Review

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A Literature Survey on AI-Aided Beamforming and Beam Management for 5G and 6G Systems

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Abstract: The performance of modern wireless communication systems is highly dependent on the adoption of multiple antennas and the associated signal processing. In 5G and 6G networks, beamforming and beam management become challenging tasks due to aspects such as user mobility, increased number of antennas, and the adoption of higher frequencies. Artificial intelligence, and more specifically, machine learning, are efficient tools to reduce the complexity involved in generating beams and the overhead associated with beam management without sacrificing system performance. Therefore, AI-aided beamforming and beam management have received a lot of attention recently. This article presents a complete survey on this topic, emphasizing open problems and promising directions. The discussion includes architectural and signal processing aspects of modern beamforming and beam management. The article presents communication problems and respective solutions using centralized/decentralized, supervised/unsupervised, semi-supervised, active, federated, and reinforcement learning.

Keywords: Artificial Intelligence; Beamforming; Machine Learning; MIMO; 5G; 6G

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1. Introduction

Artificial Intelligence (AI) comes in handy when the configuration of a communication link becomes complex, such as when the number of antennas increases considerably. The use of Multiple-Input and Multiple-Output (MIMO) antenna systems in wireless networks is becoming increasingly typical as the number of users and frequency bandwidth increases each year significantly [1]. When employed, MIMO techniques provide spatial reuse (i.e., multiplexing), increase the gain of the received signal and decrease co-channel interference. Such factors increase the sum-rate spectral efficiency of the whole network [2,3].

A challenge of utmost importance in MIMO antenna arrays is directional beamforming (BF). Beamforming is performed through the interaction of the signals radiated by each antenna element of the antenna array to, through constructive and destructive interference, modify the radiation pattern for a certain purpose. Changing the gain and phase of the signals transmitted in each element of the antenna array makes it possible to change the direction and shape of the array's radiation pattern. For example, a transmitter can increment by a constant factor the phase of the transmitted signal at each element of its antenna array and thus direct the antenna's main beam towards a single receiving device, increasing the directivity and reducing the multipath effect [4].

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A beamforming system can assume three types of architectures: analog, digital, and hybrid. In analog beamforming, phase adjustments are applied to the signal in the Radio Frequency (RF) chain to steer the resulting beam towards the receiver and/or transmitter [5]. The phase adjustment is applied to the digital baseband signal in digital beamforming architectures [6]. Finally, hybrid beamforming combines digital and analog beamforming architectures [7].

However, finding the optimal direction to perform transmission or reception in a MIMO system is a complex problem, especially to achieve the maximum performance of a MIMO system. To do so, it is necessary to estimate the channels for each pair of antennas between the receiver and transmitter to increase the system gain and circumvent the adverse effects of the channel. The channel estimation process becomes more expensive and may become unfeasible as the number of antennas increases [8]. In addition, steering the beams of a MIMO system also depends on the hardware limitations of the transceiver and the scenario and application these devices are intended for [9]. Therefore, it is common to use codebook mechanisms that pre-define which radiation patterns can be used by an antenna array [10]. The codebooks are matrices, and each column of these matrices, also called codewords, has a different radiation pattern.

Although the space of possibilities is reduced when adopting a codebook, the process of selecting codewords or beams, as it is commonly adopted in the literature, is still considered costly. Let's take as an example the naive method of beam selection, also called Exhaustive Search (ES). The exhaustive method searches each beam, one by one, for the combination between transmitter and receiver that will result in the maximum value of a given criterion, such as the transmitter/receiver channel gain. Assuming that the transmitter and receiver have the same number of antennas, N, the complexity of selecting beams with the ES method is on the order of N^2. Although the ES method always guarantees the optimal result, it becomes impractical due to both the exponentially increasing search time as the number of beams or radiation patterns increases [11] and the ultra-low latency requirements, which are forecast to be around $1-10\mu s$ for the Sixth-Generation of Mobile Telecommunications Technology (6G) [12,13].

The MIMO problems reported above become even more noticeable in millimeter Wave (mmWave) and terahertz (THz) bands. These two bands are located in the frequency spectrum ranging from 30 to 300 GHz and from 0.1 to 100 THz, respectively. They are considered promising technologies due to the expressive amount of frequency spectrum barely used in these bands [14]. However, the benefit of occupying a large and still unexplored part of the spectrum comes with a high attenuation cost in free space. To address the high attenuation, some literature approaches use highly directional MIMO antennas, whose gain compensates for the path loss. Nevertheless, it demands precise and efficient beam selection methods to ensure the required application data rate and demanded delay requirements [15]. Another challenge such bands pose is the low diffraction capacity and severe blocking caused by most materials. Measurements in [16] showed that the attenuation in stained glass could reach 40.1 dB and in bricks 28.3 dB. Furthermore, blocking caused by human bodies can cause attenuation between 30 and 40 dB and reduce the data rate on mobile networks in outdoor environments by up to 32% [17,18].

Currently, Machine Learning (ML) algorithms allow wireless networks to learn how to extract information when interacting with large amounts of data. These algorithms become a potential tool in cases where there is no known solution through the traditional analytical approach or where the solution requires the manual configuration of many parameters, allowing some of the ML techniques to contribute to the estimation of these parameters. Academy and industry consider these algorithms essential for communication networks, applying them to detect anomalies and failures in the network and predict unseen scenarios. In addition, these algorithms allow the network to: adapt itself to environments that vary frequently, gain insights into complex problems with large amounts of data, and generally discover hidden (or latent) patterns [19]. ML techniques are often studied in MIMO applications [20,21] which, as already mentioned, are of fundamental importance for modern wireless

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communications and demand a lot of network resources (time and bandwidth) that must be used efficiently.

Beam management is an essential aspect of 5G networks that enables the steering of directional beams to improve the efficiency and reliability of wireless communication. It is achieved through a combination of techniques such as beamforming, beam tracking, and beam selection and is critical to achieving the high data rates, low latency, and high reliability that 5G promises to deliver [22]. Thus, guided by AI techniques, beam management can work based on context information, which is obtained as an alternative to the conventional use of pilot signals for channel estimation. Images, geopositioning coordinates, and data from other users are examples of context information that can be used to manage beams [23,24]. Simply put, for a given input dataset, AI models map this information into the beam domain; that is, they map several input pieces of information into the most appropriate beam. The availability of information to be used with such AI models can be questioned. However, the network itself already has several indicators, such as Key Performance Indicators (KPIs), that can be analyzed together instead of using only link-level data. Other information formats, such as user location and images, are becoming increasingly plausible despite user privacy concerns. The junction between AI and beam management allows a potential reduction in the time to perform the operations related to the selection of beams and the optimization of the mechanisms of beamforming according to the scenario [25].

6G brings a promising scenario for both AI and beamforming technology exploitation. Due to the high dynamics and flexibility foreseen for 6G, the existing beamforming and beam selection techniques still have not achieved the requirements of agile response, adaptability, and modeling of the environment. With the help of ML techniques, beam management acquires more dynamic characteristics, such as online adaptation of codebooks, and effective ones, such as beam selection performed in a fraction of the time taken by the ES and with performance comparable to that technique.

Therefore, the literature requires in-depth studies on how AI techniques shorten edges in beamforming management. To fill this gap, we raised research questions and conducted a systematic review to understand taxonomically how AI techniques support beamforming and are promising towards 6G network realization. Our systematic review allowed us to delve into relevant state-of-the-art approaches surveying themselves in tracking answers to the Research Questions raised. Figure 1 depicts a tree diagram summarizing the detected problems and the most used AI techniques to tackle each one.

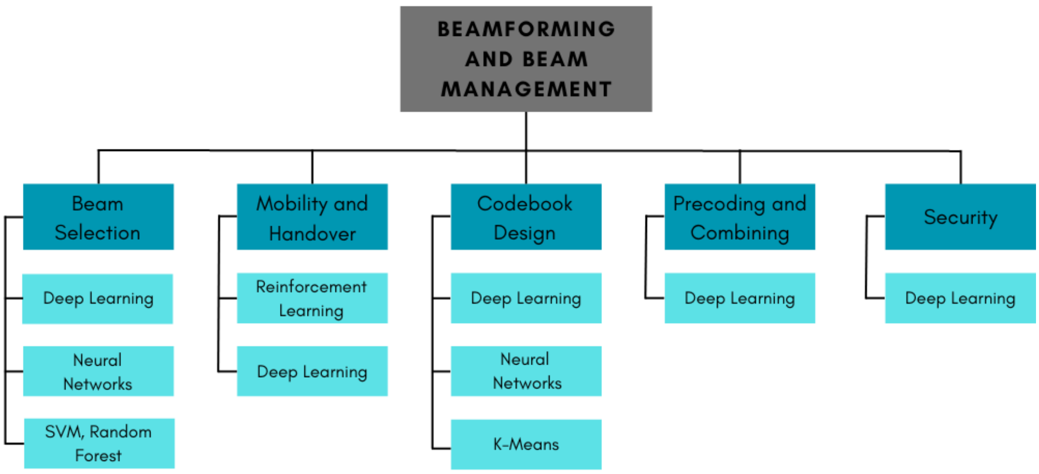

Figure 1. Detected beamforming and beam management problems and related AI techniques.

The remainder of this paper is organized as follows: Section 2 presents a background of beamforming architectures, followed by Section 3, where we present the rationale for the systematic review that guided our survey. In Section 4, we contrast our survey with those found in the literature.

Later, Section 5 brings the efforts towards beam selection in MIMO Systems. Section 6 brings mobility and handover state-of-the-art review. Section 7 delves into codebook design, and Section 8 details precoding and combining in MIMO with hybrid or digital architectures. In Section 9, we present the security of AI models issues, and in Section 11, we present open problems and future research directions, closing with Section 12, where we draw some concluding remarks.

2. Beamforming Architectures

The evolution of mobile networks usually arises from the demand for higher transmission rates, lower energy consumption, massive connection of devices, low latency, and communication with high reliability [26]. In 2010, with the arrival of the Fourth-Generation of Mobile Telecommunications Technology (4G), it became possible to have systems capable of supporting MIMO communication, enabling multiple antennas at the transmission and reception chains [27]. By using MIMO technology, multiplexing and diversity gains can be provided, further improving the capacity and quality of the wireless links [28].

With the growing demand for even higher data rates, mmWave and THz frequency bands have emerged, along with MIMO technology, as potential candidates for future wireless communication systems [29]. In contrast with systems operating at frequencies below 6 GHz, these bands offer large available bandwidths, allowing for high data rates, but their propagation characteristics (i.e., high attenuation in free space, absorption by atmospheric gases, and blockages) pose significant challenges [30]. To overcome these challenges, highly directional antennas must be employed, and beamforming techniques become essential. Beamforming allows for the creation of highly focused beams, enabling communication between devices even in the presence of obstacles [31]. With the development of beamforming techniques, it is now possible to exploit the potential of mmWave and THz frequencies, leading to the emergence of 5G and beyond wireless communication systems [32].

Beamforming is a technology capable of modifying the radiation pattern of an antenna array, making it more directive if necessary or modifying the direction of the main beam [33]. To maximize the Signal-to-Noise Ratio (SNR), beamforming technology modifies the beam by controlling the power and phase of each element of the antenna array.

In massive MIMO systems, unlike the traditional way (i.e., Single-input Single-output (SISO)), beamforming might provide spatial multiplexing depending on the implemented architecture, as we discuss next. As shown in Figure 2, the spatial multiplexing technique aims to increase the transmission capacity of the channel, transmitting different signals in different antennas or groups of antennas. These signals can be transmitted simultaneously and on the same frequency, thus multiplying the number of bits transmitted over the channel per second [33,34]. This technique imposes a high complexity on the receivers due to its need to separate multipath components and the need to know the channel [35,36].

Beamforming can be performed at either baseband frequencies or at Intermediate Frequencys (IFs), and its implementation is accomplished by analog, digital, or hybrid architectures [37].

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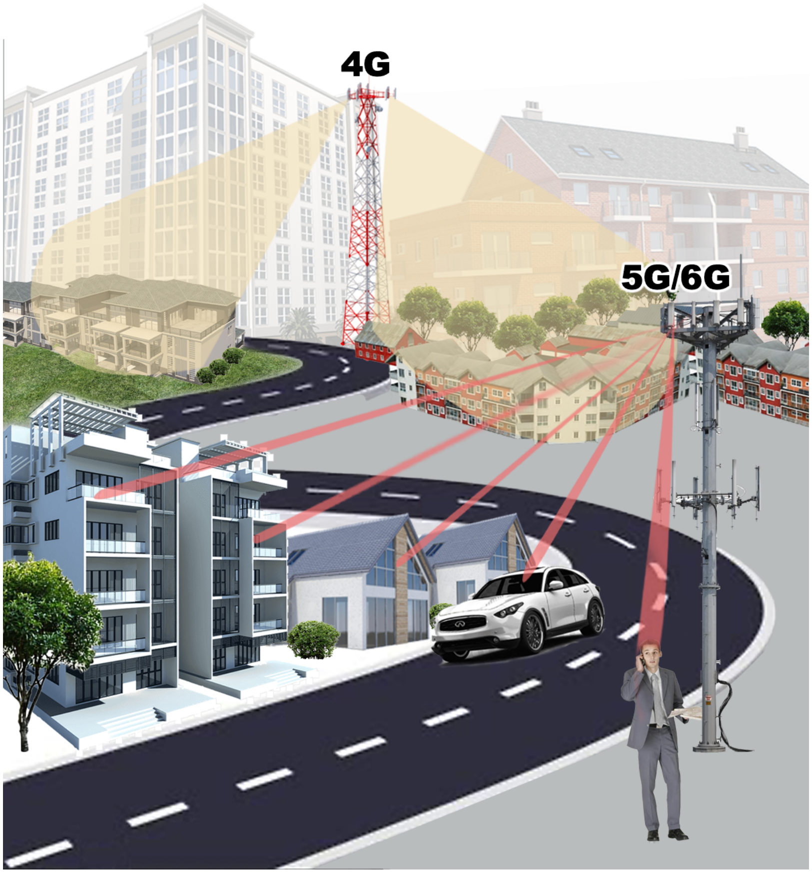

Figure 2. Beamforming system.

2.1. Analog Beamforming

The main idea of analog beamforming is to use low-cost phase shifters to control the transmitted signal's phase at each element of the antenna array [38].

The block diagram of the analog beamforming system architecture is shown in Figure 3 subfigure (a). The system comprises only one set of baseband processing, Analog to Digital Converter (ADC), RF chain connected to phase shifters and antennas. In this architecture, the same signal is fed (through the RF chain) to each antenna after having its phase adjusted by analog phase shifters that are used to steer the signal emitted by the array of antennas.

In this architecture, each antenna array element is connected to a phase shifter. The purpose of this phase shifter is to control the phase of each element of the antenna array so that the transmitted signal is constructively added to the receiver. Adjusting these phase shifters makes it possible to modify the beam pattern shape and direction.

One can also control the amplitude of the input RF signal using an Variable Gain Amplifier (VGA) [39], for instance. As main advantages, this architecture consumes less energy than the others, and the beam benefits from the antenna array's total gain, obtaining greater coverage [40,41].

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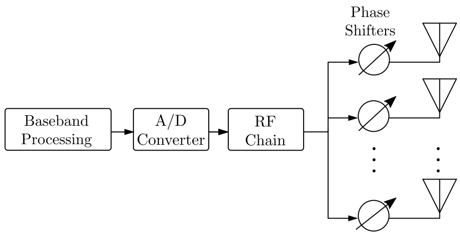
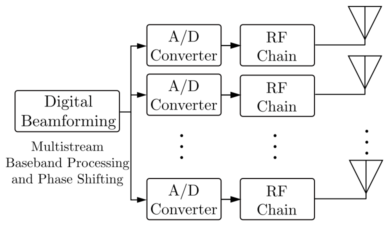
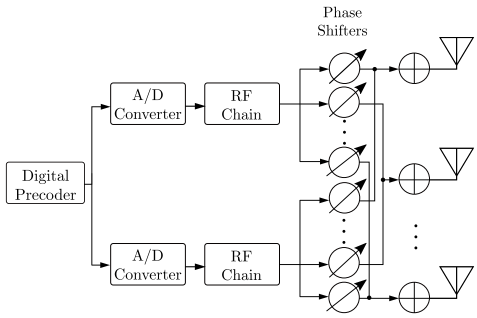


(a) Analog Beamforming



(b) Digital Beamforming



(c) Hybrid Beamforming

Figure 3. Beamforming architectures.

