precoder. Each one of the components is responsible for a different task.

Pilot Transmission

During a transmission of a signal, it might be contaminated with various interference. The problem is further enhanced with the addition of multiple cells. As they interfere with one another, the communication could be very problematic. To combat this, various methods have been implemented, from the use of CSI to estimate the propagated signal, to each BS trying to find the optimal pilots that can be used by other BSs.

Encoding Techniques

Using encoding, the data which are going to be transmitted are converted to symbols. This method makes the data suitable for transmission. Various methods are also applied, that require or don't require CSI.

Detection and Decoding

After a signal is transmitted, it has to be detected and then decoded. A detection is the estimation of the transmitted signal accurately, either by knowing the received vector or the channel. These systems use algorithms, that produce values which are predicted to be similar (soft) to the transmitted data or very similar (hard). The complexity is directly link to the prediction method used, based on how similar we want the predicted values to be. The values are encoded and fed as input to decoder systems that decode the signal to retrieve the original.

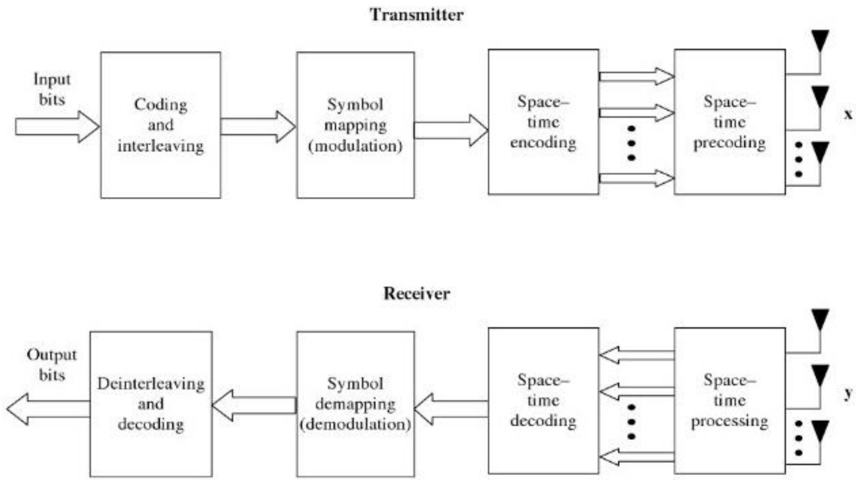

Figure 2. Basic Blocks of a MIMO system.

Beamforming

This is a technique that takes advantage of different antennas to transmit the same signal. In (Panahi & Jing 2018), the authors explain it as an optimal process of the received or the transmitted signal, by adjusting the amplitude and the phase to direct it toward the intended direction and nowhere else, thus reducing interference and the signal weakening. At the received point, only the beamforming signal is considered, and all the other signals received from other directions are discarded as interference. There are many beamforming techniques that differ on the way that the signal is directed to the desired location. With the use of millimeter waves (mmWaves), the beamforming process is improved and there are many benefits (Zheng et al., 2015).

Precoding

It is an approach of beamforming that enables multi-streams transmission. It is used to eliminate the need of very high data rates. It is also used as a power-efficient mechanism to reduce the power constraint in the entire system. The two main categories are linear and non-linear precoding.

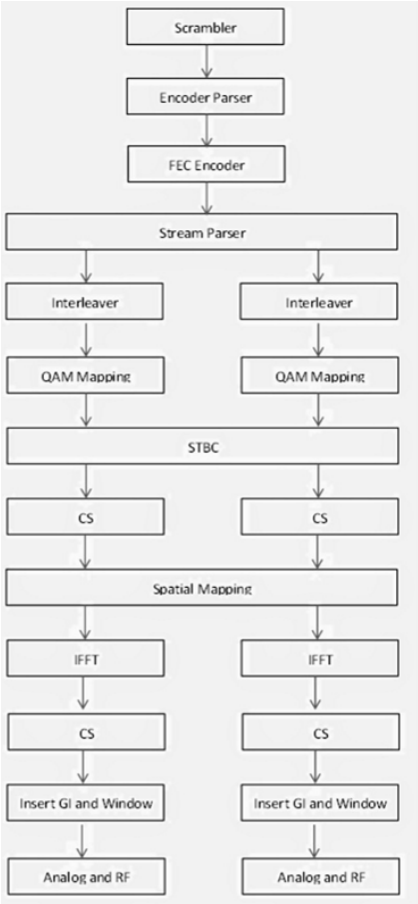

Figure 3. Inside a transmitter/receiver.

