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Beam alignment for mmWave and THz: systematic review

Sundire Madhekwana^{1,2} · Muhammad Arslan Usman¹ · Ahtisham Ayyub¹ · Christos Politis¹

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Abstract

This compact study investigates published research on beam management frameworks for large antenna arrays in mmWave and terahertz (THz) systems. The systematic literature review (SLR) focused on beam alignment and initial access frameworks for mmWave and THz. The investigation uncovered 596 relevant articles, including journals and conference papers from different sources using defined criteria, leading to 73 final studies post-filtering, following our SLR-defined 3-stage screening process. We explained the taxonomy of mmWave and THz beam alignment frameworks by classifying them into beam sweeping-based, context information-based, compressive sensing-based, and Machine Learning/Artificial Intelligence (ML/AI)-based frameworks, as well as Integrated Sensing and Communication (ISAC)-based frameworks, which combine ISAC with other frameworks. In addition, we presented research gaps by identifying and analyzing the limitations of the current frameworks. Lastly, challenges and possible opportunities for future research were highlighted.

Keywords Beam alignment · MmWave · THz · Compressive sensing · Beam sweeping · ML/AI · Context information · Beam management

1 Introduction

1.1 Background

The next-generation wireless network technology, 6G, has the potential to revolutionize the data user experience [1] as we know it from current technologies like 4G and 5G. The vast bandwidth availability in the mmWave and THz regions [2] paves the way for new applications that were previously unthinkable, such as holographic communication and applications in the metaverse domain. However, the main drawbacks and challenges are due to its small coverage range. The mmWave and THz signals suffer high path

losses. To address these challenges, beamforming technologies with large antenna arrays or multi-antenna systems are utilized to extend the coverage and enhance data throughput [3]. Multi-antenna systems, also known as Multiple-Input Multiple-Output (MIMO) systems [4], utilize multiple antennas at both the transmitter and receiver to significantly enhance communication performance. This technology is particularly crucial for beam alignment in Terahertz (THz) communications. The short wavelengths in the THz band enable a high number of antennas in a small space, resulting in narrow beams that pose challenges in maintaining a stable connection between the transmitter and receiver. By employing multiple antennas, MIMO systems can generate highly directional beams that can be precisely steered towards the intended receiver. This beamforming capability facilitates efficient signal transmission and reception, effectively overcoming the limitations of narrow beams and ensuring reliable communication within the THz spectrum. However, the use of multi-antenna systems at these frequencies makes the beams highly directional, so the beams need to be aligned before any link can be established. The beam alignment process establishes and maintains a communication link between a transmitter and a receiver by aligning the transmitter and receiver beams. This process becomes particularly crucial in the mmWave (30 GHz -300 GHz)

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[5] and THz (0.1-10THz) [6] spectrum range because of the characteristics of these frequencies, including high path loss, vulnerability to blockages, and susceptibility to atmospheric conditions [7]. In lower-frequency wireless systems, omnidirectional antennas or simple sectorized antennas have been used, as the wider beam patterns can accommodate mobility and provide coverage over a larger area. However, using narrow beamforming antennas in mmWave and THz systems enables highly directional transmission, which offers several advantages, including increased spatial reuse, improved capacity, and reduced interference. Beam alignment plays a fundamental role in achieving the benefits of directional transmission in wireless communication systems. It involves two main processes: beam training and beam tracking.