However, for applications that employ high frequencies or broadband operation, these architectures, in addition to being bulky, have high costs and are not capable of transmitting multiple streams simultaneously to achieve spatial multiplexing diversity. Limiting the transmission rate and flexibility of the system.

To mitigate these limitations, other architectures with digital generation of the transmission signal are sought.

2.2. Digital Beamforming

In the 1980s, Barton proposed Digital Beamforming (DBF) [42]. This system is based on transmitting digitally generated signals in each antenna array element. With this, the shape of the beams is controlled in the digital domain [43].

In this architecture, each antenna element has a dedicated ADC and RF chain, and the signal feeding it suffers independent baseband processing [44]. DBF can be divided into fixed and adaptive [45]. In fixed DBF, each amplitude and phase control is predefined and cannot be changed during communication. However, in adaptive DBF, the control changes according to the system's needs, such as increasing SNR and directivity at certain positions, modifying the beam shape due to obstacles, etc.

To obtain the appropriate beam pattern for communication, the amplitude and phase of each element is digitally controlled by the signal processor in the baseband before the conversion into pass-band [46].

Because the control is performed in baseband through digital signal processing, this architecture allows the implementation of beamforming algorithms with greater flexibility than analog ones. One of the advantages of DBF over its analog counterpart is the possibility of having several simultaneous beams, which allows spatial multiplexing. Moreover, this architecture allows adaptive beamforming with digital control [44]. However, as shown in Figure 3 subfigure (b), this architecture has the disadvantage of increased energy consumption and high cost due to the need to have an RF chain for each element of the antenna array [31].

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2.3. Hybrid Beamforming

Hybrid beamforming is based on a combination of analog and digital beamforming to overcome their disadvantages [47]. Its objective is to improve the performance of the analog beamforming technique by allowing more streams and to decrease the complexity presented by the digital one in the form of several independent ADCs and RF chains.

The block diagram of a typical hybrid beamforming architecture is shown in Figure 3 (c). The architecture consists of a digital precoder, ADCs, RF chains, phase shifters, and N elements. The figure shows that each RF chain is connected to a set of antenna elements, making it less costly and complex than the fully digital architecture [10]. In addition, each user's data is pre-encoded and fed into a dedicated RF chain. Thus, the signal is transmitted using a set of antenna elements with individual phase-shifters [31,48]. Hybrid beamforming also allows the implementation of spatial multiplexing [41].

Concerning the digital architecture, hybrid beamforming has the advantage of a lower hardware cost, reducing the number of RF chains. Furthermore, compared to the analog architecture, it does not interfere between users, as it has several beams and is able to obtain greater precision in beam formation [41]. Moreover, hybrid beamforming also allows spatial multiplexing if the system is equipped with distinct ADC and RF chains, and the feeding signal suffers independent baseband preprocessing.

3. Systematic Review

In this paper, we proposed and followed a consistent and systematic review protocol according to Figure 4. This systematic review aims to survey the works that tackle beamforming and beam management problems using ML and AI solutions. This section describes the steps taken in searching and selecting these papers.

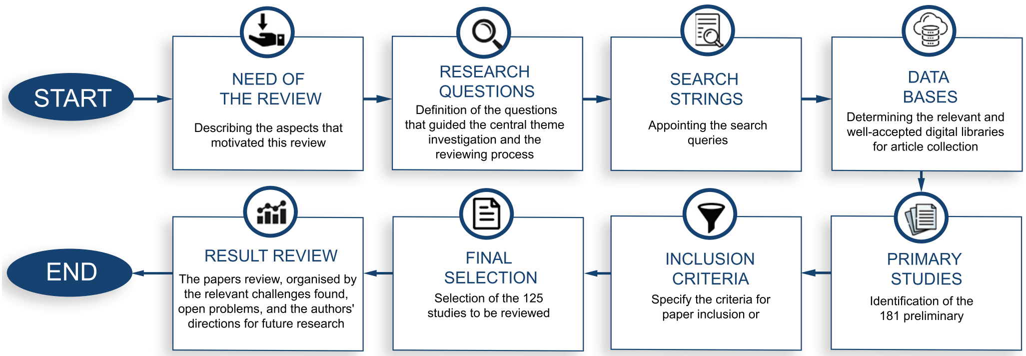

Figure 4. Process of the systematic review.

3.1. The Need of this Review

Beamforming is in the spotlight of current and future communication standards, although it is still a work in progress. In fact, how beamforming will be implemented and massively deployed is not yet completely defined. Exhaustive search and Discrete Fourier Transform (DFT)-based codebooks have been playing this role until nowadays, working well for small antenna arrays. However, it is common sense that the number of antennas is about to scale up. This increase in the number of antennas is why the exhaustive search cannot be the straightforward choice regarding the beamforming algorithm. Likewise, DFT codebooks are limited, considering the numerous applications and environments where antenna arrays will be deployed.

In the literature, we found some surveys and reviews on beamforming, beam management, and AI algorithms for wireless network applications, such as [49–51]. Although, to the best of our knowledge, there are no works that combine both themes together and consider a wide range of aspects, for instance, mobility, different beamforming architectures, and Radio Access Technology (RAT). Furthermore, ML

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and AI emerged as enabling technologies for many fields in telecommunications. Thus, beamforming and beam management can significantly benefit from ML generalizing capabilities. In this survey, we point out several beamforming and beam management AI-aided applications, use cases, and future directions.

Also, we aim at the modern and future generations of communication standards, e.g., Fifth-Generation of Mobile Telecommunications Technology (5G) and 6G. Although we included some papers focusing on other wireless communications technologies, we dive into 5G and beyond and the full support to the cloud, which will lead to AI full integration. For 6G, AI will play a key role, enabling a myriad of applications and ambitious performance indicators, such as augmented reality, Industrial Internet of Things (IoT) with 10^{-7} reliability and 1 Gbps user perceived data rate on dense urban scenarios [52,53].

3.2. Research Question

Our research question stems from the main challenge of beamforming and beam management, which is to realize beamforming with the highest accuracy and lowest complexity possible. This challenge involves generating the beams and associating the best pairs for the communication between Base Stations (BSs) and users. As a tool, AI techniques show potential to solve many problems in the wide wireless networks field of research, with promising integration with the network in the 6G. Thus, combining beamforming and beam management challenges with AI became a popular trend in the academy and industry, confirmed by the number of works published recently. Below, we enumerate the Research Questions $\mathcal{RQ}$ that guided our study:

$\mathcal{RQ}$ 1: What are beamforming and beam management challenges to face, and which are susceptible to AI solutions?
$\mathcal{RQ}$ 2: What ML techniques are adequate and often applied for beam-related problems?
$\mathcal{RQ}$ 3: What are the benefits and downsides of applying ML algorithms to beamforming and beam management problems?
$\mathcal{RQ}$ 4: How were the datasets composed and used for ML training and simulation?
$\mathcal{RQ}$ 5: Which are the future directions of research for AI-based beamforming and beam management?

3.3. Search String Definition

We searched digital libraries using the search strings according to Table 1. The queries were repeated throughout the surveying process to include recently published papers. The chosen strings are reflected in the outline of this survey such that beamforming and beam management challenges, such as beam selection, codebook design, and mobility, were covered. It is important to point out that papers returned by queries were just the starting point of our literature survey. Papers mentioned in those articles and not in the set of papers returned by our search were also added to our surveyed list of works.

Table 1. Database and search string table.

Database	Date of Search	Search Strings	Number of Selected Papers
Google Scholar	March 2021	"machine learning", "beam selection"	36
	April 2021	"machine learning", "codebook", "mimo"	21
	April 2022	"beamforming", "machine learning"	7
		"beamforming", "artificial intelligence"	5
		"beam selection", "machine learning"	6
		"machine learning", "beam selection", "mmwave"	16
		"machine learning", "handover", "mmwave"	29
	December 2022	"Beamforming", "Beam-selection", "machine learning", "artificial intelligence"	25
IEEE Explore	April 2021	"Beam selection", "machine learning", "artificial intelligence"	36

3.4. Criteria for Inclusion and Exclusion

The first criterion for including or excluding a paper is the year of publishing. We included papers published from 2017 to the end of 2022 that encompass the seminal and most popular works

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on beamforming, beam management, and AI, also guaranteeing that this survey is aligned with the state-of-the-art. Also, by the abstract and title, we excluded the papers that do not explicitly mention one of the challenges listed, machine learning or artificial intelligence. In order to exemplify, we considered some papers outside the criteria to exemplify concepts.

3.5. Identify Primary Studies

We consider papers with a two-year window behind the current state of the art. The number of selected papers on each search and the date of search are summarized in Table 1, totalizing 181 papers in this preliminary stage. We first organized the papers by title, author, and year of publishing. Finally, after the entire read, the papers out of the already mentioned criteria or lacking quality were eliminated, narrowing down the paper compilation to 137 papers.

Then, after reading the articles, we also identified some remarkable works and research groups which led us to investigate the bibliography they produced. Additionally, some articles that were well criticized in one of the surveys listed in Section 4 or a related article were included in this survey to provide completeness and enrich the discussions. Therefore, we summed up 125 articles matching the criteria mentioned in this section.

3.6. Review Results and Contributions

From Section 5 to Section 9, we classify and summarize the key contributions of the included papers. In addition, in each section, we include a table with overviews of the cited papers to guide the reader and to address the raised research questions. Thus, we attempt to indicate for each added paper which type of dataset was used, how data was interpreted, what ML technique was applied, how the technique was assessed and compared with other techniques and available ground truths, and how it is related to real applications. Finally, we would like to highlight Sections 11 and 12, where we draw our outcomes and conclusions about the state-of-the-art, previous research, and what we think are the future research directions for AI-aided beamforming and beam management.

4. Related Works

In recent years, beamforming techniques have received a lot of attention due to their important role in establishing and maintaining communication links. Many studies have organized these efforts to shed light on how these methods are evolving, being used, and how other technologies such as AI and combinatorial methods play a pivotal role in this trend [54,55]. There are approaches to organizing these efforts in a binary way considering digital and hybrid beamforming techniques, and others that take into account energy efficiency maximization [41,56]. Recently, some works surveyed beamforming technologies for 5G networks [47,57]. Our survey organized the beamforming technologies considering emerging technologies such as machine learning, frequency, antenna, radio transmission paradigm, mobility support, and antenna array type. Hence, we highlight some of those efforts that shed light on beamforming technologies.

Araujo et al. [49] survey new topics that have gained attention recently in the research community, such as hybrid beamforming, ADCs with low resolution, signal detection complexity in massive arrays, and deeper discussions on the Time Division Duplexing (TDD) and Frequency Division Duplexing (FDD) paradigm. Our contribution relies on organizing the beamforming technology considering the AI methods.

Zardi et al. [58] overview AI applications in adaptive and reconfigurable antenna arrays. They present five AI applications: adaptive nulling, wireless localization, MIMO communications, element failures, and array calibration. Their work relates to ours as it deals specifically with antenna arrays. However, they do not address the use of ML algorithms to configure the antenna array and to ensure reliable communication over mmWave.

Pham et al. [50] bring an overview regarding intelligent processing signal radio, wireless physical layer, modulation classification, signal detection, beamforming, and channel estimation.

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Furthermore, they dive into the theme of AI applied to MIMO systems and channel estimation concerning beamforming contribution. Moreover, the authors provide a consistent comparison of beamforming techniques and how they are used to tackle beamforming challenges. Differently, we take an approach to the matter in this work by surveying the beamforming state-of-the-art considering different approaches such as applications, beamforming architectures, and machine learning paradigms.

Murray et al. [46] present a survey of various cognitive techniques for beamforming. They organize and categorize techniques based on their application in Multiple-Input and Single-Output (MISO) and MIMO systems. The survey treats the problem of defining the antenna array coefficients as an ML problem. Additionally, it reports using neural networks, Genetic Algorithms (GAs), and game theory in issues like interference reduction, noise suppression, power allocation, capacity, etc. Unlike our work, they do not discuss challenges like beam selection, codebook design, channel estimation, and the use of ML to tackle them.

Naeem et al. [51] survey the integration of Reinforcement Learning (RL) and Deep Learning (DL) techniques into MIMO systems. They present RL and DL applications for different MIMO problems: detection; classification, compression; channel estimation, positioning; detection and location; Channel State Information (CSI) acquisition and feedback, security and robustness; mmWave communication, and resource allocation. It addresses the use of AI for beamforming in mmWave bands and its use for managing and allocating resources. However, our paper goes beyond that, providing a classification taxonomy in how AI-based solutions enhance beamforming techniques and architectures.

Considering the MIMO system's challenges, Rajarajeswarie *et. al.* [59] bring a short survey and discuss the main issues present in these systems, namely, pilot contamination, channel estimation, modeling, beamforming, and precoding. Furthermore, they present the main challenges and some solutions for MIMO but do not consider mmWave bands. Our paper thoroughly reviews the state-of-the-art contributions considering the frequency bands at which the beamforming systems operate.

ElHalawany et al. [60] propose a taxonomy based on the availability of CSI for beamforming and the application of ML techniques. Their work reviews the use of beamforming for Non-Orthogonal Multiple Access (NOMA), energy transfer, coordinated beamforming, and beam tracking and presents a case study using Multi-Armed Bandit (MAB) for beamforming training. Our work fills the gap left by their work by organizing and classifying state-of-the-art beamforming algorithms into ML technique, frequency, mobility, and antenna array type.

Wu et al. [61] discuss adaptive antennas and survey AI methods applied to antenna arrays and beamforming systems. Their paper compares the configurations carried out by adaptive intelligent antenna arrays and those carried out by traditional methods. Furthermore, they show how ML algorithms can enhance the performance of this technology. Moreover, the paper surveys antenna selection strategies, categorizing the adopted ML approaches into different learning paradigms. However, their work briefly discusses and compares the different works found in the literature, presenting a short table comparing works. On the other hand, our paper provides extensive analysis and comparisons of different works, diving into how ML algorithms and different learning paradigms are applied to support mobility, different frequencies, and codebook design.

The article [62] provides a comprehensive and detailed analysis of the recent state-of-the-art AI applications in beamforming. First, the paper briefly overviews beamforming techniques and Direction of Arrival (DOA) estimation methods. Then it explores the most essential and efficient Deep Neural Network (DNN) topologies in depth. Next, the authors provide several examples of how DNNs can be used as standalone beamforming and DOA estimation techniques or combined with other implementations, such as ultrasound imaging, MIMO structures, and intelligent reflecting surfaces. The article also highlights the realization of beamforming or DOA estimation via DNNs topologies. Finally, the authors conclude with significant findings and an exciting discussion on potential future aspects and promising research challenges. However, one limitation of this article,

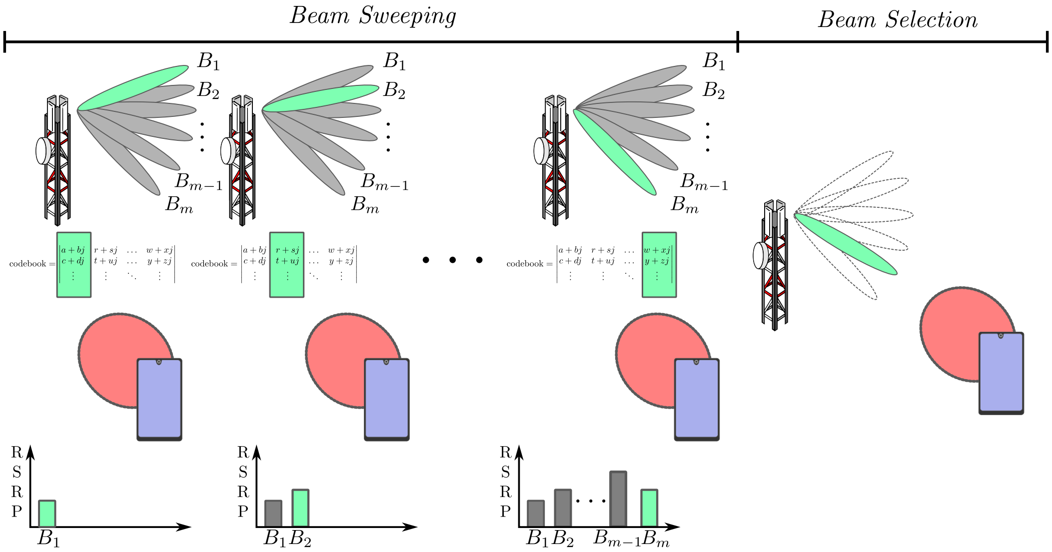

Figure 5. Illustration of a codebook-assisted beam sweeping and the further beam selection.

covered by our work, is that it primarily focuses on DNN-based beamforming and does not provide a comprehensive overview of other ML techniques that can be used in beamforming. Additionally, differently from what we present in this survey, the article does not provide a critical analysis of the limitations and challenges of DNN-based beamforming, which could limit the practical application of these techniques.