The most basic components of any MIMO system are the transmitter and the receiver. As their names state, they are responsible for receiving and transmitting the signals during the communication process. The Basic Block Diagram of a MIMO System can be viewed below. The x and y represent the transmit and receive signals, respectively. First, the information being transmitted is encoded and interleaved, and then the symbol mapper maps the encoded information to data symbols. The data symbols are then sent to a spatio-temporal encoder, which creates a stream of spatial data. This stream is transmitted by various antennas. The transmitted signal is received by the radio receiving array through the channel.

Furthermore, the transmitter and the receiver can be broken down into their respective basic components as seen above in Figure 3.

The scrambler acts as a replacement for zeros and ones in data received or transmitted while the encoder parser multiplexes the bits so that they are encoded. Next, a Forward Error Concatenation (FEC) encoder encrypts the data to enable error reconciliation. The stream parser splits the encoder's output into blocks called spatial streams and feeds them as input to various interleavers and mapping devices. The interleaver then wraps the bits in each spatial stream and transmits them to the FEC decoder as a lengthy sequence of noise bits. The sequence of bits in each spatial stream is graphed in various patterns through the Quadrature Amplitude Modulation (QAM) mapping, and the spatial stream is plotted in space-time by the Space-Time Blocking Code (STBC). A cyclic shift is also used throughout the high-throughput preamble to prevent beamforming when similar signals are broadcast over various spatial streams. During the data section of the packet's transmission, the same cyclic shift is performed to these streams. Spatial mapping is applied to map such spatial streams to the various transport chains. This most commonly involves either direct mapping, in which each space-time stream is mapped directly to another transport chain, or spatial extension, in which the space-time stream is multiplied by a matrix to be transmitted via another transport chain. Then an Inverse Fast Fourier Transform (IFFT) is applied to transform the constellation point block into a time domain block and apply another cyclic shift on top of it. Finally, we insert guard intervals (GIs) and windows to soften the edges of each symbol and increase the depreciation of the spectrum. On the receiver side, all processes are reversed to get the original data sent from the transmitter.

MIMO sets the goal of wireless and mobile networks to primarily improve data rates and reduce latency. To reduce errors and boost speed, smart antenna technology is incorporated into MIMO electronics. It is a well-known technology in BS, and it is currently utilized in the MIMO 4th generation mobile network, although it has a totally distinct aspect. Four, eight, and sixteen antennas on the transceiver and receiver sides are common variants of basic MIMO. This number may differ depending on whether you're on the transmitter or reception side. This approach is known as MIMO. Instead, Massive MIMO is a method in which each transceiver or receiver has a large number of antennas, such as 128 or 256, and it claims to be one of the main technologies in 5G mobile networks to ensure all of the following basic benefits.

Advantages and Disadvantages

MIMO allows for more powerful transmissions. It bounces and reflects signals, eliminating the need for a user device to be in direct line of sight. Video and other big-scale content can be sent in massive volumes across a network. Because MIMO allows for higher throughput, the content is received faster. The visual and acoustic quality of several data streams is improved. They also reduce the likelihood of data packets being lost. Assuming that digital data is being conveyed, the error rate will be affected. The principle of diversity is to transmit to the receiver multiple copies of the same signal. The chances of them all being affected at the same time are considerably lowered if the signal path can be modified to affect them in separate ways. As a result, variation helps to stabilize a link and boosts performance, lowering the error rate. There are various different kinds of diversity to choose from, each with its own set of advantages. Time diversity allows a message to be sent at different times by using different timeslots and channel coding. Frequency diversity is a type of diversification that employs a variety of frequencies. It could take the form of employing different channels or employing spread spectrum/OFDM technologies. MIMO is built on the concept of space diversity, which is defined in the fullest sense of the term. It makes use of antennas in various placements to take advantage of the many radio pathways available in a typical terrestrial setting. By managing the signal propagation phase over numerous antennas, MIMO allows us to electrically guide the directivity of an RF signal. This has two key advantages: First, beam steering can guide RF energy onto a specific user while disregarding the surrounding space. It's also feasible to monitor the user, which reduces interference and boosts SNR regardless of where the user is. Second, by determining the optimal path and directing RF energy in that direction, beam steering can alleviate the problem of RF multipath. Environmental changes affect the multiple paths that an RF signal can take even when transceivers are fixed, therefore dynamically changing and selecting the optimum path maintains best connectivity and extends range in severe interference conditions.