- Beam training** - This is the first step in beam alignment, where the transmitter and receiver explore different beam directions to find the best beam pair with the highest received signal strength [8]. The transmitter typically sends a series of training signals with different beam directions, using a codebook or defined protocol, and the receiver measures the signal strength for each beam direction [9, 10] and selects the best one. Through feedback or explicit signalling, the transmitter adjusts its beam direction to align with the receiver's beam direction, which yields the strongest received signal. Codebook and protocol design in THz systems is essential to achieve robust beam training and overcome challenges such as beam squint, where beams optimized for the centre frequency LoS gain at other frequencies, causing misalignment and performance degradation. [11] introduced a specialized wideband codebook that ensures each beam maintains sufficient gain across the entire bandwidth, enabling low-complexity beam training that avoids full channel estimation and complex real-time optimization. By maximizing the worst-case wideband beam gain and tailoring spatial zones, this design delivers consistent signal quality even at coverage edges while simplifying beam alignment and reducing training overhead. Furthermore, THz massive MIMO systems require precise beam alignment to combat high-frequency challenges and severe path losses, yet traditional narrow beams are impractical under dominant LoS conditions and weak pilot signals. [12] introduces algorithms that generate wide-beam codewords with broad angular coverage, flat main lobes, and suppressed side lobes, enabling efficient beam training without full CSI and reducing real-time.
- Beam tracking** - [2, 13]: This is performed to continuously update the beam directions as environmental conditions change beyond the initial alignment. This is particularly important in mobile scenarios or environments with moving obstacles. Many different methods can be used for beam tracking. [14] and [15] give such

examples of methods that can be employed for Beam training and beam tracking. [14] introduces a unified 3D beam training and tracking procedure for THz communications that bypasses the need for real-time CSI. The authors used a hierarchical 3D codebook with wide beams for broad coverage and narrow beams for high gain, enabling a grid-based training protocol that efficiently identifies the optimal beam pair with far fewer tests than an exhaustive search. Once the beam pair is set, a grid-based hybrid tracking protocol employing two dynamic modes to refine and predict the beam. Whereas [15] introduced an exhaustive method to estimate angles for both direct LoS and Intelligent Reflecting Surface (IRS)-reflected links, due to the high complexity in THz massive MIMO systems, it proposes a low-complexity cooperative beam training scheme. This approach combines a partial search at the IRS-scanning key angle differences in the sine space—with a ternary-tree hierarchical search at the BS and user using two specialized codebooks to efficiently narrow down the best narrow-beam pair. Once training establishes an optimal beam pair, beam tracking continuously updates the pair based on received signal quality, ensuring sustained high beamforming gain in dynamic. Beam tracking helps maintain the alignment of the communication link, compensating for beam misalignment due to factors such as user mobility, blockages, or antenna misalignment.

Beam alignment techniques can vary depending on system requirements, channel conditions, and available resources. Various frameworks and methods have been proposed to achieve efficient and accurate beam alignment [16]. Some of these frameworks include codebook-based techniques, compressed sensing-based approaches, machine learning-based methods, hybrid beamforming, channel estimation-based techniques, pilot-based beam alignment, and adaptive beam alignment. However, none of these frameworks have been standardized, implemented in real-world systems, or proven adequate for large-scale antenna arrays. The performance evaluation of beam alignment techniques involves several metrics, such as signal-to-noise ratio (SNR), bit error rate (BER), throughput, beam misalignment angle, beam training overhead, energy efficiency, and latency. Comparative analysis of different beam alignment techniques helps assess their strengths, limitations, and trade-offs across various scenarios and deployment contexts [10].

Challenges in beam alignment arise from the characteristics of mmWave and THz frequencies, including multi-path propagation, interference, hardware constraints, mobility, and environmental factors [2, 10]. While mmWave and THz channels share several similar characteristics, the effects of path loss, atmospheric absorption, and scattering are significantly more pronounced in THz frequencies [17].

Consequently, THz communication systems require more sensitive, rapid, and complex alignment techniques than mmWave due to the narrow beams and extreme signal attenuation.