5. Beam Selection in MIMO Systems

The beam selection problem consists of finding the best pair of beams so that the transmitter and receiver can communicate, exploring the best possible antenna configuration for a given scenario. For this, one possible approach is to use pre-defined codebooks on the transmitter and receiver sides. From these codebooks, the codewords that lead to the most significant gain for the existing channel between transmitter and receiver should be selected. Figure 5 illustrates the process of beam sweeping from a predefined codebook and the selection of the beam that attained the highest Reference Signal Received Power (RSRP). As mentioned before, this problem becomes unfeasible to be addressed exhaustively, requiring a long time of beam training, consequently delaying the communication of valuable data. Other approaches besides the exhaustive one were raised in the literature, such as the hierarchical one, as well as several heuristics and those using AI.

In 5G New Radio (5G NR), there is a period for transmitting control messages in the downlink. During this period, training sequences are sent on each one of the beams, and the mobile station decides which beam should be used for the communication between them based on received power [63]. This procedure gets more complex if the receiver also employs beamforming, meaning it also has to select the best beam. With an ML approach, once the model was trained in the BS, the optimal transmission beam can be chosen faster than the exhaustive approach while optimizing different parameters, as we will see later.

In 6G, with the significant increase in the number of connected devices and the even greater demand for capacity and low latency, MIMO systems should present efficient solutions to meet this new demand. From 4G to 5G, there was an increase in the maximum number of antennas from 4 to 64 ones, which will enable up to 1000$\times$ increase in data transmission capability [64]. Given the greater dynamism and stricter requirements in terms of performance, the 5G New Radio (NR) exhaustive approach will become inapplicable to the 6G. Then, the 6G will depend even more on the union between MIMO and ML.

The AI-based approaches for the beam selection problem categorize it as a classification problem. Supervised learning approaches predominate for this kind of problem. In supervised learning, several

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instances of a data vector $\mathbf{x}$ are associated with a known output y (also called a label), and the adopted ML model is trained to determine a general rule that maps the inputs and outputs of a training dataset. Later, in the testing phase, the ML model must predict the outputs for unseen inputs, estimating the probability $p(y|\mathbf{x})$ or particular properties of the probability distribution existing between these two vectors [65].

In the beam selection problem, the input vector, $\mathbf{x}$, is usually composed of data such as the user position, environment configuration, and network situation, to name just a few. From the input dataset, which is composed of several instances of the input vector $\mathbf{x}$, the ML algorithms estimate a set of beams for the transmitter or receiver in order to optimize some parameters. Traditional approaches to the problem are limited to received power or Signal-to-Interference plus Noise Ratio (SINR), such as the initial access procedure of 5G NR or the hierarchical beamforming of Institute of Electrical and Electronics Engineers (IEEE) 802.11ad.

For instance, in [66], the authors approach the beam selection problem in vehicular networks by exploring variations in a data set containing context information. Context information can be position coordinates or geolocation of the mobile station, its displacement, and information about the environment in which the station is located, among others. In this work, the set of context information has different types of coordinates and noise insertion in the location of vehicles. They have tested different antenna array sizes and the number of recommended pairs of beams. In that case, the proposed RF-based method can reach up to 99% of the maximum throughput. Even with arrays equipped with 16×16 antennas, if compared to other ML methods, such as Gradient Boosting (GB), DL, and Support Vector Machine (SVM), it achieves an accuracy of 95% in recommending the three best transmitter/receiver beam pairs for all tested antenna arrays.

The selection of beams from context information is a highly non-linear classification problem. DNN can handle this problem adequately because their multiple layers are composed of highly non-linear neurons. Rezaie et al. [67] use this technique, where the beam selection problem is treated as a multi-label classification problem. The authors trained a deep neural network using receiver position and orientation for beam selection. Other types of context information that can be exploited by ML methods for the beam selection problem are the received power, the Angle of Arrival (AoA) [68], the Direction of Arrival (DoA) [69], the gains of the multiple paths that reach the mobile station [70], context and social preference information of vehicles and passengers [71], and images [72].

The most popular approach to deal with the beam selection problem is to exploit location and positioning information, which has become widely available in recent mobile devices through Global Positioning System (GPS) systems. For example, the fingerprint technique associates beamforming related data, such as beam index, SNR, and AoA, are associated with user coordinates forming a database, which is queried with the User Equipment (UE) every time a new UE needs to beamforming with an Access Point (AP). In [73], the training dataset is generated using the fingerprint technique for each AP deployed in a city area. Besides, location information can also leverage knowledge about the environment and surrounding users using prior information about building and vehicles' positions and dimensions [74,75] and also use historical data as a first estimation of the beam to be used [76]. However, GPS coordinates from domestic devices have inherent inaccuracies due to the limited implementation. For example, in [77], authors consider errors in the GPS coordinates, preventing severe beam selection inaccuracies during the learning process. Besides, shortcomings of fingerprinting techniques are the database information out-dating in an intensive dynamic context and the time to query the database in a user-dense urban scenario.

ML methods are also very efficient and widely used for processing and extracting information from images. In [78], context information, such as the shape, position, and even the materials of surrounding buildings, cars, and trees around, is used. These data are obtained by multiple images taken by offline cameras in order to build a 3D image. This image is the input of a deep neural network, which aims to adapt itself to different environments. The network outputs vectors with the optimal beamforming indices of the transmitter/receiver. Another approach presented in [79] uses two cameras

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in two stages. In the first stage, the camera images are used to reconstruct a 3D image and locate the transmitter and receiver. In the second stage, a one-channel image derived from the first stage is given as input to a Convolutional Neural Network (CNN) to predict the best communication beam. In [80] and [81], images are formed from the power received by the different beams and treated as a problem of searching for peak heat in an image. The image is created from the reception power matrices, which are transformed into a power heat map. Therefore, each matrix associated with different received beams has a unique power map. In [82], the user positioning is converted into a 96×96 low-resolution image. Once a CNN analyzes the images, the available best beams are given as the output of this neural network.

Another possible strategy that can be employed is the generation of training data at frequencies below 6 GHz, known as sub-6 GHz bands. Due to the multi-path effect, the sub-6 GHz bands are not often explored in channel probes and massive MIMO systems, but knowledge about the network can be established even in these bands. Jagyasi et al. [83] consider a heterogeneous communication network, where small BS operating at mmWave coexist with sub-6 GHz macro-cell BSs. Through basic signals extracted from the sub-6 GHz channel, a deep neural network model is applied in order to divide the problem into two sub-problems, one for BS selection and another for beam selection. In [84], the Power Delay Profile (PDP) of the sub-6 GHz channel was used for beam selection estimation in indoor and outdoor scenarios. BS selection was treated as a classification problem, while beam selection was mapped into a regression problem. Alrabeiah et al. [85] used a deep neural to estimate the occurrence of blockages in the mmWave band and determine which pairs of beams would optimize communication between devices. Similarly, but also using images from cameras close to the BSs, Alrabeiah et al. [86] applied a neural network with the same objective of detecting blockages and estimating the best beam pairs for transmission between BSs, also for users spread in an urban scenario.

In addition to supervised learning, beam selection is also often modelled using RL algorithms. RL comprises an agent interacting with an environment and receiving positive or negative reinforcement responses, called rewards, from the environment due to its experiences. These algorithms are composed of two phases. In the first phase, the agent explores the environment by taking actions and receiving rewards obtained from these interactions. In the second phase, the agent creates a strategy based on the rewards collected in the previous phase to maximize the upcoming rewards. In [87], authors describe a framework for reinforcement learning applications on user scheduling and beam selection, integrating virtual world components with mobile elements including Unmanned Aerial Vehicle (UAV), and ray-tracing generated channels samples. This framework offers some possible agent inputs, like 3D coordinates and orientation, packets and buffer information, bit rate, and channel magnitude, composing a thorough environment for experiments on reinforcement learning. In [88], a Q-learning agent has to learn the optimal beam, i.e., the action, that maximizes the overall system throughput, i.e., the reward, based on channel, user, and buffer states in a massive MIMO system where RF slices with the help of subsets of antennas are subleased for Mobile Virtual Network Operators (MVNOs). Shafik et al. [89] applied this same approach in selecting 3D beams for UAV using traffic data from Google Maps. The results show that the proposed approaches outperform the classical ones.

An emerging technology that is strongly reported by the literature as a beamforming enabler is Light Detection and Ranging (LiDAR) sensor. LiDAR sensors use a laser for scanning the surrounding area, and by the delay of the reflections, it can measure the distances to each surface and re-construct the points in a three-dimensional image. In [90], emulated LiDAR data and mmWave signals via ray-tracing feed a DNN combined with vehicles' positioning information, achieving 91% accuracy for a LiDAR-aided distributed architecture. Similar joint applications of LiDAR and GPS coordinates are found in [91] and [92], in the latter Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) link identification through LiDAR aided the beam selection, and in the former, LiDAR proved to improve the accuracy of beam prediction when compared with GPS-only beam selection. Likewise, an autonomous vehicle measurement campaign conducted in [93], exploited the use of camera images, LiDAR, and GPS on a vehicle achieving 99% top-1 beam accuracy with 54% drop in latency if compared to IEEE 802.11ad

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beam selection. The challenge is the price of LiDAR sensors, which are very expensive and with very restricted implementation nowadays but sound very promising in the near future with the evolution of self-driving cars.

Although the high accuracy achieved by the ML algorithms, the beam selection performance is arguably tied to the overhead of the beam-sweeping process. Indeed, it is crucial for beam selection algorithms to focus on reducing overhead, and, in terms of ML algorithms, the result of the online training or the online learning process must reduce the complexity of the beam sweeping compared to the other approaches. The training phase of the ML algorithms is usually executed offline, where the results of an analytical optimal solution [94] or exhaustive search [95] are used as the training dataset. After the training, in the testing phase, the ML algorithm reduces the complexity compared with the former solutions. For example, in [96], the authors achieved lower overall complexity using a biased version of the Single Value Decomposition (SVD) compared to a sub-optimal method for analog beam selection. Then, compared to the exhaustive search, its goal is to have comparable beam accuracy or SNR and reduce computational complexity, as in [97,98], which significantly reduces the complexity even for a large number of UE. In the same way, a prediction method analyzes a sample of the available beam pairs, so reducing the overhead compared with an exhaustive search, and a DL predicts the RSRP of all beam pairs to choose the best one [99].

To increase the algorithm's accuracy, some approaches estimate a set of m beams instead of a single best beam [100]. However, such an approach reduces the efficiency, as the m beams need to be tested via beam sweeping, though with less overhead than the exhaustive search, since a smaller number of beams need to be verified. In [101], when compared to an optimal solution, the time of the running solution of the learning algorithm is less 10%, while the traditional Zero-Forcing (ZF) beamforming is 80%.

The input data and extra information required by some ML algorithms may cause overhead in the network or sometimes be unavailable due to connection restrictions or privacy matters. For example, an UE with a lack of power might not have the GPS system running to save battery. Consequently, the location information would not be available to aid the ML algorithm. In this way, some authors consider the use of ML methods with constrained input data availability, for example, the KPI already available at the UE device or at the BS, such as RSRP, Receive Signal Strength Indicator (RSSI) or SINR. In [102] and [103], authors used only the received signal to infer the better beam to align and also LoS/NLoS status. In [104], a limited feedback channel is assumed in order to reproduce real-world scenarios, so a limited CSI is used by a DNN regression for beam allocation, resulting in near-optimal performance in the -10 up to 20 dB SNR regimen. The authors in [105] propose the use of standard ACK/NACK messages transmitted by the UE to the BS during the Hybrid Automatic Repeat Request (HARQ) procedure as input to an online RL scheme to lower the signaling overhead required for beam tracking and rate adaptation. In [106], the RSRP reported by the UE is used to feed a ML assisted beam change prediction scheme based on Long Short-Term Memory (LSTM), and helps saving more than half the power used by the UE for Beam Management (BM) compared to other methods.

ML versatility is highlighted by the myriad of scenarios and architectures that can be benefited from ML. For example, in [107], a human pose dataset is used for beamforming on Wireless Body Area Networks (WBAN), relying on an external camera, Generative adversarial networks (GAN), for generating additional data, and deep-learning for beam prediction. As mobility is an important feature of wireless networks, it is of utmost significance to invest in architectures that can support proper user mobility, as proposed in [108]. In the urban canyon scenario, with lamp-post mounted BS and blockage caused to the moving UE by elements also traveling in the scenario, the deep learning algorithm showed robustness to the intermittent blockages. Also, cloud-based architectures are necessary for data and computational offloading, and also for centralizing decisions, having a bigger comprehension of the network status as proposed in [109]. Another possible architecture is to apply dual connection schemes, which can increase data rate and provide transparent handover. In dual connection schemes,

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the UE stays connected to two BSs simultaneously, reducing the overhead when a context transfer is needed and increasing the data rate. However, dual connection also increases overhead and complexity, which is tackled in [110] using a SVM classifier for codeword selection from the available CSI samples.

The authors of [111] propose a method to enhance the performance of classification algorithms such as K-Nearest Neighbors (KNN) and RF by increasing the quantity of data used during their training. The lack of datasets with a wide variety of scenarios motivates this work. Furthermore, the need for extensive and assorted datasets hinders training more complex algorithms such as deep learning. Their method applies an algorithm based on the Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic data, augmenting the training dataset. The proposed method increases the dataset used for training classification models for beam selection. Their results show that the proposed method confers higher F1 scores to the classification algorithms compared to the same algorithms using the original data only.

In [112], the authors propose a computer vision-aided beam selection algorithm for mmWave indoor multi-user communications. The motivation for their work is the significant overhead in selecting very narrow beams in a multi-user environment. Therefore, they propose equipping a BS with a camera, which is used to predict the angles to the users, facilitating the beam selection process. Their algorithm, based on the predicted angles and the number of available RF chains at the BS, employ two Neural Networks (NNs) for joint beam and user selection. Their numeral simulations show that the proposed algorithm outperforms conventional beam selection techniques regarding multi-user angle prediction, achievable sum rate, and computational complexity.

The article [113] proposes a novel method for optimizing flight trajectory and power allocation in UAV communication systems using Computer Vision (CV). In addition, the paper addresses the challenge of accurately localizing the UAV and grounded receivers in complex scenarios where mmWave communication is used. The proposed scheme relies on cameras equipped at the UAV to capture visual information for accurate target localization, eliminating the need for costly radio frequency transmissions, i.e., pilot transmissions. Moreover, the authors propose a joint optimization scheme for flight trajectory and power allocation. Finally, the paper presents simulation results that demonstrate the efficiency of the proposed schemes, showing promising performance improvements compared to traditional approaches.

In [114], the authors propose a DL-based approach for beam selection and power control in mmWave massive MIMO communication systems, where obtaining accurate CSI is challenging. The proposed framework leverages the beam-steering technique to estimate the signal strength from the BS to the user. Furthermore, it employs a novel learning approach to determine the suitable beam for a specific user and the transmit power to minimize the cost, including the transmit power and the unsatisfied rate when the channel is unknown. The article also addresses the missing data problem and employs LSTM to select the suitable beam. The proposed learning framework is validated using the Deep MIMO dataset, constructed based on accurate ray-tracing channels. Numerical results show that the proposed framework outperforms state-of-the-art prediction strategies and approximates the best performance when the CSI is available.