Through spatial multiplexing, MIMO can increase data carrying capacity without requiring extra bandwidth. According to the well-known Shannon-Hartley theorem, a channel's data carrying capacity is proportional to its bandwidth in Hertz (Goldsmith, Jafar, Jindal and Vishwanath, 2003). However, MIMO has the advantage of channelizing space: Each spatial channel can become self-contained, bypassing Shannon-limitations. Although an infinite number of spatial channels is not feasible, the potential to boost data rate by 50%, or even double, while maintaining the same bandwidth usage is a significant benefit. Because MIMO allows for the separation of transmission over many pathways, the signal can be encoded more efficiently when the effect of those routes is considered. Because each version of the RF broadcast will be received with various delays and SNRs, space-time encoding employs optimally encoded copies of the RF transmission. Within a MIMO transmission, the encoding seeks to mitigate for losses and increased noise in each of the spatial channels while also introducing redundancy that can fix bit errors. Multiple channels, each with its own delay and loss, are required for this sort of encoding. As a result, this approach cannot be used by a single antenna system. MU-MIMO systems provide for a level of direct gain in multiple access capacity resulting from multi-user multiplexing techniques (Yang & Hanzo, 2015). The number of base station antennas used is proportional to this. Some propagation difficulties that affect single user MIMO systems appear to affect it less. Channel rank loss and antenna correlation are examples of these; while channel correlation reduces diversity on a per-user basis, it is not a severe concern for multi-user diversity. It also allows for spatial multiplexing gain at the base station without requiring multiple antennas at the user end thus enabling the manufacture of low-cost remote terminals.

In comparison to a single antenna-based system, the resource needs and hardware complexity are higher. For radio signal processing, each antenna requires its own RF unit. Furthermore, to run advanced mathematical signal processing algorithms, a sophisticated Digital Signal Processor (DSP) is required. The increased power requirements are due to the hardware resources. Due to the processing of complicated and computationally expensive signal processing algorithms, the battery drains faster and as a result, MIMO-based devices' battery life is reduced. Due to additional hardware and complex software requirements, MIMO-based systems are more expensive than single-antenna systems. Because most users value the comfort of not being tethered to any fixed infrastructure, and because this automatically results in multipath on single lines and interference in cellular networks, MIMO systems can not only alleviate the negative impacts of this, but also leverage the spatial dimension. The usage of multiple-element arrays allows us to manage the signal's geographical distribution and so use multipath to boost the link's capacity (Burr, 2005). Individual user channels are still spatially uncorrelated, but under favorable propagation conditions, their channel vectors asymptotically become pairwise orthogonal. There are a few practical challenges with antenna arrays and hardware that apply to huge MIMO systems. Very large MIMO systems have the potential to improve spectral efficiency (measured in bits/s/Hz sum-rate) by one or two orders of magnitude while also improving energy efficiency (measured in bits/J) by three orders of magnitude. Simple linear processing at the BS, such as MRC or ZF, and channel estimations received from UL pilots make this practical. (Ngo, E. Larsson & Marzetta, 2013).

Services and Applications

In (3rd Generation Partnership Project (3GPP) TS 36.913), the parameters are laid out to allow the incorporation of new wireless technologies that will improve the users' experience. These include an increase in peak data rate, peak spectrum efficiency, average user spectrum efficiency, cell spectrum efficiency, cell edge user SE and bandwidth. These parameters can only be achieved through the use of enhanced MIMO services.

A prime example is the use of MU-MIMO over SU-MIMO. The difference between the two is that SU-MIMO uses all its resources with a particular frequency to serve the same user, whereas MU-MIMO distributes the antennas over several users. It provides several gains over SU-MIMO, such as cell throughput and capacity. But it also has some challenges that need to be addressed. For the UL, the same detection methods that are used for SU-MIMO, are also used for MU-MIMO. Unfortunately for the DL it is much more challenging. During the DL process, the problem of inter-user interference arises. To solve this issue, CSI must be included in the transmitter level. Furthermore, in 3GPP-LTE the same precoders that are used in SU-MIMO can also be applied in MU-MIMO.

Even though MU-MIMO, provides significant advantages over SU-MIMO it does display several tradeoffs. One such example is inter-cell interference, which could prove to be catastrophic in situations where the capacity is limited. It is also a harder puzzle to solve in cases where there are requirements of high spectral efficiency. To address this, a network coordination technique was introduced in (Karakayak, Foschini & Venezuela, 2006), which makes the MU-MIMO a multi-site MIMO. It introduces a coordinated transmission across the BSs. Unfortunately, it requires near perfect conditions to enjoy the full benefits of a full coordinated MIMO, such as a perfect channel knowledge. The benefits, though, even in sub-optimal conditions are still significant.

Another application on the basic MIMO model is massive MIMO. Massive MIMO in essence takes the basic MIMO architecture and scales it up by many orders of magnitude. It uses a few hundred antennas simultaneously in order to serve lots of users or terminals. It allows the development of future broadband technologies which will be more energy efficient and secure. Much like before, to benefit fully from massive MIMO, a full knowledge of the channel is required. This is required in both the UL and the DL. Overall, the benefits are worth the tradeoff. Massive MIMO increases the capacity of the network by many folds, while also being able to be built with inexpensive and low power consuming parts. Furthermore, it reduces the latency and increases the robustness.