These challenges necessitate research and development efforts to overcome obstacles and improve the robustness and efficiency of beam alignment techniques. As wireless communication systems continue to evolve, integrating beam alignment frameworks with advanced networking technologies, such as 5G/6G and the Internet of Things (IoT), becomes essential. Cross-layer optimization, security considerations, machine learning advancements, and standardization efforts further contribute to the continuous improvement of beam alignment in wireless communication systems. Overall, beam alignment plays a critical role in enabling reliable and efficient communication in high-frequency wireless systems. Ongoing research and advancements in this field aim to address challenges, optimize performance, and facilitate deployment. Our motivation for this compact review of existing beam alignment frameworks is to explore unexploited opportunities and potential challenges. The systematic review aims to contribute to:

- The knowledge of the design of alignment frameworks.
- Improvement of beam alignment frameworks.

The study intends to answer the following research questions (RQs), as shown in Table 1.

1.2 Principal contributions and organization

We analyzed various existing beam management research works that cover beam alignment frameworks with a strong focus on large antenna arrays, mmWave, and THz systems. We investigated the studies in terms of their contribution to the areas depicted in the figure 1: The purpose of this study is to:

- Develop a taxonomy of beam alignment frameworks and categorize existing beam alignment frameworks.
- Compare them and identify their limitations.
- Examine their prospects for standardization
- Evaluate their suitability in meeting the challenges faced in beam alignment and the areas depicted in the figure 1. The conducted research examined the existing beam alignment frameworks in recognized journals and conferences.

The developed taxonomy categorizes the beam alignment solutions and describes each framework to give an overview of existing difficulties and the latest existing techniques. All the selected frameworks have been evaluated in terms of beamforming architecture, beam alignment frameworks,

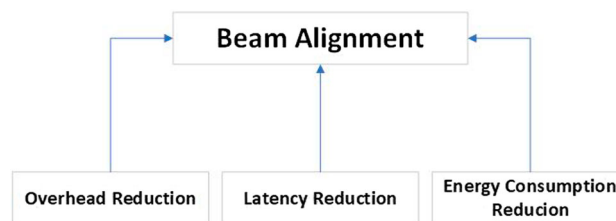


Fig. 1 Focus of research area Contributions

Environment, mobility, number of beams, performance metrics, key findings, etc. Additionally, the limitations of the frameworks were identified as well as the existing research gaps.

Section 2 gives an overview of the previous works. Section 3 categorizes the results of existing solutions and techniques that help solve beam alignment challenges into five different classes. Section 4 discusses the latest research on beam alignment frameworks in detail. In this section, we review the research works within the defined frameworks, providing existing solutions and evaluating the identified research problems. Section 5 offers a qualitative comparison and outlines the limitations of the framework types. Section 6 presents future directions and opportunities. Finally, we conclude in Section 7.

1.3 Findings overview

In this section, we provide an overview of the findings of the investigation. According to [19–21], beam alignment frameworks can be implemented in various ways: exhaustive searching, out-of-band information exchange via sensors mounted on the transmitter and receiver nodes, compressive sensing, machine learning, and Integrated Sensing and Communication (ISAC)-based beam alignment. These approaches can be used in numerous ways to develop beam alignment (BA) frameworks that address specific problematic scenarios. Table 2 categorizes the BA frameworks identified based on their implementation features. To facilitate this classification, researchers decided to create the following categories:

- Beam sweeping
- Context Information
- Compressive Sensing
- ML/AI
- ISAC beam alignment

For this study, beam sweeping, context information, compressive sensing, ML/AI, and ISAC beam alignment were considered. We considered the beam sweeping technique as any method that uses either exhaustive beam searching, adaptive sweeping method, or hierarchical beam sweeping