In [115], the authors used an approach of deep learning for beam selection. Theirs used contextual information (location and orientation user) to select pair beams. The authors propose the use of neural networks with three different structures: single-task (DNN-ST), multi-task (DNN-MT), and extended multi-task (DNN-EMT). In this work, were considered 8, 8 and 4, 4 Uniform Planar Array (UPA) at the TX and the RX, respectively. The transceivers sense and select the pair of beams that provides the highest RSS, from the candidate list. For data collection was used ray-tracing (Altair Feko-Winprop software) an indoor environment. The authors compare the performance between strategies proposed against baseline strategies (Generalized Inverse Fingerprinting Method and Hierarchical Beam Search), and the results were present in terms of misalignment probability. Their results show that DNN-ST method has less misalignment probability with both LOS blockage probability (0.5 and 0.2) followed by DNN-MT and DNN-EMT. However, the DNN-ST had the best performance but was necessarily the largest dataset. On the other hand, the DNN-MT and DNN-EMT networks had much less computational complexity.

The beam selection problem is relevant for the evolution of wireless networks, especially in terms of mobility, as in vehicular networks and networks for UAVs that will be even more common in 6G. The beam selection mechanism must adapt to these networks' dynamic blocking and traffic patterns, as in [69]. Despite the significant number of works dedicated to this topic, the selection of beams is still seen as an isolated problem, focused on optimizing metrics such as received power, capacity, and data rate. The literature is still lacking approaches that, for example, use power-constrained transmission antennas [116], minimize interference [117–119], perform beam tracking [120] or allow concurrent transmissions [121]. In addition, the use of emerging technologies, such as LiDAR [90] and Intelligent Reflecting Surface (IRS) [122,123], can provide further support to address the beam selection problem. Finally, creating datasets with MIMO channels can facilitate the application of ML in MIMO systems, providing data to be used during the training phase [124,125]. The beam selection papers are compiled in Table 2.

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Table 2. Beam Selection.

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Situational Awareness	• RBF-SVM • GB • RF • FNN	Leverages situational awareness, such as vehicle coordinates, type, and speed.	Requires the neighboring vehicles to be connected to the network for best accuracy.	This paper evaluates different coordinate systems and several levels of available side information.	[66]
	• Linear Regression • SVM • RF-R • GB	• Leverages situational awareness. • Requires low overhead.	The lack of information on trucks' positions has a large impact on the method's performance.	This work proposes predicting the received power with different beam power quantizations using regression models through situational awareness.	[74]
	• RF-C • MLP • SVM • Adaboost	The classification models have smaller feedback and better overall performance.	The regression models require feedback.	This work proposes optimal access point and beam pair predictions for establishing communication by exploiting UE's localization and machine learning tools.	[73]
	CSML	• Shows that context and social information of vehicles and passengers are relevant for beam allocation. • The results show improvements in the received data.	Only permanent blockage is considered.	This paper brings a double-layer online learning algorithm based on user context and social preference information.	[71]
	RL	Using only GNSS data, the ML algorithm has a good beam prediction accuracy.	Although the beam prediction with LIDAR data is more accurate, it is computationally demanding.	This work investigated the use of GNSS and GNSS + LIDAR data for beam selection with NN using Raymobtime datasets.	[92]
	FML	• Low-complexity and scalable online learning algorithm. • Does not require either accurate or previous information. • The paper proposes a real-scenario protocol for supporting the mechanism.	The algorithm relies on GPS coordinates, which can be inaccurate in domestic devices.	An online learning algorithm based on CMAB is proposed, enabling mmWave BS to learn from the context autonomously, and it provides a scalable solution to increase the deployment density of mmWave BS.	[75]
	MAB	• Defines an exploration and exploitation algorithm for each algorithm layer. • Criticizes the model limitations. • Efficiently broadcasts content to UEs with the same interest, maintaining the SNR.	• Does not specify the control functions for exploration timing. • The content is only related to movies, which might be of limited scope for real scenarios.	• Uses a two-layer RL online algorithm to learn surrounding blockages from context information instead of using CSI. • The algorithm aggregates UEs with interest in the same content through beam broadcasting.	[69]
Position aided	DNN	• Reduced outage and beam misalignment probability.	• Having access to user data might be difficult. • Needs large training datasets.	The results vary with the number of obstacles for training and test datasets, highlighting the robustness of train-test mismatch.	[67]
	MAB	• The algorithm assumes errors in the positioning coordinates. • Two mechanisms are proposed for beam pair selection, greedy and risk-aware. • Authors also proposed a beam pair refinement based on Hierarchical Optimization.	The paper lacks a discussion on practical implementations and the algorithm's computational complexity.	Proposes an online method for beam selection to speed up the process.	[77]
	LtR	• The authors define the scoring and ranking functions to determine the best beam pairs. • A communication concise protocol is described as an example for implementing the technique in a real scenario.	• The offline training requires careful data updates and periodic re-training. • The baseline algorithm is not well explained.	Authors use context information and past beam measurements to determine potential beam pointing directions.	[76]
	• CNN • DNN	The algorithm presents high accuracy for low-resolution images.	• The authors did not compare the proposed technique with other ML techniques. • The images used as input are unusual. • The positioning info, when available, could be used instead for a simpler system.	Proposes a CNN algorithm for beam selection and switching using low-resolution images as input.	[82]

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Table 2. (continued from previous page) Beam Selection.

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Angle of Arrival Aided	• KNN • DNN • Singular Vector Class.	Evaluates the impact of using imperfect and realistic information for the AoA and received power estimation by using Capon and MUSIC estimation methods.	The BS performance degrades for a low number of UEs compared to the available antennas.	Proposes the use of AoA and received power as input of a DNN to select the best beamformer on a codebook rather than the complete channel matrix, which is a realistic approach.	[68]
Vehicular Networks	SVM	Higher sum rate and lower complexity than channel estimation-based method.	The training depends on the link density, which is hard to estimate and may vary substantially in real scenarios.	Proposes a tailored SVM/SMO algorithm for beam training.	[70]
3D scene-based	DNN	The 3D-scene reconstruction achieves better accuracy than LIDAR, which is more expensive.	• The UE coordinate estimation can be erroneous. • Computational complexity is not evaluated.	In this paper, a 3D scene reconstruction is used to identify the best beams.	[78]
Beam Domain Image Reconstruction	• CNN • DNN	Reduced beam selection overhead without degrading the beamforming performance.	The training is based on historical data.	This paper treats the beam selection as an image reconstruction problem without requiring channel knowledge.	[80]
Low overhead	LSTM	The proposed scheme finds the narrow best beam based only on wide beam measurements reducing the beam training overhead.	Only DFT codebook is tested as both high and low-resolution codebook.	This paper proposes a DL-based low overhead analog beam selection scheme.	[81]
Sub-6GHz channel information.	DNN	• Detailed DNN description. • Good accuracy with a partial dataset.	Lacks comparisons with other algorithms using the same scenario (i.e., DeepMIMO O1).	This paper relies on sub-6GHz channel information to deduce the resources in the mmWave band.	[83]
	DNN	• Compares the results with prior work. • Robust to NLoS conditions.	• Marginal gain increasing the number of neurons. • Implementation cost and energy efficiency not taken into account.	A dual-band scheme to predict beam and blockage from the sub-6GHz band to aid in the mmWave band.	[85]
	DNN	Presents a prototype validation of an indoor scenario, which shows that the ray-tracing and the beam selection method are very close to the real scenario.	• The sub-6GHz channel was modeled like a SISO channel. • Although there is a prototype validation, the results are not compared with any other ML-based beam selection approaches.	The PDP of the sub-6 GHz channel, which is highly available and does not demand beamforming, was used as input of a DNN for beam selection estimation in indoor and outdoor scenarios.	[84]
Blockage prediction	CNN	The use of RGB images reduces beam selection and blockage prediction overhead.	• High training complexity. • Simplistic scenario. • It does not work in dynamic environments.	The paper joints images and sub-6GHz channel information to identify mmWave blocked users.	[86]
Intercarrier Interference (ICI) Mitigation	DNN	Low computation time yet high spectral efficiency algorithm.	The paper lacks profound analysis for more users and if the grouping is effective.	This paper proposes an optimal user group beam selection scheme aiming the spectral efficiency maximization.	[117]
Small cell networks	SVM	Reduced complexity with quick and high ASR in the BS.	Though the paper assumes analog beamforming, the side-lobe interference is ignored.	This paper aims to maximize Average Sum-Rate (ASR) for concurrent transmission on an analog beamforming mmWave network by analyzing the BS spatial distribution.	[121]
LIDAR data	DNN	High accuracy for top-M beam-selection classification.	The one LIDAR per vehicle premise is not feasible due to LIDAR cost.	Proposes using LIDAR information to select beams in vehicular applications using deep learning, comparing centralized and distributed LIDAR.	[90]
	CNN	The use of LiDAR data reduced beam-selection overhead for LOS situations.	Overhead increases on NLOS occasions to maintain a tolerable throughput ratio.	The use of LIDAR data with CNN reduces the beam selection overhead for Vehicle to Infrastructure (V2I) communications.	[91]
	DL	• The use of multiple sensors, such as cameras, LiDAR, and GPS • Accuracy improved and delay decreased when compared to IEEE 802.11ad	The measurement setup is complex and hard to be reproduced	The authors establish guidelines for beam-selection dataset generation and release a real experiment dataset with the paper results	[93]

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Table 2. (continued from previous page) Beam Selection.

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
IRS-Assisted Beam Selection	DL	• The beam management mechanism utilizes user positioning information and environmental information to build reliable beam selection. • Enabling mobility is approached through updates on the historical database.	The algorithm depends on high BS-UE and UE computational capabilities to provide full mobility awareness.	This work presents an IRS-assisted mmWave network to improve coverage, handover, and beam-switching.	[122]
Channel Data Generation and Position aided Beamforming	• SVM • Adaboost • DNN • DQL • Decision Tree	Beam selection performance is simulated for several classification methods.	The paper is focused on data generation and classification methods for beam selection.	It describes a methodology for generating mmWave channel data, including realistic traffic simulation.	[124]
Low complexity	SVM	The computational complexity of the proposed data-driven approach is significantly lower than the sub-optimization method.	The number of analog beams considered is too small.	The authors propose a novel method, called biased-SVM, that determines the optimal parameter of the Gaussian kernel function to achieve optimal beam selection with low computational complexity.	[96]
	RF-C	The model complexity decreases as the number of users increases and is lower than the other compared methods, which is an advantage for delay-sensitive applications.	The simulation tool is not mentioned, which inhibits the results' reproductivity.	• Authors compared the computational complexity with a large number of users. • The results show a better trade-off between computational complexity and system performance compared to exhaustive and SVM approaches.	[97]
	DL	The authors propose a sampling method, reducing the number of seeped beams, and the DL predicts all beams, increasing the search space for the beam selection	The beam combination method cannot be generalized, so in practice, each scenario may require a different combination	A method for sampling a fraction of the beam pairs is proposed, combined with a DL for predicting the RSRP of all beams from the samples	[99]
	RBF	Reduced complexity by several orders of magnitude, with near-optimal performance compared with conventional methods..	• Needs large training datasets • Performance depends on the dataset size.	• In this work the authors propose using a RBF-NN model to perform the beam selection procedure. • The results reveal a reduction in the complexity, beam selection overhead, and latency.	[98]
	Q-learning	The performance is close to the optimal solution but takes fewer iterations.	Depends on knowledge of the channel matrix.	The paper minimizes the training time for beam selection using Q-learning to find the best-quantized analog precoders.	[94]
	DNN	This approach is appropriate for practical massive MIMO systems due to the complexity of the algorithm, which is not proportional to the number of beamforming vectors, using only one pilot signal.	• Good accuracy is only achieved for a large number of training epochs. • The capacity comparisons do not include other beam selection mechanisms.	This work proposes a novel algorithm (named Deep Scanning) based on deep Q-learning.	[100]
	CNN	• The model-driven proposed in this work solution reduced the computational complexity and execution time of the data-driven technique. • Authors include optimal solutions, providing upper bounds for the simulation.	The paper assumes a perfect complex channel matrix as input, which can be hard to obtain in a real scenario.	Authors propose a novel model-driven technique based on CNN, which calculates only essential and passes it through a low-complex beamforming recovery algorithm.	[101]
Body area network	GAN	Authors generated a dataset for WBAN based on a human pose dataset used for computer vision.	Does not address how the beam prediction would be made without an external camera, and only one set of sensor's location is provided	This work proposes employing a non-intrusive beamforming method in the WBAN with the use of GAN method for mmWave beam predictions using human pose images.	[107]

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Table 2. (continued from previous page) Beam Selection

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Highly mobile systems	DNN	Authors develop low-complexity mmWave coordination strategies for coverage coordination and latency reduction using omni-directional + directional beams in the offline training phase and only omni-directional transmission in the testing phase.	• Single user and simplistic channel scenario. • Although the effective achievable rate is greater than the baseline, the proposed method is more sensible to NLOS scenarios as the rate variation in such scenarios is larger.	To reduce the overhead, the BSs use DNN to determine the best beams using quasi omni-directional patterns during the online test phase.	[108]
Out-of-band information	CNN	• The dataset generated is of academy and industry interest. • The proposed technique reduced the beam sweeping time by 93% on different scenarios.	• The proposed method was not compared with other algorithms. • Only one transmitter and receiver positioning was tested, as well as only one camera location.	The authors created an experimental setup with mmWave hardware, obstacles, and cameras, which originated a dataset of images and beam pairs. Furthermore, the dataset was used for image-based beam prediction.	[79]
Large Scale MIMO	Q-learning	Outperformed state-of-the-art in terms of capacity.	Only assumes Rayleigh fading channel.	Beam scheduling method for enhancing the RF spectrum utilization by subleasing RF slices.	[88]
Limited Feedback	DNN	The method achieves high sum rates in the low SNR regime and Rician fading.	• It used a MISO system only. • The operating band is not described in the paper.	• The beam allocation problem is treated into two different strategies, classification, and regression. • The time prediction of the proposed approach is 6 times shorter than the optimal solution prediction time.	[104]
Interference Rejection	CNN	• No prior knowledge of the DOA is required. • The computational complexity is reduced for both space and space-time processing.	Needs large training datasets and offline training.	The CNN is employed for space and space-time processing, evaluated in two scenarios with different interference and DOA configurations.	[118]
Power restrictions	CNN	The intensive computational training phase is done offline.	Considers perfect CSI-only.	The goal of this paper is to maximize the downlink SINR based on power restrictions per antenna at the base station and improve the performance complexity trade-off.	[116]
Cloud Assisted	Conv-LSTM	The proposed solution improves positioning prediction accuracy while reducing storage costs by using Cloud and Edge collaboratively.	The load caused in the backhaul and the Cloud service is not taken into account.	This paper proposes a collaborative cloud-edge architecture. The BS uses Conv-LSTM to predict the user distribution and, through this, decide on a better set of beams.	[109]
Scheduling	RL	• B-BeamOracle RL agent presents the best performance • The proposed environment emulates a variety of scenarios.	• Poor agent modeling. • The B-RL achieves performance close to the B-Dummy.	Its used CAVIAR methodology for communication systems combined with the AI models, and the virtual world components for terrestrial and aerial beam selection.	[87]
Dataset generation	GRNN	Provides a baseline solution that predicts future beams based on the sequence of previous ones.	The baseline solution does not take the generated images into account.	This work used computer vision with AI algorithms to predict blockage through image classification-aided beam selection.	[125]
Beam Alignment	KSBL-LTS	• Beam selection policies were employed using both theoretical and real-world channel models. • The proposed algorithm obtained a faster learning rate when compared with Omnidirectional training with slowly time-varying channel support.	• Only MISO systems are used. • The algorithm's complexity is not evaluated.	The Authors developed a KBSL algorithm for mmWave beam alignment and beam selection policy to validate which policy would result in the most efficient beamformer: the linear Thompsom sampling, the omnidirectional, random, and greedy policies.	[120]

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Table 2. (continued from previous page) Beam Selection