MIMO technologies are used in a variety of domains in our daily lives. The following are a few of them. Wi-Fi is a wireless network that is broadcast through small devices in an indoor environment and can support adaptive array systems. Increased range, interference correction, and uniform coverage are the key benefits of MIMO application for WiFi. Various Voice over Internet Protocol (VoIP) applications can benefit from consistent coverage, which necessitates a high level of service reliability (QoS). Multiple antennas can be used from an access point or mobile client because the same frequency is always utilized. It offers the same benefits as higher data rates. MIMO also applies to WiMax (Worldwide Interoperability for Microwave Access), which uses multiple beam antennas from a base station and adaptive arrays from clients. Applying MIMO from a base station provides a wider range and increases capacity due to space reuse. Adaptive arrays from clients can help overcome signal fading originating from buildings. You can now use WiMax inside the building instead of outside the building via MIMO. Also, as with WiMax, multi-beam antennas are used in mobile networks that can achieve higher data rates during data transfer while increasing coverage and capacity. More applications can be found in RFID (Radio Frequency Identification) and Ultra-wideband where MIMO is applied to increase the range. Moreover, MIMO has made it possible to transmit a large amount of data that consists of both digital audio and video in Digital Television Systems. MIMO has also become a vital part of Satellite Communications. It is used in Satellite tracking, where multiple antennas are placed on top of vehicles roofs to permit the tracking of moving vehicles and in Satellite Radio to provide even more extensive coverage to satellite radio receivers and also to improve indoor reception.

Machine Learning and DUDe/MIMO in 5G Networks

Machine Learning in 5G Networks

The simulation of human intelligence processes by machines, primarily computer systems, is known as AI. AI systems are primarily concerned with gathering data and developing rules for sorting it, selecting the appropriate data to produce the intended result, and fine-tuning the data sorting for the most accurate results. Adopting 5G networks has numerous difficulties, and one way the industry is addressing those issues is by incorporating AI into networks. AI integration is primarily focused on lowering capital expenditures, improving network performance, and generating new revenue streams. 5G systems today use significantly more energy than they should and deliver lower data rates than promised. ML is a subset of AI that uses patterns and inference to build mathematical models based on training data to generate algorithms and statistical models to do a certain task without using explicit instructions. Known signal processing techniques have the potential to significantly reduce power consumption and enhance density, throughput, and accuracy in the next generation of wireless devices. 5G allows several IoT devices to connect at the same time, generating vast volumes of data that must be analyzed using ML and AI. Intelligent base stations will be able to make decisions for themselves, and mobile devices will be able to construct dynamically flexible clusters based on learned data, thanks to the integration of ML into

5G technology. Deep Learning (DL) is a subtype of ML in which the algorithms utilized have multiple levels, each of which interprets the data differently. DL will substantially reduce battery consumption and increase performance by replacing standard wireless methods. The aim of edge computing is to process and analyze data in servers that are closer to the applications they support. Because the 5G network architecture easily accommodates AI processing, it accelerates the transition. The future of AI will be altered by the 5G network and beyond design. 5G will improve the speed and integration of other technologies, while AI will enable robots and systems to operate at human intelligence levels. In other words, 5G accelerates cloud services while AI analyzes and learns from the same data more quickly. At present time, a semi-automated security framework is more appropriate; but, as AI technologies advance and feasibility studies of safe application of these technologies are conducted, the final aim of complete automation will be determined. (Noman, Zeeshan & Muhammad, 2020).

5G networks are both more in need of and more amenable to automation than previous generations. ML is not yet ubiquitous in carrier-grade networking, and automation technologies are continuously growing. Automation, AI and ML will be used more in the future, according to emerging standards and the open source software community. The activities of important suppliers bolster the vision and promise of artificially intelligent network operations. Given that 5G core networks are becoming more reliant on software and general computing resources, AI solutions could aid carriers in making the most efficient use of infrastructure while handling different traffic types that change dynamically and meeting a variety of service-level agreements. Future installations will very certainly have orders of magnitude more traffic-carrying capacity than current infrastructures. ML is expected to be required by many providers, academics, and developers in order to make effective use of 5G technology. ML applications in the research and development stages could have an impact on every layer of the communications stack. Generally, 5G and beyond networks, extremely dynamic traffic patterns, service-based network architecture, distributed network operations, and authentication across several servers necessitate a security framework that is relatively strong, adaptable, and fully automated. For distributed ad-hoc network architecture delivering various network tasks, AI can dramatically increase security. AI can be used in mitigating resource utilization in a physical layer of Sounding Reference Signals (SRS) on predicting an UL SINR, which is based on SRS using an Artificial Neural Network (ANN) based scheme that holds value for enhancing the most valuable aspects of Radio Resources Management (RRM) by increasing throughput, saving UL power, and increasing Bandwidth (BW) efficiency for 5G networks through prediction (Saija, Nethi, Chaudhuri & Karthik, 2019).