Table 1 Research Questions

Question	Motivation
<i>RQ1: Which beam selection or alignment frameworks exist for mmWave and THz?</i>	The next-generation wireless network systems will use the vast bandwidth available in mmWave and THz regions with highly directional beams to compensate for the high path losses suffered by such signals. However, the Transmitter and receiver's directional beams must be aligned [18]. The beam sweeping framework [16] was standardized for beam alignment in 5G NR with the assumption of a maximum of 64 beams. However, next-generation wireless system beyond 5G is anticipated to use very large antenna arrays with up to 1024 antenna elements and very directional beams. The beam-sweeping framework will not be adequate due to the high beam alignment latency, high energy consumption and high overhead that grows with an increasing number of beams. Although there is a substantial body of literature on this topic, further research is needed. This question is crucial for establishing existing frameworks and the challenges they have addressed, determining the status quo, identifying knowledge gaps, and exploring potential standardization solutions.
<i>RQ2: How do these Frameworks compare to each other?</i>	This question aims to compare the different frameworks to identify common issues that have been addressed and to highlight differences. Additionally, gaps are identified by showing the issues that have not been addressed by any of the established frameworks.
<i>RQ3: What are the challenges and limitations of these frameworks?</i>	Challenges in beam alignment arise from the characteristics of mmWave and THz frequencies, including multi-path propagation, interference, hardware constraints, mobility, and environmental factors. These challenges necessitate research and development efforts to overcome obstacles and improve the robustness and efficiency of beam alignment techniques. Although many of the challenges have been addressed by different approaches, some of these will spill over to 6G [10]. Specifically, the challenges and limitations that are not addressed by existing frameworks need to be identified through these questions.
<i>RQ4: What are the future directions and research opportunities?</i>	After establishing the existing solutions and their limitations, the future directions and research opportunities will be apparent, thereby answering this question.

technique. Any technique that uses in-band or out-of-band signalling of position, direction, or other information to the transmitter or receiver was considered a context information technique. Compressive sensing techniques are those that exploit sparsity characteristics of the mmWave or THz channel. Approaches that use any of the machine learning techniques were classified as ML/AI. Approaches that combine any of the primary frameworks with Integrated Sensing and Communication (ISAC) were classified as ISAC-based beam alignment or hybrid.

The summary of research distribution per category is depicted and summarized in figure 2. Table 2 shows the studies that fall into each category and the distribution of the selected articles according to the framework categorization. Machine learning has the highest number of samples found.

Figures 2 and 3 illustrate the distribution of publications by framework and year of publication, respectively. An initial classification was conducted to highlight key clusters within emerging beam alignment techniques. These

Table 2 Beam Alignment Classification

Classification	References	No. of Refs
Compressive Sensing	[22–31]	10
Beam Sweeping	[10, 32–40]	10
Context Information	[41–55]	16
Machine Learning	[56–82]	26
ISAC Beam Alignment	[83–93]	11

categories address various challenges by leveraging and capturing the unique characteristics of mmWave and THz signals. Notably, the data shows a significant increase in research activity from 2022 onward. It is also important to emphasize that frameworks involving Machine Learning (ML) and ISAC have become dominant in recent research, indicating their growing importance in this field.