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
No Reference Signal	NN	Does not depend on prior knowledge.	The proposed technique only works in LOS conditions.	• Authors proposed an AMPBML algorithm for beam alignment and beam training reduction. • Partial beams were used to predict the beam distribution vector.	[102]
	DL	More efficient and accurate than MUSIC but with comparable performance.	• Parameter tuning. • As it is based on AoA estimation, it is limited to LOS.	• A two-step NN model is proposed to estimate the Uplink signal's AoA with high accuracy. • Comparing with MUSIC, the results show the same or similar estimation performance in terms of data rate in moderate to high SNR regimes and outperforms it in low SNR ones.	[103]
Dual Connectivity	SVM	• Low computational complexity. • Memory-efficient approach.	Training time significantly increases with the dataset size.	• A SVM algorithm is used with sequential minimal optimization SMO algorithm in each iteration. • The proposed method based on channel parameters and transmitted power is compared to the optimal codeword, and the results show a reduction in the beam selection complexity with a high ASR.	[110]
Non-ideal Channel conditions	NN	Reduced overhead compared to the exhaustive search and model-based approaches.	• Marginal post-alignment beamforming gain loss of 1 dB. • Neglects NLOS channels.	• This work proposes a compressive sensing-based method for reducing the number of channel measurements. • A NN model addressed the CS dictionary mismatch issue caused by radio hardware impairments. • The results show a 90.2% reduction in the overhead compared to an exhaustive search approach.	[95]
Beam tracking and rate adaptation	MAB	• The proposed online RL method achieves significant throughput gains compared to other methods. • Uses ACK/NACK messages that are part of the HARQ procedure instead of explicit control messages, thus reducing signaling overhead. • Both real and simulated indoor and outdoor data are used. • The method selects both the best beam and modulation coding scheme (MCS) without making assumptions about the channel model or mobility pattern.	• The proposed RL method performance degrades at high speeds. • Only a single UE was considered.	Proposal of a novel restless MAB framework for beam-tracking for mmWave cellular systems using ACK/NACK messages instead of explicit control signaling. The method implements an online RL technique called adaptive Thompson sampling, which selects the best beam and MCS pair.	[105]
Data Augmentation	SMOTE	• Offers a solution to the lack of datasets containing complete 5G scenarios. • Evaluates the performance of several classification models, providing insights into which models are best suited for beam selection.	Lack of comparison of the SMOTE-based method with other algorithms found in the literature.	A method to augment datasets with synthetic data.	[111]

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Table 2. (continued from previous page) Beam Selection

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Angle Estimation and User Selection	DL	• Reduction of the beam selection overhead and consequent reduction of the computational complexity involved in this task. • Good performance in terms of achievable sum rate and multi-user angle estimation with a single camera.	• The angle estimation accuracy is limited by the single camera's field of view and resolution and the quality of the image processing algorithm used for angle estimation. • No experimental validation is provided. Numerical simulation may not capture all the real-world factors that can impact system performance.	A computer-vision-based method to estimate the beam angle, consequently selecting the beam and user.	[112]
CV-based UAV localization	CNN	• Compared to traditional schemes, their proposal significantly saves implementation costs and overhead (e.g., pilot transmission and consequent bandwidth waste). • The proposed joint optimization scheme can help improve the efficiency of the system.	• Assumes the UAVs can obtain accurate visual information from the cameras, which may not always be possible in real-world scenarios. • Requires prior knowledge of the locations of the grounded receivers, which may not always be available or may be subject to errors, especially in dynamic scenarios where the receivers may be moving. • Simulation results are based on idealized assumptions and may not fully capture the real-world challenges and complexities of mmWave UAV communication systems.	A CV-aided joint optimization scheme of flight trajectory and power allocation for mmWave UAV communication systems.	[113]
Power control and beam alignment	LSTM	• Proposes a novel learning framework for beam selection and power control in mmWave massive MIMO communications. • Addresses the missing data problem and employs LSTM for temporal processing of inputs. • Designs a learning agent to predict the proper transmit power based on the required transmission rate.	• The proposed framework is only evaluated through simulations and has not been tested on real-world data. • The proposed framework requires accurate ray-tracing channels for training, which may not be easily available. • The complexity of the proposed framework may be high due to the use of deep learning techniques. • The proposed approach assumes that the user locations are known, which may not be the case in some scenarios.	Proposal of a DL framework for beam selection and power control in massive MIMO - mmWave communications to optimize transmit power and beam selection for users with unknown channel state information.	[114]
Beam change prediction	LSTM	• The proposed scheme uses LSTM-enabled models to predict whether a beam change is likely to occur during the next measurement cycle. • Train and test data are generated using 5G NR compatible hardware in an outdoor environment.	• Only a single outdoor scenario was measured. • Low mobility, as the measurements were performed during walks.	The LSTM-based beam change prediction scheme can achieve over 58% power reduction regarding beam management compared to deployed commercial schemes.	[106]
Beam alignment	DNN	• Reduction of the overhead compared to ES and improves the accuracy compared to Hierarchical beam search. • Uses a uniform planar array on both sides of the link, with the goal of analyzing the effects of rotation in 3D space.	The solution presents high computational complexity.	This approach proposes using contextual information (position and orientation of user) for the initial beam alignment procedure through deep learning techniques.	[115]

(End Table)

6. Mobility and Handover

Mobility management is a great challenge not yet fully covered by 5G, but that will be a technological milestone for 6G systems. It ensures users do not lose connection with the network. Wireless networks have the range of their cells limited by the maximum allowed transmission power. Therefore, due to this limited coverage area, a user moving across the network undergoes several

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cell changes, known as handover. A handover requires the network to manage a connection from a serving base station to another base station, known as the target base station. Ideally, handovers are transparent to the user, which should not notice the service interruption caused by the cell change.

To make matters worse, when wireless networks operate in mmWave and THz bands, blockages become complex to overcome. As millimeter and THz waves propagate solely by LoS links, a blockage of the link between the user and the base station implies the disconnection of the communication session, which affects the overall system's quality of service and reliability. Moreover, re-configuring the user's session to another base station imposes beam selection overhead, and latency issues [126].

Besides the intrinsically high propagation loss of such bands, surrounding obstacles also impose losses (i.e. attenuation) to the transmitted signal, further reducing the cell range or causing unnecessary handovers. As a result, traditional handover algorithms based on received power differences do not perform satisfactorily in mmWave, and THz communications scenarios [127]. Usually, these algorithms lead to unnecessary or anticipated handovers, increasing the probability of a user having access to the network interrupted.

Thus, the application of ML techniques has been studied as a way to minimize and optimize handovers, which increases the throughput, and decreases latency, consequently improving Quality of Service (QoS) and Quality of Experience (QoE). Furthermore, ML techniques can use data already available, such as CSI, received power, and throughput measurements [128]. ML aims to assist in the decision-making process that performs handovers, making it more efficient and offering more significant support to users who are on the move.

In [129], the authors propose using Red, Green, Blue, and Depth (RGB-D) cameras to tackle blockage challenges. The images from these cameras are used to observe the BS's coverage area and help it proactively conduct a handover before a blockage can cause degradation to the quality of service experienced by the users. In this work, the authors use an online ML algorithm called Adaptive Regularization of Weight Vectors (AROW) for estimating throughout based on depth images. The estimation learned by the algorithm enables the BS to start the handover procedure proactively.

Approaches similar to the previous one are found in [130–133]. In [132], the authors present a Q-learning-based solution that employs information on the location and velocity of a pedestrian to trigger a handover decision. The RL-based solution learns how to optimize handover decisions by maximizing the expected future throughput based on a pedestrian's current location and velocity. The work in [130] develops a method for proactive performance prediction to improve handover management. The proposed method uses Deep Reinforcement Learning (DRL) to choose the best base station and performs handover. The input to the DRL agent is augmented with video from RGB-D cameras. The authors of [131] propose a proactive image-to-decision handover framework that directly maps camera images to a handover decision, avoiding temporal degradation in the link quality. The proposed framework employs DRL for creating optimal mappings between images and handover decisions, showing that proactive handovers outperform reactive ones. In [133], the authors employ information from multiple cameras and DRL to proactively take a handover decision. The images from several Red, Green, and Blue (RGB) cameras are used to predict blockages so that the network controller can start a handover process preemptively. Furthermore, the idea behind using multiple cameras is due to possible blind spots a single camera might present. As a result, the proposed multi-camera operation outperforms a system with only a single camera.

Aimed at vehicular networks, the authors of [126] propose using a Gated Recurrent Unit-Neural Network (GRU-NN) model for improving reliability and decreasing latency in high-mobile applications without requiring cooperation among BSs. In their work, the model at the serving BS utilizes the history of beam indexes used to serve a user over the past coherence interval to calculate the probability of a blockage happening in the next interval. This strategy allows the serving BS to proactively hand the user over to a BS with a better link. Their results show that it is possible to predict blockages with 95% accuracy, reducing the chances of service interruption, which improves reliability and decreases latency.

In [134], the authors use a Extreme Gradient Boosting (XGBoost) classifier to make BSs predict handover success rates from prior measurements collected from both sub-6 GHz and mmWave bands. The proposed approach learns the relationship between sub-6 GHz and mmWave measurements and employs it to determine whether a handover will succeed or not. Using this approach, the handover decision taken by the BS can be overridden, if needed, based on users' handover success history. Compared to standard handover algorithms, their results show that the proposed approach improves inter-RAT handover success, maintaining user sessions in the optimal band/technology for longer periods.

The dual-band approach was also adopted in [135]. In this work, the authors employ CSI, acquired at sub-6 GHz frequencies, as the input to a KNN model, which is trained to predict vehicles' positions. With the predicted position information, BSs operating in sub-6 GHz bands proactively inform mmWave BSs close to vehicles requiring handovers. This scheme overcomes the beam discovery problem caused by the coverage blindness phenomenon (i.e., a situation where beams radiate somewhere the handover vehicle is not in). Furthermore, they propose using the KNN to speed up handovers. Finally, they employ past handover information to determine relationships between the status information sent by vehicles requiring handovers and the final handover decision.

The authors of [136] tackle the problem of handover and power allocation in a two-tier (i.e., macro and small base station) heterogeneous network by employing a multi-agent DRL solution. They model the problem as a fully cooperative multi-agent problem, where the proposed solution aims to maximize the network's throughput while reducing the frequency of handovers. The solution leverages centralized training and decentralized execution of actions to solve the problems at hand. They use global information such as signal measurements, the number of UEs served by a BS, etc., to train individual policies for each UE then, after training is over, each UE receives a policy that it uses to make decisions based on local observations. The centralized training approach makes the decentralized agents work more cooperatively, mitigating potential instability and vicious competition issues, which are common to this kind of approach. Their simulation results demonstrate that the proposed solution outperforms existing solutions.

To maximize the throughput and minimize unnecessary handovers in mmWave communication systems, the authors of [137] propose a proactive handover solution based on a DRL model. The proposed solution employs decentralized multi-agents to make a proactive handover decision. From their trajectories, the proposed solution learns the optimum mapping between UEs and BSs. The optimal mapping is achieved when the connectivity between a UE and a BS is the longest possible among all possible BSs. Every UE acts as a single agent in this work. Their results show that the proposed solution minimizes the number of handovers and maximizes the overall throughput, outperforming a heuristic handover approach.

With the minimization of common handover problems such as the ping-pong one, the authors of [138] propose a two-stage DL-based handover mechanism that allows for the dynamic optimization of handover performed by the network based on the users' past behavior and their RSRP. Moreover, the proposed solution is also trained to predict users' locations. Their results show that the number of handovers is significantly reduced without penalizing the network's throughput. Additionally, it is shown that the predicted user's location has an accuracy of a few meters.

In mmWave frequency bands, due to the blindness coverage phenomenon, it is hard for both BSs and UE to identify the correct direction of beams, which renders the handover process quite complex. Moreover, when considering the communication of IoT devices, it is essential to consider minimizing the energy consumed by such devices during the handover process. With this in mind, the authors of [139] use the XGBoost algorithm to predict the handover success rate through channel state information. As a result, the proposed approach reduces handover failures and improves the energy efficiency of the network. Consequently, the XGBoost-based solution proves to be better than a previously implemented KNN-based handover solution.

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The authors in [140] propose jointly optimizing resource and handover management to provide seamless connectivity for multi-user mobile mmWave systems. The handover algorithm selects a set of backup BSs for each set of UEs and allocates the resources to maximize the sum of achievable rates of the UEs while minimizing the number of handovers and the number of outage events. The problem is modeled as a non-convex optimization problem, where minimizing the number of outage events and frequent handovers is more important than maximizing the sum rate. A Deep Deterministic Policy Gradient (DDPG) method is employed to approximate the solution to the optimization problem as it is capable of dealing with a large number of states and action spaces. Numerical results show that the proposed method achieves higher sum data rates and prevents frequent handovers compared to the benchmark, namely the random BS backup allocation and the worst connection swapping algorithms.

The most common 5G handover method is based on RSRP measurements of access beams, such as wide beams used for sending control and synchronization signals. In contrast, user data is carried over link beams. Therefore, the actual throughput depends on the link-beam gains. These beams are narrower than access beams and have deeper cell penetration. Hence, in order to improve throughput, the authors in [141] propose including the link-beam gain information in the handover optimization. The adopted formulation for the RL problem is called Contextual Multi-Arm Bandit (CMAB) problem. Each serving BS collects measurement data from UEs and then forwards the data to a centralized CMAB agent, which will then decide the handover actions. The objective of the RL agent is to maximize the average link-beam gain for all UEs and, hence, their throughput. A major advantage of this method is that it relies solely on current 3GPP signaling, but additional information such as location, speed, and antenna configurations can be provided to the CMAB agent.

The adoption of mmWave systems imposes the use of directional communication between BSs and UEs, which in turn requires the use of beamforming to improve channel gain. Besides, the need for dense deployment of BSs to provide better coverage increases the handover management problem. The authors in [142] propose jointly optimizing beamforming and handover. On the one hand, channel estimation and beamforming are performed more efficiently by only sending pilot signals through a set of pre-calculated paths called path skeletons. On the other hand, the downside of this approach is the need for a path skeleton database. RL is then used to select the best backup BS for a given location and predicted path, minimizing the number of required handovers while maintaining an almost constant data rate. Simulated results using outdoor environments showed superior performance compared to other methods.

In order to reduce the number of handovers and still maintain the QoS requirements of the user, the authors in [143] proposed an algorithm based on RL called SMART for mmWave HetNets. The algorithm is divided into two parts. In the first part, the algorithm uses the data about channel characteristics and QoS requirements to perform a handoff. In the second part, two algorithms are used: SMART-S and SMART-M. Based on the Upper Confidence Bound (UCB) algorithm, SMART-S selects the BS for a single user, and SMART-M selects the BSs for multiple users. As a result, the proposed method reduced the number of handovers by 50% compared to traditional methods.

In [128], the authors propose an RL method to reduce unnecessary handovers due to frequent short-term LOS blockage in mmWave cellular networks. The aim is to choose the next BS so that the connection can last as long as possible. To achieve this, the method exploits the empirical distribution of the UEs trajectories and LOS blockages post-handover, which is learned online through a multi-armed bandit framework. One of the advantages of the method is that it uses Received Signal Strength (RSS) signals from surrounding BSs to obtain a coarse location of the UE. This eliminates the need to use GPS information and reduces overhead. Numerical results show that the method performs better than similar methods regarding the number of handovers and connection time, mainly when the UE trajectories follow regular patterns emulating the movement on sidewalks. However, the UEs move at a relatively low speed (1 m/s), leaving questions about performance in higher mobility scenarios open.

The consequence of having a large number of handovers is the deterioration of user data rates and a decrease in UE's battery life. To minimize this issue, the authors in [144] proposed a multi-agent-based deep reinforcement learning solution, calling it Reinforced Handover (RHando). The proposed solution is fully distributed, thus limiting signaling and computing overhead, rendering RHando a candidate to meet the latency requirements of 5G networks. Furthermore, taking into account the collisions that occur when the number of users is greater than the number of possible connections in the BS, the authors proposed two solutions. The first one is the Fully cooperative RHando (RHando-F) solution. In this approach, users receive the same reward, favoring the optimization of the global network. The second solution, called Self interest RHando (RHando-S), considers only the perceived data rate for each user's reward. As a result, the proposed algorithm can reduce the number of handovers by up to 70% and increase the average network throughput by up to 18%, compared to the solution based on maximum RSS. The handover and mobility papers are compiled in Table 3.

7. Codebook Design

MIMO systems rely on directional beamforming schemes, which encode or decode signals to be transmitted through multiple antennas and take advantage of this feature to increase network performance. To generate an appropriate beam pattern, the transmitter needs to get information about the state of the channel (with or without feedback). The process by which beamforming directs the radiation pattern of the MIMO system using channel estimates is also called beam training, i.e. the process of discovering the best beam configuration.