The supervised learning technique family is based on well-known models and labels that can be used to estimate unknown parameters. In cognitive radio, they can be used for massive MIMO channel estimation and data detection, spectrum sensing and white space detection, and adaptive filtering in signal processing for 5G communications. They can also be used in higher-layer applications like inferring the locations and behaviors of mobile users, which can help network operators enhance the quality of their services. Unsupervised learning is a heuristic approach to learning that relies on the input data itself. It can be used in cooperative ultra-dense small-cell networks for cell clustering, ubiquitous WiFi networks for access point association, HetNets for heterogeneous base station clustering, and HetNets for load-balancing. It can also be used to detect anomalies, faults, and intrusions, as well as to classify users' behavior. Reinforcement learning is based on a dynamic, iterative decision-making and learning process. It can be used to infer mobile users' decisions under unknown network conditions, such as during channel access under unknown channel availability conditions in spectrum sharing, distributed resource allocation under unknown resource quality conditions in femto/small-cell networks, and base station association under unknown base station energy status in energized networks. To improve the performance of 5G networks, computational intelligence paradigms like Neural Networks (NNs) and neuro-fuzzy methods, swarm intelligence algorithms like ant colony optimization, and evolutionary algorithms like the competitive imperialist algorithm can be used. NNs and deep learning are two of the most intriguing techniques currently available. In general, a NN is made up of a number of neurons connected by weighted connections, with the neurons acting as variables and the weights acting as parameters. To ensure that the application of a set of inputs produces the correct set of outputs, the network should be properly designed using learning techniques. Explicitly, this can be accomplished by iteratively altering the weights of existing connections among all neuron pairs using learning based on labeled or unlabeled input for supervised or unsupervised learning. (Jiang, Zhang, Ren, Han, Chen & Hanzo, 2017).

With greater reliance on cloud-native resources in telecommunications networks, opportunities for ML are emerging. In a 5G network, a connection event is defined by a large number of parameters, far more than in previous generations. That is why, in full-scale 5G operations, ML may be a requirement, not just an optimization tool, for optimal resource utilization. Network administration activities such as fault management assurance, configuration, accounting, performance, and security are being targeted by developers. By assigning appropriate modulation parameters and swiftly scheduling beams that are calculated to meet immediate demands, ML can ease congestion. Enhanced mobile broadband (eMBB) enables new applications with higher data rate demands to be deployed across a consistent service area. The scalable connection requirements for extending the number of wireless devices with efficient transmission of small amounts of data over broad coverage areas is a major feature of 5G communication services. Massive machine-type communications (mMTC) is the term for this. In ML applications, high-quality data is critical, and the type of data (labeled or unlabeled) is a key component in determining which sort of learning to employ and which hyperparameters to utilize. When all conceivable data-generated distributions are averaged, the No Free Lunch theorem states that every ML algorithm will have the same performance when inferring unobserved data. As a result, ML must determine what type of distribution is relevant to a certain 5G application and which ML method performs best based on the data. As a result, a tradeoff must be made between total accuracy and data interpretation while maintaining privacy and security. In comparison to infrastructure, it is determined that application level is the best fit for addressing the gaps of 6th Generation (6G) difficulties. When paired with a 6G wireless communication network, various ML techniques may be executed intelligently. To improve smart applications, we need to design a solution for present ML and future 6G that addresses existing difficulties such as latency, power allocation, privacy, security, model interoperability, and so on at the application and infrastructure levels. (Kaur, Khan, Iftikhar, Imran & Emad Ul Haq, 2021).

DUDe and MIMO in 5G Networks

The application of MIMO in 5G networks comes with its challenges. In these types of scenarios, the main reasons for applying ML are CSI estimation, coding/decoding method representations, error detection, device prediction position, magnetic interference, beam. It is intended to solve common problems such as forming definitions and radio. The frequency response detects multiple users and defines radio parameters.