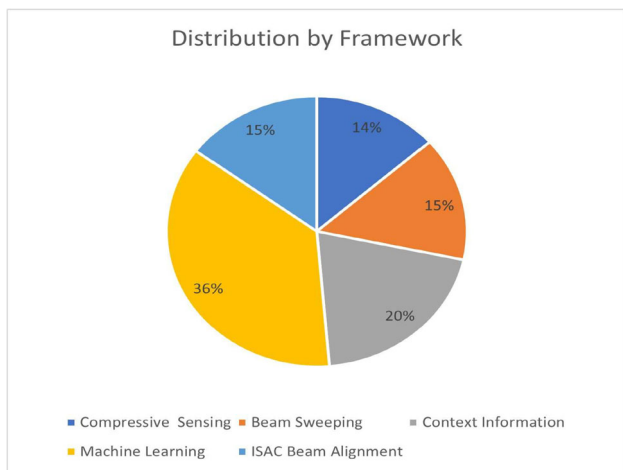


Fig. 2 Distribution of Articles by Framework

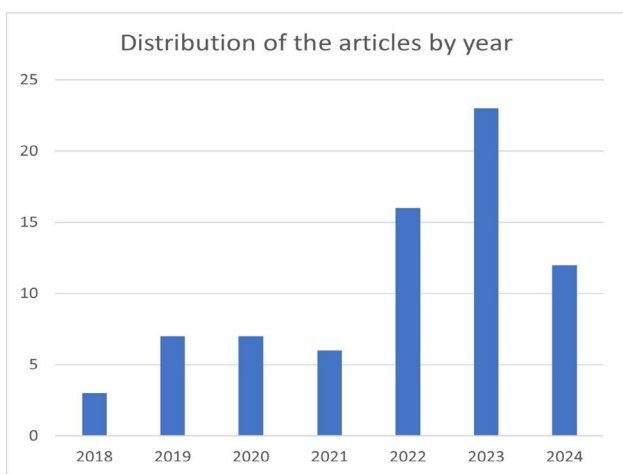


Fig. 3 Distribution of Articles by year

2 Related works

There is a vast body of recent literature related to our work that has investigated beam management and alignment for mmWave and THz bands. These studies include [17, 94–100], and are described as follows:

[17] and [94] highlighted major challenges in beam management for mmWave, discussing the trends and issues behind these challenges. Some of the identified challenges include inefficient beam sweeping, multi-panel optimization, high mobility, and DL/UL beam correspondence failures. The authors proposed potential solutions such as compressive sensing, machine learning (ML), reinforcement learning (RL), multi-base station cooperation, and robust codebook design. However, their work primarily focused on challenges related to standardized 5G NR beam management based on beam sweeping, and technical implementation was not thoroughly addressed. [95] Wang et al. provided a comprehensive overview of mmWave technologies in sce-

narios such as 5G networks, fixed wireless access (FWA), vehicle-to-everything (V2X), and indoor networks. The work highlighted challenges encountered in these scenarios, including high path loss, blockage, atmospheric absorption, and hardware limitations. Although the paper offered a broad overview of mmWave, it did not cover the THz bands or aspects like scalability, energy efficiency, and interoperability, and it lacked detailed technical depth in beam management. [96] Yi et al. presented an in-depth overview of beam training and tracking algorithms for mmWave in scenarios such as 5G networks, FWA, V2X, and indoor and urban environments. The study highlighted challenges such as high path loss, blockage, mobility, and real-time tracking and discussed how blind beam training, prior information-aided beam training, and ML-based mechanisms can reduce training overhead. The authors focused mainly on mmWave, with less emphasis on broader 5G/6G contexts, such as THz bands. However, aspects like low latency, beam management, scalability, and energy efficiency were not fully addressed. [97] Khan et al. provided extensive coverage of ML techniques specific to beam management for both mmWave and THz bands.

The study explored how to address challenges like data availability, computational complexity and model generalization using supervised learning, reinforcement learning, and federated learning. Scenarios such as autonomous vehicles, smart cities, UAVs, and indoor networks were also considered. Despite the thorough exploration of ML applications in beam management, non-ML approaches were not covered. [98] Xue et al. focused on ML-based beam management for both mmWave and THz bands, examining current achievements with an emphasis on artificial intelligence (AI), integrated sensing and communication (ISAC), and reconfigurable intelligent surfaces (RIS). They also highlighted the use of multi-agent collaboration techniques like federated learning and transfer learning. Despite the extensive analysis of ML-based beam management, the paper did not provide a broader analysis of beam management, as it neglected advancements in non-ML-based approaches.

[99] Häger et al. focused on design aspects that optimize beam training for mobile users in 6G mmWave networks. The authors examined the impact of mobility both during and after beam training, proposing a trade-off approach in the design of beam training systems. This approach balances the quality of the communication link, the delay introduced by the beam training process, and the coverage area. The design should incorporate a quality-of-service (QoS)-aware beam search algorithm that dynamically adjusts the beam training process according to the required link quality. Such algorithms enable a balance between speed and robustness, which is particularly crucial for mobile users who need quick yet reliable link establishment. However, the study primarily concentrated on design aspects, with less emphasis on