The high cost and energy consumption of high-frequency circuits make the digital beamforming architecture unfeasible for antenna arrays with many elements. Therefore, most MIMO systems tend to follow analog or hybrid beamforming architectures. These beamforming architectures, due to their hardware restrictions, are used with the aid of previously defined beam codebooks, usually with one beam per codeword. However, these codebooks may not be efficient in all scenarios to which a MIMO transceiver is applied. In order to increase network performance, it is desirable for a codebook to adapt itself to the conditions under which the transceiver will be exposed [145]. We summarize the expressive codebook works in Table **??**, in which we emphasize the main purposes of each research with its limitations and contributions.

A generic codebook is the DFT codebook, based on the Fourier transform property that a translation in space becomes a phase shift in the Fourier Domain. With progressive phase weights applied to each element of each codeword, the DFT codebook steers the beams around the angular space according to these weights and the antenna elements. Despite being simple and robust, this codebook has some limitations: although it may cover all directions, many of them may not have direct use and increase the time of the beam training [146]. Because they are generic, these codebooks may have their performance compromised by imperfections in the hardware of the transceiver [145]. These factors then led academia and industry to research adaptive codebooks, generated with the help of AI.

The most direct way to adapt the codebook is to use existing indicators or estimates from the channel itself. Jiang et al. [147] used a deep neural network to extract propagation features from the channel samples, using these features to classify the samples through the K-means algorithm. After the clustering, the centroids for each channel characteristic are combined as coordinates of vectors in a multi-dimensional space, in which the axes are the characteristics. Finally, to reduce the dimension of the total space and the feedback overhead, the authors remap the channel sequences in the total space and discard combinations of centroids that do not satisfy a minimum criterion of mapping probability. Also, from this perspective of adaptation, not only to the scenario but also to hardware limitations, an artificial neural network was proposed in [148] to generate codebooks, whose phase adjustments reflect the neural network weights. The proposed neural network performed better than the DFT codebook, especially in situations with more than 16 beams and when multiple beams were activated simultaneously.

Due to limitations in the storage and acquisition of information that feed the methods mentioned above, the authors in [149] proposed an offline learning algorithm that trains from artificially generated samples. The output generated by the training with the current sample is used to generate a new

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channel sample and train again. This incremental process converges to a quasi-optimal solution for the precoding and combining optimization problems.

Alrabeiah et al. [145] used a neural network to derive an optimal codebook using complex values, together with a self-supervised neural network that does not require pre-existing channel information, enabling the online learning process. Based on the pilots received in an uplink transmission, with the proposed architecture, the codewords that generate the highest gain for the received pilot are chosen and adjusted according to the back-propagation algorithm. To maximize the normalized average gain of beamforming, Bhogi et al. [146] proposed a beamforming codebook generation model where learning adapts to propagation conditions. Using the k-means model, the results showed improvements in beamforming compared to CSI quantization techniques and still managed to reduce the codebook size.

To solve the problems of the complex wireless environment and the high-dimensional data of the massive MIMO channel, the authors in [147] proposed a codebook project based on a deep cluster (DC). With this, the DNN learns the propagation characteristics of the channel, and then the algorithm generates the centroids of each propagation characteristic. The results of the proposed algorithm were superior to the traditional methods. Zhang et al. [148] developed a new architecture based on neural networks to learn beamforming codebooks for MIMO systems. The model can adapt to user locations and takes into account hardware restrictions. About traditional works, the results demonstrated the ability to reduce the codebook and learn multi-lobular bundles.

Seeking to solve the challenges of the ES, Chen et al. [149] proposed a low-complexity algorithm based on Cross-Entropy Optimization (CEO) in which the results showed an almost ideal performance reaching 98% of the results obtained through ES. Zhang et al. [150] used a deep learning algorithm with the received power as input and no other data about the channel. In the first phase, this method defines an optimal action in terms of the phase changes for each antenna element, regardless of constraints. In the second phase, using the KNN algorithm, the optimal action is approximated to the most viable actions, which will be evaluated in the next phase. Then the codeword is defined, and the learning strategy is updated.

Another way to employ AI in codebook design is to optimize a performance metric. Jiang et al. [151] designed codebooks to increase the data rate by minimizing the sum of distances from the actual channel information to the channel statistical information. The clustering process is based on the well-known K-means algorithm. Then, different methods can be used to assemble codebooks from the obtained centroids. Lee *et. al.* [152] aimed, through deep reinforcement learning methods, to define a precoder belonging to a predefined set in order to minimize the Bit Error Rate (BER), giving the method greater adaptability.

The adaptability provided by the various techniques of ML to the design of codebooks meets the 6G objectives. However, there are still a few works that assume stricter premises, such as those that will be found in commercial devices. Even so, ML can still be integrated into existing codebook design algorithms in order to optimize the parameters of these algorithms when applied to specific environments. These approaches make these algorithms more efficient, adaptable, and simple. For example, the works by Takabe et al. [**?**], He et al. [**?**], and Balatsoukas-Stimming et al. [**?**] used deep neural networks to adjust the parameters of the biConvex 1-bit PrecOding (C2PO) algorithm.

Jiang et al. [153] proposed an algorithm for codebooks based on the clustering of self-organized maps (SOM) for MIMO systems with limited feedback. This algorithm can adaptively learn an arbitrary environment, so the proposed model adapts according to CSI. The results showed that real-world channel data could improve the performance of achievable data rates.

Kang et al. [154] developed an algorithm adaptable to any Rician factors. The proposed work seeks to solve the complexity of traditional models, which require an infinite number of optimal codebooks. The Rician channel consists of a deterministic LoS component and a Rayleigh-distributed NLoS component. Regarding quantization distortion, the proposed model was superior to conventional models. To overcome the overhead introduced by CSI estimation in FDD communication, the authors

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in [155] proposed an unsupervised learning model based on RSSI feedback. As a result, the spectral efficiency of the system was improved. It is known that the use of unsupervised learning models improves training time and cost. In their work, they used a deepMIMO model for evaluation, and the results were similar to the hybrid pre-encoder HSHO.

In [156], the authors proposed a deep neural network-based algorithm for a MISO system using the combination of two beamforming schemes to solve the challenges in interference channels, maximum transmission ratio (MRT) and zero-forcing (ZF). As input to the deep neural network, they used the transmission powers, achieving a 99% sum rate. Furthermore, using the MISO system, Xia et al. [157] proposed a model to optimize the downlink beam formation. The model in that work is based on convolutional neural networks. The structure is composed of three neural networks to solve three typical problems, the SINR balancing problem, the power minimization problem, and the sum rate maximization problem. The results obtained for the first two problems can reach almost optimal solutions, and the performance of the third problem was close to the solution using the weighted minimum mean squared algorithm.

To maximize the weighted sum rate (WSR) in a MISO channel, the authors of [158] developed a model based on deep learning named beamforming neural network. The model is based on LSTM layers. Different versions of the proposed model were used to tackle three optimization problems: SINR balancing, power minimization, and sum-rate maximization. The results of the proposed model outperform the Weighted Minimum Mean Squared (WMMSE) model at high SNR and are comparable when the SNR is low.

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Table 3. Handover and mobility

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Beam selection and blockage prediction	Kernel-based KNN	Employs sub-6 GHz CSI to predict vehicle's positions and, consequently, pre-activate the target BS as a way to speed up handovers preemptively.	• As it is a lazy learner algorithm, KNN requires the whole dataset to be stored in memory, consuming a large portion of it if the dataset is large. • The cost of calculating the distance between the new input and each existing example is huge, and sub-optimal solutions may degrade the performance of the algorithm.	• Uses sub-6 GHz CSI and a Kernel-based ML algorithm to predict vehicles' positions. • Use historical handover data and the KNN algorithm to accelerate handovers without complicated target selection and beam training processes.	[135]
Handover success prediction	XGBoost	• Performs preemptive handover procedures based on estimates of the mmWave channel conditions taken from collocated LTE cell measurements in the sub-6 GHz band. • The proposed approach has the potential to decrease latency and increase QoS and QoE.	• The proposed solution only works if the mmWave and sub-6 GHz cells are collocated. • XGBoost algorithm is required to be retrained if any of the cells operate at different frequencies.	• Introduces the concept of partially blind handovers. • Employs XGBoost to predict handover success rate from sub-6 GHz to mmWave frequencies. • Show that the combination of XGBoost and partially blind handovers improve the handover success rate.	[134]
Throughput estimation	AROW	• Employs a time and memory-efficient online ML algorithm. • The BS does not need to transmit any control frame, reducing the overhead and increasing throughput.	• The experiments were carried out with static mmWave BS and devices, which makes the results less useful. • Online learning algorithms suffer from noisy updates, which might affect the proposed solution's performance.	Estimates mmWave throughput using depth images and the AROW algorithm.	[129]
Blockage prediction and preemptive handover	DRL	Uses received power signals and video from depth cameras to train a DRL agent to overcome the computational complexity of learning the optimal handover policy, decreasing handover time.	• Only two base stations are used, and the experimental setup is rather contrived, which makes the results complicated to be extrapolated to other cases. • Requires some time for the DRL algorithm to converge as it learns from trial and error attempts. • The experimental setup is rather contrived.	Shows that blockage prediction is improved by augmenting the input to the DRL agent with video from depth cameras.	[130]
	DRL	Improves blockage prediction and handover reaction time by using depth images from multiple cameras.	Blockage caused by pedestrians being out of the camera's coverage is hard to be avoided, requiring a greater number of cameras to be solved.	Employs DRL with received signal powers and images from multiple cameras as states to predict blockage and proactively initiate handovers.	[133]
	GRU	• Decreases the latency caused by handovers as the current serving BS proactively knows the next serving BS, and then, it can start off the handover procedure before the UE loses the connection with the serving BS. • Does not require cooperation among multiple BSs, which decreases the overhead associated with coordinated transmissions, consequently reducing power consumption.	• The proposed model does not account for mobile blockages, only working for stationary blockages. • Requires a relatively large dataset to achieve reasonable accuracy.	Presents a blockage prediction and proactive handover solution that reduces latency and increases the system reliability in high-mobile applications without requiring high cooperation overhead of coordinated transmission.	[126]
Load balancing handover	DDPG	Maximizes the sum rate of all UEs moving along different trajectories while minimizing the number of handover and outage events.	• Does not consider interference from other active UEs, only from other BSs. • Assumes the UEs' trajectories are deterministic (perfect mobility prediction). • The decision process requires estimating the channel capacity and its backup BSs, thus requiring the CSI between the user and multiple BSs.	Maximizes the sum data rate of all users and minimizes the number of handovers and outage events using the DDPG algorithm.	[140]

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Table 3. (continued from previous page) Handover and mobility

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Beam gain maximization	CMAB	• Traditional 3GPP signaling can be used. There is no need for special measurements or new signals. However, information such as location, speed, and antenna setup can be used for context. • Link-beam performance gain of 0.3 to 0.7 dB compared to the methods in practical propagation environments.	• A centralized RL agent is required to handle measurement reports from UEs. • UE mobility model used for the numerical results is simple (UEs only move on vertical lines).	The handover mobility optimization considers current 5G deployment aspects and uses current 5G signaling.	[141]
Joint handover and beamforming optimization	Q-Learning	• Channel estimation uses a set of location-based of path skeletons, which are defined according to the channel gain, AoA, and AoD. • Pilot signals are sent only through the path skeleton sets, thus reducing overhead. • Minimizes the number of handovers by using Q-Learning to decide the best backup BS for each UE location and using a link quality threshold to trigger the handover.	• Assumes perfect trajectory information. • Requires keeping and updating a path skeleton database, which can be costly for a dense and highly mobile scenario. • Only a few UE location points are considered for the UE trajectories.	Beamforming can be performed using a low number of pilots due to the use of path skeletons. Handover optimization uses Q-learning to determine the best backup BS for handover based on each UE location and trajectory.	[142]
Minimization of handovers	MAB	• Uses received signal strength information collected from the surrounding environment to obtain a coarse UE location estimate to feed the RL algorithm. • UE location information allows for better trajectory and LOS blockage prediction. • The proposed method achieves a lower handover number and higher average lasting time of connection in different simulation environments compared to other RL-based handover methods.	• Low mobility, as UEs are simulated always moving at 1 m/s. • Does not present data rates results.	• Achieves a lower number of handovers than other methods using current 3GGP signaling (i.e., RSS). • Does not require accurate location and trajectory information.	[128]
	DRL	• SMART's computational complexity is much lower than that of the brute force algorithm to calculate the optimal solution. • The algorithm can be implemented in a distributed way.	• The UE may not stay around a specific BS for sufficient time. Therefore, it cannot have enough historical information to estimate the reward accurately. • It is not always possible to select the BS with the highest reward.	Reduces the number of handovers and maintains the user's QoS.	[143]
	DRL	RHando-F and RHando-S adapt their policies to the channel fading characteristics, providing robustness of the proposed framework.	• The method selection is not discussed. • The two proposed methods perform differently depending on the number of connection requests.	Reduces the number of handovers, and increases the average network throughput.	[144]
Handover success rate maximization and power allocation	DRL	• Tackles the joint problem of handover minimization and power allocation. • The proposed solution addresses instability and vicious competition issues, which are common to decentralized cooperative multi-agent approaches. • They employ the counterfactual baseline to mitigate the credit assignment problem, achieving better performance.	• Higher overhead since information like individual UE states must be sent to the central model. • Overhead is also increased due to the transmission of policies to the individual UEs.	Employs a fully cooperative multi-agent DRL approach to optimize handover success and power allocation jointly.	[136]

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Table 3. (continued from previous page) Handover and mobility

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Maximization of handover success rate and user localization	DL	• The proposed solution improves the network's throughput, reduces signaling overhead, and improves the overall network's energy efficiency. • Performs better than 3GPP models under the presence of uncertainty.	• As it employs a DL model, it requires a large training dataset, which requires a more prolonged training phase. • Does not consider delayed (outdated) channel information. • As it employs the RSRP as the input to the DL model, it loses the phase information, which might negatively impact the performance of the handover and localization mechanism.	Usage of DL with users' RSRP signals as input to implement a handover and localization mechanism.	[138]
Maximization of handover success rate	XGBoost	• The proposed solution minimizes signal overhead and improves the success rate of handovers. • Reduces energy consumption due to reduction of signaling overhead.	• XGBoost is very sensitive to outliers since every classifier is forced to fix the errors in the predecessor learners. Therefore, pre-processing is required, which might increase the proposed solution's computational complexity • XGBoost is hardly scalable.	Usage of XGBoost and CSI to implement a handover mechanism.	[139]
Handover prediction	DRL	• The multi-agent solution is based on UEs' trajectories. • Agents share their policies, speeding up the learning process. • The agents use image-like states, presenting the location of UEs, BSs, and obstacles at a given time, as input to the DRL models. • Differently from other works, they consider the issue that UEs might handover to the same BS, which decreases the system throughput. The proposed multi-agent solution ensures handover minimization and the system's throughput maximization.	• It is based on the trajectories of UEs. Therefore it requires the transmission of such information, which increases the overhead. • As it is based on the trajectories of users, it cannot be applied to the initial access phase. • It is an offline learning framework that requires data to be collected before any training is performed. • As the agents share policies, it might increase the transmission overhead, decreasing the network's performance.	Multi-agent DRL approach that employs image-like states as input and takes the maximization of the system's throughput into consideration as well.	[137]
	Q-Learning	• Improves handover decisions by predicting human blockages based on pedestrians' locations and velocities. • Maximizes the throughput of users.	• If the number of access-points increases considerably, Q-Learning will suffer to learn an optimal handover policy. • The states, namely location, and velocity, are discretized, which discards part of the information conveyed by them.	Usage of pedestrians' locations and velocities to maximize their throughput by predicting the necessity of handovers.	[132]
Proactive handovers	DRL	Employs DRL to map images into handover decisions, improving the QoS perceived by users, since handovers are proactively triggered.	• Since it is a DRL-based solution (learns by trial and error), it may present a long learning curve until convergence, which might hinder its deployment. • As is uses images, it requires a relatively large number of images to achieve reasonable performance. • The delay to obtain an image might impact the performance of the proposed framework.	Usage of camera images to proactively trigger handovers.	[131]

(End table)

8. Precoding and Combining in MIMO with Hybrid or Digital Architectures

Precoding and combining are techniques that exploit the spatial diversity and spatial multiplexing of transmission when multiple antennas are used. First, the spatial diversity techniques allow fading mitigation, improving reliability. Second, in spatial multiplexing, the receivers at different positions in space receive different signals simultaneously during the same transmission, increasing throughput.