In (Mehrabi, Mohammadkarimi, Ardakani & Jing, 2019), the authors used a deep learning model used for the determination of Channel Estimation (DD-CE) in MIMO systems, thus avoiding Doppler velocity estimation. They applied it to the vehicle channel, where the Doppler velocity varies from packet to packet, making it difficult to estimate CSI. Therefore, a deep learning model was used to train and estimate the MIMO fading channel at various Doppler rates. (Qing et al., 2019), the authors estimated CSI by combining deep learning and stacked code techniques. They somehow estimated the DL CSI, and detected user data from the BS. (Jiang et al., 2019) presented an assessment of CSI estimation using deep learning. They categorized the use cases into three scenarios. The first scenario is used in MIMO with multiple users estimating Angular Power Spectrum (APS) information using a dip running model. The second is used in deep learning-based static CSI estimation frameworks, and the third is a variant of the first method but considers time variability. In (Luo, 2018), the author constructed an online-used CSI prediction model, considering related features that affect the CSI of wireless links. The authors of (Cheng, 2018), replaced the traditional CSI estimation, equalization and mapping module with an ML model to generate a residual network in a Multi-Carrier Filter Bank (FBMC). In (Kang, Kim & Chun, 2019), the authors created a ML model with the task of understanding the encoding/decoding process of MIMO and Non-Orthogonal Multiple Access (NOMA) systems such that the total squared error of the total user signal is minimized. In (Xue, Ma, Yi & Tafazolli, 2018), they designed a simple deep learning model to collectively design multi-user waveforms on the generator side and detect inconsistent signals on the machine side. The major purpose of their model, which is applicable to MU-SIMO systems, is to reduce the discrepancy between broadcast and received signals. To overcome the pilot pollution problem in large MIMO systems, the authors (Wen et al., 2015) used Bayesian learning approaches to estimate both the channel parameters of the intended links in a target cell as well as the confounding binding characteristics of the cells. In addition, for the pilot pollution problem analyzed by (Jose, Ashikhmi, Marzetta & Vishwanath, 2009), the authors of (Kim, Lee & Choi, 2018) applied a deep learning model to a large-scale MIMO system. The authors emphasized that the traditional approach to pilot assignment is based on reasoning that is difficult to deploy in real systems due to its high complexity. This model could be used in real-world MIMO scenarios because it was used to learn the relationship between a user's location and a near-optimal pilot assignment with low computational complexity.

In (Zhou, Fadlullah, Mao & Kato, 2018), the authors reviewed traffic prediction in ultra-dense networks. We consider this task to be very complex in 5G networks because beamforming and large-scale MIMO technologies exist. A deep learning model was used to predict traffic, detect whether congestion is occurring, and make decisions to avoid/reduce such congestion. The authors (Maksymyuk, Gazda, Yaremko & Nevinskiy, 2018) used reinforcement learning to create intelligent beam-forming techniques based on MIMO technology. Their proposal builds a self-learning system that determines the phase change and the amplitude of each antenna. Reinforcement learning algorithms can adjust the signal density according to the number of users in the area. If there are many users in each small area, the solution can generate a more targeted signal to the users in that area. However, if the users are spread over a large area, a wide range of signals will be sent to cover the entire area. Moreover, in (Yang et al., 2019) the authors propose a low-cost framework that is created using ML techniques for link adaptation for Spatial Modulation Multiple-Input Multiple-Output (SM-MIMO) systems. Spatial modulation (SM) provides appealing benefits in future wireless networks, such as low complexity and low-cost transceivers, but has proven a rather difficult task to apply it. In (Motade & Kulkarni, 2018) a combination of the estimation of channel and multi-user detection mechanism is proposed for eliminating various interferences and reduce the Bit Error Rate (BER), with the use of ML. They also recommend ways for selecting the measurement matrix with the least mutual consistency for appropriate pilot placement. The suggested approach for designing the pilot pattern greatly enhances channel detection outcomes in terms of Mean Squared Error (MSE), Symbolic Error Rate (SER), and bit error rate. The placement of optimal pilots minimizes computational complexity while increasing system accuracy. In (Ma, Qi and Li, 2020), the author investigates the beam placement of multiple user millimeter-wave (mmWave) large-scale MIMO systems. A partial beam alignment method using ML (AMPBML) is provided. AMPBML NNs are scaled online to predict beam distribution vectors using partial beams trained offline using a simulated environment according to a millimeter wave channel model.

The application of DUDE in 5G networks is necessary for nowadays applications which require higher data rates and faster responses. 5G HetNets based on DUDe strategy are a promising solution to challenging issues faced in 4G networks such as mitigating interference and enhanced sum-rate. The need of higher data rates for both UL and DL directions comes from applications such as video streaming, live video gaming, and social networking. These applications which are mainly used on mobile devices, have spurred the exponential growth in mobile data traffic. According to Cisco’s predictions, mobile and wireless devices will use

71% of IP traffic by 2022 (Networking Index, 2017). For the forecasted flood of mobile data traffic to be handled, the research interests have been directed into the following areas (Cui, Gu, Ni, & Liu, 2017; Liu, Zhu, & Zhu, 2017; June, Song, & Soliman, 2013) - massive MIMO, moving to mmWave spectrum and extreme densification. To achieve extreme densification, a variety of small base stations were deployed into already existing 3G network with macro BSs only, aiming to bring users and radio access nodes closer (Andrews, Buzzi, Choi, Hanly, Lozano, Soong, & Zhang, 2014). Most small BSs such as microcell, pico cell, and femto cell, combine small size and less cost using low power consumption BSs. As a result, extreme densification achieved goals like enhanced coverage in blind areas, capacity improvements for cell edge users, and traffic offloading are transferred from overloaded macro BS to small BSs in 4G networks (Kishiyama, Benjebbour, Nakamura, & Ishii, 2013; Li, Jiang, Luo, & Mao, 2017; Andrews, Claussen, Dohler, Rangan, & Reed, 2012; Li, Sheng, Sun, & Shi, 2016; Damnjanovic, Montojo, Wei, Ji, Luo, Vajapeyam, Yoo, Song, & Malladi, 2011).

Downlink and uplink coupled (DUCo) access scheme was adopted by 4G networks. In this scheme, the mobile station associates with the same BS for both downlink and uplink directions based on the strongest SINR in DL, from a variety of BSs (macro and micro). However, the existence of DL transmits power inequality between macro BSs with high power and small BSs with low power may result to a MS associating in DL and UL directions to a remote macro BS with strongest SINR rather than a small BS which is located closer. As a result, MS associated to remote macro BSs will have significant interference in UL on nearby small BSs. Thus, DUCo access scheme is not optimal, and another scheme is needed to overcome these difficulties.

Hence, 5G networks demands that MS will associate to different BSs in DL and UL in order to reduce interference in UL, balance UL's direction traffic load and maximize the sum-rate. DUDe, a cell association scheme which was proposed by previous authors (Chih-Lin, Rowell, Han, Xu, Li, & Pan, 2014; Elshaer, Boccardi, Dohler, & Irmer, 2014; Boccardi, Heath, Lozano, Marzetta, & Popovski, 2014; Boccardi, Andrews, Elshaer, Dohler, Parkvall, Popovski, & Singh, 2016), enables MSs to associate to same or different BSs in DL and UL in HetNets. Using DUDe in 5G networks has shown sum-rate increment of $200 - 300\%$ in dense HetNets (Elshaer, Boccardi, Dohler, & Irmer, 2014) which indicates the importance of the DUDe scheme in 5G networks.

5G and Beyond Networks

5G refers to the fifth-generation mobile networks and it is a new global wireless standard that follows 1G, 2G, 3G, and 4G networks. 5G wireless technology is intended to provide peak data speeds of up to 10 gigabits per second (Gbit/s), ultra-low latency, enhanced dependability, massive network capacity, increased availability, and a more uniform user experience to more users with larger bandwidth. Higher performance and efficiency are possible thanks to AI and IoT. Cellphone firms began deploying 5G networks around the world in 2019, which are expected to succeed the 4G networks that connect most of today's devices. The service area of 5G is divided into cells, or tiny geographical areas. A local antenna in the cell connects all 5G wireless devices in the cell to the Internet and telephone network via radio waves. New antennas will use Massive MIMO technology, which will allow several transmitters and receivers to deliver more data at the same time. eMBB which transfers multi-gigabytes on demand, mMTC which connects many terminals and sensors, and ultra-reliable and low-latency communications (URLLC), which enables rapid feedback for mission-critical applications like autonomous driving, are all expected to be enhanced in 5G. However, due to a lack of available radio spectrum and severe spectral congestion, particularly in microwave frequencies, providing services concurrently would be problematic.

Future generations of mobile wireless communication systems are referred to as "5G and beyond." Beyond 5G or 6G networks, generalized seamless networks comprising of multiple transmission media such as optical fibers, Free Space Optics (FSO), and high-frequency radio-waves including millimeter-wave (mmWave) and THz-waves will deliver these services simultaneously. Beyond 5G, decentralized solutions and improved networking techniques are expected to support huge traffic. Future network architecture will rely on enhanced networking mechanisms and intelligent software that benefit from data analytics and shared contexts and knowledge in this context (Coll-Perales et al., 2020).