Precoding (combining) works on the transmitter (receiver) side, encoding (decoding) the transmitted (received) signals with amplitude and phase adjustments that maximize the gain of the transmitted (received) information. When we refer to the precoder, we will also be referring to the combiner, which is its counterpart on the receiver side. We summarize relevant beamforming approaches highlighting their strengths, weaknesses, and their main objectives in Table 5.

As a consequence of the more significant number of antennas required for communications in mmWave and THz bands, the known channel estimation techniques might be prohibitive. Such channel estimation techniques depend on the probing and feed-backing of each pair of antenna elements between the transmitter and receiver, establishing all the channels available. Thus, they are not feasible due to the overhead that channel estimation would bring. Therefore, it is necessary to investigate low-complexity algorithms to establish the precoding matrix, especially algorithms dealing with multiple users. For this, a promising approach is the use of AI, which can, from different information about the channel, user, or BS, determine the formation of an optimal precoding matrix according to some criterion of interest, like the spectral efficiency [159], for example.

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Table 4. Codebook Design.

Challenges	Algorithm	Highlight (pros)	Limitations (cons)	Key contribution	Ref.
Hardware and deployment awareness	• NN	• Robust to hardware impairments. • Decouples learning process from communication. • The codebook is refined while communication goes on.	• the offline learning process can be time consuming and requires accurate channel state information. • for reduced number of codewords the performance is not satisfying.	• online machine learning framework. • adapt the codebook, and avoids the need for explicit channel state information.	[145]
Limited Feedback	K-means	• adapt well to the underlying channel distribution. • reduce the feedback overhea.	K-means clustering will suffer with dimensionality.	reduces the codebook design problem to an unattended clustering problem in a Grassmann collector.	[146]
Limited Feedback	• DC; • DNN	• Networks could learn the key propagation characteristics of CSI. • Clustering algorithms acquire the centroids of the corresponding characteristic.	• The offline learning process can be time consuming and requires accurate CSI. • Network performance for smaller antennas is lower than for larger antennas. • the number of spatial lobes affects the accuracy of the alignment direction.	Reduce the dimension of the full space and the feedback overhead.	[147]
Environment awareness	• NN	• artificial neural network based framework for learning environment. • aware beamforming codebooks. • developed neural network architecture takes into account hardware constraints.	• the optimizer book can still reach more than 85% of the upper limit with 64 codes and 90% of the upper limit with 12 bits. • nearly performs or even outperforms the same 64-service DFT codebook with just 16 services.	• learning environment aware beamforming codebooks.	[148]
Exhaustive search algorithm (ESA)	• CEO	• guarantee a result that is within 98% of that obtained by ESA with substantially lower complexity.	• limitations due to the use of phase shifter. (finite resolution)	• Design of efficient algorithms. • Convergence analysis.	[149]
Large codebook sizes	• RL	• Does not require channel knowledge. • Evaluates hardware impairments.	• Complex deep reinforcement learning architecture.	• Designing a deep reinforcement learning. • relies only on receive power measurements and does not require any channel knowledge. • Framework capable of learning a codebook for users in the surrounding environment.	[150]
Maximize the achievable rate	K-means	proposed codebook design can recognize and adapt to arbitrary propagation environment.	large amounts of channel state information (CSI) is stored as the input data.	characteristics extracted from the clustering centroids are used as the key channel information.	[151]
Optimal precoding policy for complex (MIMO)	• DRL	• proposed precoding framework can outperform the conventional approximation algorithm in the complex MIMO environment.	• Does not compare with any other solution in the literatur.;	• DQN and DDPG-based agents can learn the near optimal policy for the precoder selection problem.	[152]
Limited Feedback	• SOM	• Simple implementation • Better than DFT Codebook.	• Initial codebook depends on prior massive channel data. • ignores the impact of noise over the channels samples.	proposed method is able to update the codebook adaptively according to the instantaneous channel state information.	[153]
Limited Feedback	• GLP	• codebook adaptive to any Rician factors. • proposed codebook substantially outperforms conventional methods.	when the Rician factor is small, the impact of the NLOS components is greater. As a result, the average quantization distortion increases.	• Deduces the distribution of the angle between the channel vectors and the LoS component, as well as a precisely approximated distribution of the angle in tractable form.	[154]
CSI Feedback	• DL	• can be implemented in real-time systems due to low computational complexity. • works in FDD mode. • decreased training time as it is unsupervised.	• Might not be as precise as CSI trained DL models.	• design and evaluation of two unsupervised deep learning methods to train a multi-tasking DNN and directly design the hybrid beamforming using only quantized RSSI. • method to design the codebook which reduces the complexity of the DNN.	[155]
Balanced MRT-ZF combined optimization	• DL	• Outperforms MRT and ZF in terms of data rate. • Computational complexity below the optimal solution.	• A low number of user is used in the simulation results. • Only considers Rayleigh Channel model.	• This paper uses DL to build beamforming vectors based on the sub-optimal solutions provided by the MRT and ZF methods.	[156]
Interference mitigation (SI & CCI)	• MLP	• The trained model presents lower computational complexity than the ODD approach.	• Training dataset depends on complex optimization problem solution. • The solution quality is coupled to the dataset size. • The proposed MLP-based solution has scalability issues.	• The proposed solution presents a sub-optimal solution that is comparable to the traditional optimization-driven design (ODD) approach.	[157]
SINR balancing and power minimization	• BNN	• Achieves high beamforming accuracy when combining supervised and unsupervised learning.	• The beamforming prediction must be trained previously.	• framework is designed based on the CNN structure. • it was proposed a hybrid two-stage BNN with both supervised and unsupervised learning.	[158]

Increasingly popular, neural networks are often employed in precoder designs, as neural networks can achieve highly accurate results even in non-linear and complex applications. For example, Ma et al. [160] use a deep learning neural network to generate samples of artificial channels and train a hybrid precoder with these samples, comparing the results with a simulated environment. On the other hand, Elbir et al. [161] generated precoder from artificial channels using a convolutional neural network, achieving better results than the heuristic, deep learning, and Multilayer Perceptrons (MLP) solutions that were compared in the article. However, samples of real-world network indicators are abundant in most cases, such as AoA and Angle of Departure (AoD) [162], the pilots present in different frame configurations [163], and samples from the channel [164], and, therefore, can also be used to train neural networks and result in more accurate precoders, tailored to specific conditions.

Different strategies can be employed to generate precoder matrices. As the antenna array has several radiating elements, it is possible to form sub-arrays in some cases. In [165], the authors propose a two-step method for forming a hybrid precoder with sub-arrays of dynamic arrays. In the first step, a hierarchical clustering algorithm is used to group the array antennas in order to explore the characteristic variations of frequency-selective channels. In the second step, an algorithm based on Principal component analysis (PCA) generates an optimal low-dimensional precoder with a flat frequency response from a frequency-selective precoder. In [166], the authors propose splitting a multi-user codebook into inner and outer precoders. The inner precoder is focused on spatial multiplexing, while the outer one is focused on spatial division, that is, the inner precoder is divided into user sectors, and the outer one divides the users within each cluster. The inner precoder uses ZF beamforming to alleviate the interference among the users of a cluster. A DNN is employed to solve the outer precoder problem. The article's approach keeps the number of groups fixed, and the performance is close to the established optimum, which uses ES for the best codebook.

Some authors criticize the traditional method of estimating the channel and specifying codebooks separately. Attiah et al. [167] proposed a method employing a DNN that directly uses the pilots received in baseband for an end-to-end design of the precoding matrix. Li et al. [168] proposed the creation of a precoding matrix for beamforming with joint optimization. First, the precoding matrix is created using a cross-entropy method. Later, ZF or block diagonalization algorithms can be used to reduce interference between users with one and multiple antennas, respectively.

The precoding and combining project aided by ML techniques prove to be a possible way to provide the adaptability and performance necessary for high-frequency communications. In addition, it is possible to serve multi-user systems, contributing to the advances towards 6G, whose planned network capacity is beyond the capacity achieved today. Concrete steps are being taken so that ML techniques can be confirmed as a method for designing precoding matrices, such as the integration with 5G NR and the interaction with IRS [155,169]. However, there is still a lack of alternatives in the literature for real-time learning that can be applied to real-world equipment, which are challenges to be explored by academia and industry.

In [170], the authors propose using a neural network with a structure based on random Fourier features (RFF) to determine the most appropriate precoder matrix based on the user's location only. Their approach is capable of handling both LoS and NLoS channels [170]. They show that, depending on how the users' locations are obtained, it is possible to reduce or even eliminate the need for pilots.

Huang et al. [171] proposed a novel framework named Extreme Learning Machine that is capable of jointly optimizing transmitting and receiving beamformers of MU-MIMO systems. They used hybrid beamforming algorithms based on fractional programming and majorization-minimization techniques. They show that the proposed solution not only outperforms the system sum rate of conventional methods but also has a short computation time.

Due to high computational complexity and performance loss, Almagboul et al. [172] proposed a method based on the diagonal loading technique along with phase-only named Robust Adaptive Beamforming (RAB). Through integration with deep-learning for analog and digital beamforming and Spatial matched Filter-based to scale an appropriate identity matrix. Also, DNN is used to find digital beamforming weights combined with metaheuristic particle swarm optimization.

Lee et al. [152] present a performance evaluation of two techniques based on RL for precoding problems in single-user MIMO systems. Similarly, Li et al. [173] brings an auto-precoder system targeting to optimize the compressive channel sensing vectors and construct RF beamforming of hybrid architectures. Their numerical results surpass conventional approximation algorithms in complex MIMO environments.

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9. Security of AI models

6G is the latest instance of next-generation wireless networks. This new standard is expected to rely heavily on AI models, especially NN-based ones (e.g., DL), for improved system performance [175]. However, potential security risks associated with AI models are typically ignored. For example, NN-based models are susceptible to a set of attacks known as adversarial attacks, being the most common evasion attacks [176], data poisoning attacks [177], Byzantine gradient attacks [178], and model extraction [179]. These attacks can drastically impact the performance of networks employing AI.

The integration of ML to 5G and 6G technologies might lead to potential security issues. Trained ML models can be tampered with to produce faulty results. In [180], the authors show that ML models trained for mmWave beam prediction can be manipulated to output wrong predictions. In this work, the authors consider poisoning ML-based beamforming prediction by using a technique known as an adversarial machine learning attack. This technique tries to deceive ML models by feeding them with craftily designed input signals so that they produce faulty predictions. The attack method adopted in this work is the Fast Gradient Sign Method (FGSM), one of the most straightforward and powerful attack types. It works by using the gradients of a neural network model to develop an adversarial signal that is employed to evade the model. They propose an adversarial learning mitigation method based on using the gradient of the victim's model and then retraining it with adversarial samples and their respective labels. By comparing the effective achievable rate, the proposed technique efficiently defends ML models from such adversarial attacks.

Beam selection is a time-consuming and complex task performed by mmWave communication systems. The issues associated with this task are mitigated by adopting DL solutions. However, DL-based solutions are vulnerable to adversarial attacks. With these vulnerabilities in mind, the authors of [181] study four different types of adversarial attacks and propose two methods of counterattacking them: adversarial training and defensive distillation. Their results reveal that the proposed methods effectively defend the DL models against the studied adversarial attacks.

ML algorithms, especially neural network-based ones, offer important benefits to next-generation wireless networks. However, considering the security implications involved in their adoption is of utmost importance and practically ignored by the research community. Therefore, security is also a critical part of ML algorithms since attackers might be able to poison and confuse the models. In this regard, the authors of [182] study how adversarial attacks can deceive and confuse trained DL models employed in mmWave beam prediction applications. Their study employs the fast gradient sign method attack, which adds a specially crafted noise signal to the input data to fool the DL model. Furthermore, the authors propose a method to mitigate adversarial attacks on mmWave beam prediction applications using iterative adversarial training. The proposed method can be applied to other adversarial ML attacks. The results show that the model employing their method performs quite close to that of a model not being attacked.

Table 5. Precoding and combining in MIMO with hybrid and digital architectures.

Challenges	Algorithm	Highlight (pros.)	Limitations (cons.)	Key Contributions	Ref.
Channel Estimation	DL	Solves two problems with a similar approach.	• Large NN offline training overhead. • based on artificial channel measurements.	A comparison between a DL compressed sensing channel estimation for MIMO and deep learning quantized phase hybrid precoding.	[160]
	DL	• Lower computational complexity. • Imperfect CSI premise. • Better than others state of art greedy and sum-rate optimization precoders.	Needs large training dataset to provide robustness.	• A CNN that accepts an imperfect channel matrix and outputs analog precoder and combiners. • A exhaustive search algorithm for analog precoder to feed the CNN training. • A solution that is capable of training with large amounts of data.	[161]
	DL	Good results with lower computational complexity if compared to SVD and GMD-based methods.	The simulated communications environment is poorly described.	• A novel framework that incorporates DL into hybrid precoding. • A DNN with lower computational complexity requirements in the training phase. • DNN provided accurate hybrid precoding while supporting channel feedback.	[162]
	DL	The proposed solution can be generalized to unseen environments.	The training time was not discussed to assess the feasibility of the proposed solution.	• Joint DNN architectures for high generalization. • DNNs achieve outstanding performance in scenarios where downloading training dataset is very limited.	[163]
	Deep Learning Integrated Reinforcement Learning (DLIRL)	The hybrid beamforming method spectral efficiency that surpluses the fully digital precoding	As it is a new ML scheme, it lacks a complexity assessment to fairly compare it to the other algorithms	The authors propose a new way of combining DL and RL for beamforming leveraging high spectral efficiency and overall beamforming efectiveness	[174]
Dynamic subarrays	AHC	Proposed hybrid precoding, which can efficiently avoid mutually correlated metrics.	• The authors do not mention the simulation tools used. • The clustering algorithm misses information about the training phase.	• Optimal hybrid precoder on PCA. • Agglomerative Hierarchical Clustering to grouped dynamic subarrays. • Energy efficiency for passive and active antennas.	[165]
Two-stage precoding	DL	Proposed an ML-based approach to finding optimal dimensions with good accuracy and closer to the brute-force solution.	• The authors do not describe the dataset nor its size and format. • The training phase required too many iterations.	• A DNN algorithm to predict the dimension output in MIMO. • A customized DNN algorithm to cope with the requirements.	[166]
Hybrid, analog, and Digital Precoding	DL	• Generalizable for many systems with many parameters. • Numerical results suggest the performance of the proposed approach is closer to optimal.	Missing some ML algorithm details.	• Proposes a joint channel sensing and downlink precoding solution that avoids explicit channel estimation. • Introduces an end-to-end design that directly builds precoders from the received pilots without the intermediate channel estimation step.	[167]
BF-based on IRS	DL	• The combination of BF-based on IRS with BS enhances the system sum rate. • Uses a NN to achieve the optimal configuration. • Good generalization rate achieved by ML algorithm.	• The convergence time was not discussed. • Different DNN architectures could be evaluated.	• A combined BF based on BSs and IRS. • An optimization method for implicit channel estimation. • A DNN performance assessment for BF.	[169]

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Table 5. (Continued from previous page) Precoding and combining in MIMO with hybrid and digital architectures.

Challenges	**Algorithm**	**Highlight (pros.)**	**Limitations (cons.)**	**Key Contributions**	**Ref.**
Location-based	DL	A method capable of handling LoS and NLoS propagation.	• The solution does not predict the user location in BF. • The solution does not predict the channel vector directly.	• A supervised learning method to map user location to an appropriate precoder. • Reduces the need for pilot symbols.	[170]
Complexity reduction	DL	The proposed method has low computation complexity when compared with CNNs.	The computational complexity relies on the learning technology design (CNN or ELM).	• Novel, robust, and low-complexity Hybrid BF algorithms. • An optimization method based on fractional programming to provide labels for the training set.	[171]
	DL	Using PSO combined with DNN, the authors reduced computational cost in managing antenna arrays.	Does not present accuracy, which hinders the performance assessment.	• A novel DL with phase-only digital BF for MIMO. • A metaheuristic method based on DL was used to reduce the computational complexity.	[172]
	DRL	• Online adjustment of parameters to minimize BER. • Uses a bi-fold approach for finding optimal precoding policy and the codebook and non-codebook-based precoding.	• Does not compare with any other solution in the literature. • Does not discuss the convergence time of the proposed algorithm.	A hybrid ML approach for precoding policy for complex MIMO systems.	[152]
	DL	• Lower baseband precoding and combining training overhead. • Detailed experimental evaluation description supports reproducibility.	Leveraging prior knowledge with DL has an underlying training cost to collect information about the end-to-end channel and network training.	• A reduction of training overhead compared to classical (non-ML) solutions. • A novel DL-based approach to optimize channel measurement vectors.	[173]
Channel estimation and Power consumption	DL	• Can be implemented in a real-time system due to low computational complexity. • Works in FDD mode. • Short training time as it is unsupervised.	Might not be as precise as CSI-trained DL models.	• Evaluation of unsupervised learning to design the Hybrid BF. • Use of ray-tracing model in the deployment environment. • A loss function proposal that is based on sum-rate for classification and regression. • Evaluation of non-DL and DL hybrid BF for the realistic channel model.	[155]

(End table)

Table 6 summarizes works found in the literature dealing with the security of AI models. It presents the beamforming challenge involved, the algorithm employed to study how the attack and counterattack measures affect the DL models' performance, the benefits and limitations of the proposed solutions, and their key contributions.