6G is expected to rollout somewhere around 2028-2030 (Calvanese Strinati et al., 2019). It is expected to incorporate the satellite communication networks and 5G, thus achieving coverage throughout the globe. 6G aims to arrange the wide variety of satellite networks, including telecommunication satellite networks, earth imaging satellite networks and navigation satellite networks, in order to provide to mobile users better connectivity and an overall better experience (Gawas, 2015). With the above mentioned, 6G promises to provide certain services that previously were thought to be unobtainable. Holographic communications that will provide to users a more immersive experience and reaching near face-to-face communications, may become a reality (Klaus and Berndt, 2018). Such communications require data rates that 5G cannot support (Li, 2018). High-precision manufacturing that will pave the way for Industry 4.0, that should reduce the human interaction on industrial machinery to the bare minimum. To be achieved, communications must be carried out with a latency to the order of 0.1 millisecond (ms) round trip time and with a very low delay jitter, in the order of 1 μsec (Berardinelli et al., 2018). Sustainable development and smart environments can strongly contribute to the improvement of health care, the development of smart cities, such as autonomous transportation and intelligent energy distribution systems. By depending on 3D communication systems that may deliver distributed edge cloud features, 6G will prove to be the determining element for such developments. Reliable safety procedures are required in some circumstances, such as autonomous driving, to prevent accidents. This will necessitate extremely high levels of communication reliability as well as very low end-to-end latency (below 1 ms). Furthermore, car-to-car communication will be a major strategy for reducing the danger of accidents. 6G will be able to maintain a traffic capacity of 1-10 Gbps/m^3, both DL and UL data rates will be capped at 1 Tbps, a latency of 0.1 msec and an energy consumption of 1 pJ/bit.

For the above to be achieved several factors must first be resolved. A new architecture that will support high-precision manufacturing with low latency and low energy consumption, is required. It should be able to combine different resources into a single framework and also include a new data plane, a new control plane and a new management plane (Calvanese Strinati et al., 2019). An introduction of AI and ML on the network is going to play a key role in various aspects: self-optimization of network resource allocation, development of smart mobile applications, development of semantic inference algorithms and semantic communication strategies to incorporate knowledge representation in communication strategies which will be particularly useful for an effective deployment of holographic communications. Also needed is a new physical layer that will be able to incorporate sub-THz bands. As a result of the aforementioned services, very high data rates are needed, which requires the use of sub-THz bands. In addition, the use of visible light communications is suggested as transmission technologies for the achievement of peak data rates. Furthermore, a need for a new Internet Protocol (New IP) has arisen due to the limitations of the current Internet Protocol (Li, 2018). Current IP networks are not equipped with mechanisms to monitor the transmission of packets and take actions for reducing any loss that may occur, while also maintaining a constant and consistent communication, not even for short distances. The New IP technology should evolve the existing Internet to a next generation with a focus on requirements of near-term and future applications. It embodies the network protocol of tomorrow and makes communications possible for all the future application scenarios described earlier. 6G will then act as the framework to deliver those applications. In general, 5G networks are mainly constructed to rely on infrastructure-centric communication solutions, to combat data traffic and service demands. Beyond 5G networks should also consider the combination of infrastructure-centric and device-centric communications. Device-centric wireless networks will build from D2D and Multi-hop Cellular Networks (MCNs), while also pushing the limits of edge computing and networking to smart devices, thus exploiting their mobile computing, storage and connectivity capabilities (Coll-Perales, Gozalvez & Maestre, 2019).

5G wireless networks are installed all over the world. By connecting different devices and machines, 5G technology serves large vertical applications with significant advantages in terms of high quality of service, larger network capacity and increased system throughput. 5G generally has many ubiquitous devices and is deployed in heterogeneous networks, so a secure and distributed solution is essential. One of the main requirements for 5G and future systems was security associated with 5G technology. Due to the centralized architecture, the existing 5G technology infrastructure remains an open issue in terms of reduced security, network, and computing performance. These next-generation mobiles demand high-quality visual, tactile, and auditory telepresence with low latency and high capacity (up to 1000x) as well as connection (billions of users and machines). Massive MIMO antennas, which have tens to hundreds of antennas, have lately began to take advantage of frequencies available at millimeter wavelengths (30-300 GHz), and have recently had tens to hundreds of antennas. High-power transmitters with antennas are capable of recovering significant radio losses. The more antennas there are, the higher the transmitted power will be, by combining the individual power of each antenna, a procedure known as beamforming. Massive MIMO antenna array with improved simultaneous transmission capacity; millimeter-wave spectrum to reduce spectral congestion in the current frequency band; both ultra-dense networks for short-range, high-speed data transfer are being investigated in the industry. Beyond 5G, the network paradigm is even more decentralized and automated. As a result of this trend, future networks will be better able to predict and anticipate changes in network connectivity and network environment. For Beyond 5G or 6G, more interfaces are required to convert signals and bridge various transmission media (Nguyen et al., 2020; Kawanishi, 2019).

CONCLUSION

In this chapter, we provided insights over the DUDe and MIMO technologies through a thorough analysis regarding their underlying architectures, system models, characteristics, advantages and disadvantages, services and applications. Then, we explained how these mechanisms and technologies could be fully taken advantage of with the introduction of ML techniques in order to support the 5G networks and why they are such core components of the networks of the future. After this critical comparison on the integration of the DUDe, MIMO and ML mechanisms, we offered insights for the upcoming 5G and beyond networks, which are also expected to capitalize on these techniques and extend them as far as possible, offering increased gains for anyone.

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