Therefore, as can be concluded from this section, it is of utmost importance to study and develop secure AI solutions for 6G networks. This new attack surface poses enormous risks to users and telecommunications companies if not adequately covered.

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Table 6. Security of AI Models.

Challenges	Algorithm	Highlight (pros.)	Limitations (cons.)	Key Contributions	Ref.
Beam prediction under adversarial attacks	DL	The proposed counterattack can be used against a variety of different adversarial ML attacks.	To be effective, the attacker must have access to the gradient of the loss function for a given input instance, which in turn implies having access to the model's weights, which is often unfeasible.	Proposes a mitigation method that uses the gradients of the victim's model to retrain it with adversarial samples and their respective labels and mitigate adversarial attacks, consequently improving the security.	[183]
				Proposes two methods for counterattacking adversarial attacks: adversarial training and defensive distillation.	[184]
				• Studies how adversarial attacks confuse trained DL models used for mmWave beam prediction. • Proposes a method to mitigate adversarial attacks using iterative adversarial training.	[182]

10. Limitations of AI-based Beamforming and Beam Management

AI-based beamforming and beam management have some limitations that need to be considered. Some of these limitations are:

- Limited applicability: AI-based algorithms may work well in specific scenarios but may not be suitable for other scenarios. For example, algorithms designed for pedestrian mobility may not work well for high-speed mobility scenarios such as trains or urban vehicles.
- Reliance on training data: AI-based algorithms require large amounts of training data to learn the optimal beamforming and beam management strategies. If the training data is not representative of the actual operating environment, the performance of the algorithm may suffer.
- Limited generalizability: The performance of AI-based algorithms can be heavily influenced by the training data used to develop them. Therefore, the algorithms may not generalize well to new scenarios or environments where the training data does not adequately represent the target environment.
- Complexity: AI-based beamforming and beam management algorithms can be complex and require significant computational resources. This can increase the cost and power consumption of the system.
- Limited interpretability: AI-based algorithms often rely on complex deep learning models, which can be difficult to interpret. This can make it challenging to understand why certain decisions are being made or to identify errors or biases in the algorithm's output.
- Limited robustness: AI-based algorithms may be vulnerable to adversarial attacks or other forms of interference that can disrupt their performance. This can limit their reliability in real-world applications where security and robustness are critical factors.
- Limited scalability: As the number of antennas and users in a massive MIMO system increases, the complexity of AI-based beamforming and beam management algorithms can become prohibitively high. This can limit their scalability and make them less practical for large-scale deployment.

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Overall, while AI-based beamforming and beam management have shown promising results in certain scenarios, they are not a one-size-fits-all solution and must be carefully designed and evaluated for each specific use case.

11. Open Problems and Future Research Directions

This section discusses the challenges of AI-aided beamforming management solutions and highlights various promising research directions.

11.1. Centralized and Decentralized Learning

With the inception of Cloud-RANs (C-RANs), collaborative and centralized joint processing of information became possible [185]. This joint processing can improve the system capacity through the joint processing of the information gathered from several different nodes [186].

Furthermore, in the context of AI-aided beamforming management, C-RANs offers the possibility of enhancing the solutions to related problems by training AI algorithms with data coming from several different and localized radios, which can hugely improve latency, QoS, and spectral and energy efficiency [187,188].

Centralized learning seems a straightforward and logical approach since massive amounts and different types of information can be gathered and used to train the algorithms better. Besides that, centralized processing means that enough storage and computing power is available, which is a considerable advantage over the decentralized processing occurring at radios with insufficient storage and processing power.

However, most of the surveyed works don't consider centralized processing or training approaches, relying almost exclusively on non-collaborative distributed ones. For instance, centralized processing can be used to solve the codebook design and beam-selection problems so that a given user can be served by multiple beams from different radios, increasing the system capacity [189]. Additionally, considering centralized processing, codebooks can be optimized to minimize the total transmit power subject to several constraints, such as the users' required rates [190].

Therefore, studying and proposing centralized training or processing approaches that take advantage of the vast processing power, storage, and surplus of data is a promising research direction with several still open problems.

11.2. Reproducible Research

Reproducibility is the basis of the scientific method. Research is said to be reproducible when all related information, including text, data, and code, is made accessible such that interested researchers can reproduce the results. The reproducibility of published results and the use of commonly available datasets for benchmarking are essential for creating confidence and drawing precise conclusions [191].

However, even though the number of works on beamforming, including AI-aided ones, increases daily, most of those works employ simulated and private datasets, making it difficult to benchmark the proposed solutions. For example, in [192], the authors report that only around a third of the considered papers share the dataset.

The IEEE Communications Society has created a study group called Machine Learning for Communications-Emerging Technologies Initiative (MLC-ETI) to increase research reproducibility. The group is dedicated to promoting the utilization of ML in communications by providing the source code and datasets of several published works. Their main objective is to define a set of common communications problems and their corresponding source code and datasets with which researchers can benchmark their models consistently and plausibly.

Therefore, openly available and widely spread datasets for benchmarking are of utmost importance to advance not only AI-related studies but also the research of the whole scientific community. Furthermore, open-source initiatives are significant in accelerating the embracement of AI-based solutions.

11.3. Semi-supervised, Active, and Reinforcement Learning

Most works studied for this survey use supervised learning models trained with synthetic datasets, which might not represent real-world environments. Adopting supervised learning models in wireless communications is highly desirable since they present high performance. However, as in other research areas, labeled datasets are usually unavailable, cannot be accurately created, or are costly and time-consuming to be created.

In those cases where labeled samples are not available, unsupervised learning would be the intuitive choice. Additionally, as shown in [193], the performance of unsupervised learning models might be higher than that of supervised ones. If some labeled samples are available, semi-supervised learning becomes a promising solution, exploiting the advantages of supervised and unsupervised learning.

Another option is active learning, an exciting approach to solving the labeling problem. With active learning, only a tiny fraction of samples are manually labeled and used to train a classification model that will be used to label the remaining samples automatically. During this process, automatically labeled samples can be used to retrain the model and improve its classification accuracy. A few recent studies have started looking into and using this kind of learning [194].

Yet another option is using reinforcement learning algorithms, which do not need a training dataset and learn a mapping, called policy in this context, between a given state and the action that returns the highest reward based on trial and error attempts. With this learning approach, it is possible to have a beamforming system that selects the best beams based on the current state of the channel [195].

Therefore, future research works should focus on understanding and advancing the use of unsupervised, semi-supervised, active, and reinforcement learning models.

11.4. Prototypes and Real-World Demonstrations

The necessity for prototyping beamforming and other technologies is paramount to achieving the ideas envisioned for 5G and 6G systems. Additionally, prototyping is necessary to assess whether these systems' main performance demands on energy and spectral efficiencies are satisfied.

Prototyping is vital since computer-based simulations cannot wholly capture the complexness of the several unanswered problems, which might prevent AI-aided beamforming from becoming a commercially viable solution. For instance, to thoroughly understand the propagation aspects of the channel, researchers also have to understand the impairments caused by the hardware (e.g., RF circuitry imperfections, synchronization issues, etc.) [196]. All these impairments must be well understood and accounted for to ensure effective and seamless services to users.

The bulk of the works reviewed for this survey has shown a lack of real-world implementations and demonstrations. Instead, most works concentrate on simulation-based assessments of the proposed algorithms and models and neglect the discussion of their prototyping. Therefore, this gap highly suggests a vast potential for research on implementing proof of concepts that account for and propose solutions to the joint channel and hardware circuitry impairments.

11.5. Privacy and Security

User data privacy is one of the most, if not the most, essential worries of telecom providers. But, on the other hand, as the use of ML become widespread in business, telecom providers are finding that ML models can make the most of the enormous flow of data they have in their possession.

ML models take advantage of the vast and rich datasets created by combining user data. Therefore, one of the challenges met during the deployment of ML models is how to train such models without exposing user data to privacy risks. Therefore, it is essential to devise security schemes that allow these models to be trained with data from different users without jeopardizing user privacy. One possible solution to this challenge is the use of federated learning. In this approach, user data is not sent to a centralized entity (at the BS) responsible for training the ML model. Instead, what is sent is the gradient information data collected from the users, which is then used to update the ML model [197]. This way, federated learning could be employed to avoid having users send raw CSI back to the BS for training, which mitigates both privacy and security risks [198].

Another critical concern is the security of the ML models, mainly neural network-based ones, since they are subject to adversarial attacks [199]. In this kind of attack, the performance of ML models, and consequently that of networks employing such models, can be drastically impacted by the addition of fake data to the training dataset. Therefore, in [200,201], the authors employ autoencoders, a kind of neural network, to tackle network security problems since they have shown the ability to detect anomalies under several different circumstances.

Unfortunately, the study of how adversarial attacks can affect the performance of systems deploying ML-assisted beamforming is still in its infancy, requiring much more attention as it poses high risks to such systems. However, a few works are already available in the literature discussing such issues [181].

Therefore, there is considerable interest in studying and building privacy-preserving systems and ML models that are robust against adversarial attacks.

11.6. Computer Vision

Computer vision is a subarea of AI dealing with how machines acquire high-level understanding from data from optical sensors like visible-light and LiDAR cameras. Its objective is to understand and reproduce the tasks the human visual system can carry out through computers [202].

Due to their high directivity and high penetration loss, mmWave and THz communications are mainly carried out through LoS links. Moreover, they are highly susceptible to blockages, requiring systems employing such bands to resort to beamforming techniques. Nonetheless, selecting the optimal beams in mmWave and THz links often requires significant beam training overhead, occupying necessary radio resources and decreasing spectral efficiency. This challenge motivates the design of novel solutions to select the best beams with low training overhead [203].

The reliance on LoS links and the employment of narrow beams at such frequencies renders the information on the physical location of the devices and the geometry of the surrounding environment particularly important. That prompts the use of sensors, such as visible-light and LiDAR ones, that can provide information on the position of the devices and a 3D representation of the surroundings so that the communication terminals can allocate the best beams or even predict blockages and take preemptive handover actions. Unlike traditional CSI-based methods, optical sensor-aided beamforming methods do not require CSI measurements, and they can also simultaneously decide the best beams for both transmitter and receiving devices. In addition, the accuracy of those methods can be improved by adding GPS information or fusing it with optical and CSI data [204].

Optical sensor-aided beamforming is a new and hot research topic attracting attention recently. It has several open problems ranging from handover prediction, passing by beam, and base station selection to received power prediction. The alliance between computer vision and ML algorithms can make the most out of those optical-based data and find models that mitigate or even solve all the problems mentioned earlier. To show the potential of employing optical information, the authors of [205] use LiDAR data to train a CNN-based model to predict blockages and preemptively initiate handover procedures.

Therefore, the initial results on this subject indicate that using computer vision, ML algorithms, and optical data can bring huge gains to beamforming communications in mmWave and THz frequencies.

11.7. Beamforming at low SNR regimes and joint optimization

As can be concluded from this survey, beam selection, beam tracking, and blockage prediction are the most challenging tasks in beamforming. These tasks get more complicated when beamforming

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systems operate in low SNR scenarios. For instance, classical eigen-subspace decomposition and projection methods suffer from severe performance degradation at low SNR levels [206]. Further, the high accuracy of MUSIC-based methods is only achieved when many samples are available, and the systems operate at high SNR levels. On the other hand, some very initial works show that ML-based solutions can outperform classical beamforming methods in low SNR scenarios with a limited number of channel information samples [207]. On the other hand, computer vision and ML algorithms fed with sensor and GPS data seem better contenders to tackle this problem. Therefore, the study and design of high-accuracy methods for beam selection and tracking in low SNR scenarios with limited samples remain an open issue.

Two quite exciting and still largely open issues beamforming systems face are the joint optimization of parameters like beams, transmission power, interference, etc., to maximize spectral and energy efficiency and joint beam selection and blockage prediction tasks. Solutions to these issues are highly desirable features for mmWave and THz systems. However, the extensive body of literature investigated for this survey lacks detailed studies tackling them. For example, in [208], the authors propose an online learning approach to optimize beam training, selection, and handover procedures. However, they do not study the effects high mobility has on the system's performance. Our research shows that today's models do not achieve high accuracy for such joint problems and, therefore, there still is room for advancement.

11.8. Channel Estimation

Channel estimation in mmWave and THz systems employing beamforming and beam management technologies is challenging due to several factors, such as the complexity of the channel (estimation of a large number of channel coefficients accurately), limited coherence time (short coherence time makes accurate channel estimation difficult), susceptibility to impairments (signal propagation at these frequencies is more susceptible to attenuation, scattering, and path loss), sparsity of the multipath components (signals at these frequencies are directional and sparse with few dominant paths, requiring systems to capture and model these paths), hardware constraints (limited hardware resources make channel estimation more challenging since it needs to be done efficiently and with low complexity), and beam misalignment (misalignment might occur due to changes in the user location or mobility, which can degrade the beamforming performance) [209–211]. Addressing these challenges requires developing advanced channel estimation techniques that can accurately estimate the channel parameters while also being computationally efficient and scalable.

Some open problems in this topic include:

- Developing robust and efficient channel estimation algorithms that can handle the sparsity of the channel and limited coherence time.
- Investigating new channel estimation techniques that can take advantage of the hardware constraints and limitations of mmWave and THz systems, such as low-resolution analog-to-digital converters (ADCs) and limited feedback bandwidth.
- Addressing the challenges of beam misalignment and developing adaptive channel estimation algorithms that can adjust to changes in the user location or mobility.
- Investigating the use of machine learning techniques for channel estimation in mmWave and THz systems, such as deep learning and reinforcement learning, which can potentially improve the accuracy and efficiency of channel estimation.
- Multipath interference: In mmWave and THz systems, the multipath components can arrive at the receiver with different delays and phases, leading to interference and reduced signal quality. Channel estimation algorithms need to be designed to handle the interference and accurately estimate the channel coefficients.
- Environmental effects: The mmWave and THz signals are highly sensitive to environmental factors such as atmospheric absorption, scattering, and reflection. These effects can cause

significant variations in the channel characteristics, making it challenging to estimate the channel accurately.
- Scalability: The use of a large number of antenna elements in mmWave and THz systems can lead to scalability issues in channel estimation. Efficient channel estimation algorithms that can handle a large number of antennas are needed to enable the practical deployment of such systems.
- Hybrid beamforming: In practical mmWave and THz systems, hybrid beamforming techniques are often used, which combine digital and analog beamforming. Channel estimation algorithms need to be designed to handle the complexity of such hybrid beamforming architectures.

Artificial intelligence can be used to address these challenges. This includes developing efficient algorithms that can handle the sparsity of the channel, multipath interference, and environmental effects. Machine learning techniques like deep learning and reinforcement learning can be used to improve the accuracy and scalability of channel estimation, especially in systems with hardware constraints and hybrid beamforming.

12. Conclusions

The paper presented a thorough overview of beamforming and beam management methods in the context of 5G and 6G systems. AI-aided beamforming and beam management are one of the most active research topics at the interface between communications and AI. Significant advances have been achieved in this topic in recent years. However, there are still many issues to be overcome until the technology is mature enough to be incorporated into communication standards. This article discussed not only the problems but also promising directions, such as increasing security and privacy, and using larger, publicly available datasets, to better evaluate new algorithms.

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