broad theoretical frameworks or scenarios involving non-mobile users. [100] presented a new approach to reducing multi-user interference in IRS-assisted massive MIMO systems. It uses a space-orthogonal scheme that decouples the precoder and decoder design. One part cancels interference using zero-forcing techniques. The other part maximizes the rate using singular value decomposition (SVD) and power allocation. To lower the complexity of joint beamforming, the paper introduces two IRS phase-shift design methods: water-filling segment matching (WSM) and phase iterative evolution (PIE). These methods balance performance with computational efficiency. The scheme achieves near-optimal sum-rate performance with much lower complexity than an exhaustive search. The paper's strengths include breaking down a complex problem into simpler subproblems and using IRS-partial zero-forcing to improve spatial multiplexing gains. However, it relies on accurate channel models and dominant LoS assumptions, which may limit its use in scattering environments. Scalability remains a concern for very large systems.

While existing research has made significant contributions in specific areas for instance, ML, we believe there is a gap in providing comprehensive coverage of beam alignment and management strategies. Our work aims to fill this gap by offering a broader analysis of advancements in beam management, exploring both ML/AI-driven techniques and traditional approaches. This wider scope allows us to address various methodologies and innovations, highlighting progress in all possible directions.

3 Beam alignment frameworks and taxonomy

The selected articles were classified by constructing metadata forms to organize the details and include our defined remarks for those articles. We collected only the metadata that addressed our research questions, which included the title, research objectives, methodology, beamforming architecture, beam alignment frameworks environment, mobility, number of beams, performance metrics, etc. Figure 2 shows the distribution of the publications according to frameworks. An initial classification was made concerning our research topic to demonstrate outstanding clusters of the emerging beam alignment techniques categories solving different challenges by utilizing and capturing characteristics and aspects of the mmWave and THz signals. AI/ML dominates the ranks.

3.1 Beam sweeping

We classified the published literature on beam sweeping into exhaustive beam sweeping and hierarchical beam sweeping.

3.1.1 Exhaustive beam alignment

In an exhaustive beam-sweeping framework, both the transmitter and receiver scan through all the beams to identify the beam with the maximum power and most suitable for communication [10]. The exhaustive beam sweeping was standardized by the 3GPP for 5G NR in Release 15 [10, 94]. The beam alignment overhead and delay increase with the number of beams when mmWave and THz are in operation. These challenges trigger the need for improvement in this framework.

3.1.2 Hierarchical and adaptive beam sweeping

The research in this area investigates how the standardized beam-sweeping approach can be improved in terms of overhead, delay, and energy efficiency. The hierarchical framework's beam sweeping is done adaptively. At first, wider beams are swept through, and a beam with higher power is then subsequently swept with narrower beams to determine the optimal beam accurately [34]. However, hierarchical beam sweeping is a common form of adaptive beam sweeping, allowing the system to progressively focus from wide to narrow beams. The implementation of beam sweeping can be codebook-based or hardware-based, e.g., where some antennas are switched off to produce large beams, and then all antennas are used for narrow beams. The main drawbacks of the framework are the inaccuracy caused by the wider beams that may not detect mobile stations at the cell edges [101] and the dependence on DL/UL beam correspondence, which introduces inflexibility and blockage [10].

3.2 Context information

As highlighted in beam sweeping-based BA, the overhead and delay grow with the number of beams used by the transmitter and receiver. Although the hierarchical approach reduces overhead and delay metrics, it is susceptible to errors and may not be suitable for applications like ultra-reliable low-latency communication (URLLC). The context information approach intends to reduce these metrics further by using out-of-band information that is communicated to both the receiver and the transmitter [41] to inform each other of their bearings and where to search for the beams from each other. The context information framework research can be further classified by the context information used to implement the framework, as shown in figure 4 and the subsections below:

3.2.1 Location-aware beam alignment

The location-aware frameworks exploit the position information of the base station and mobile station [41]. The base

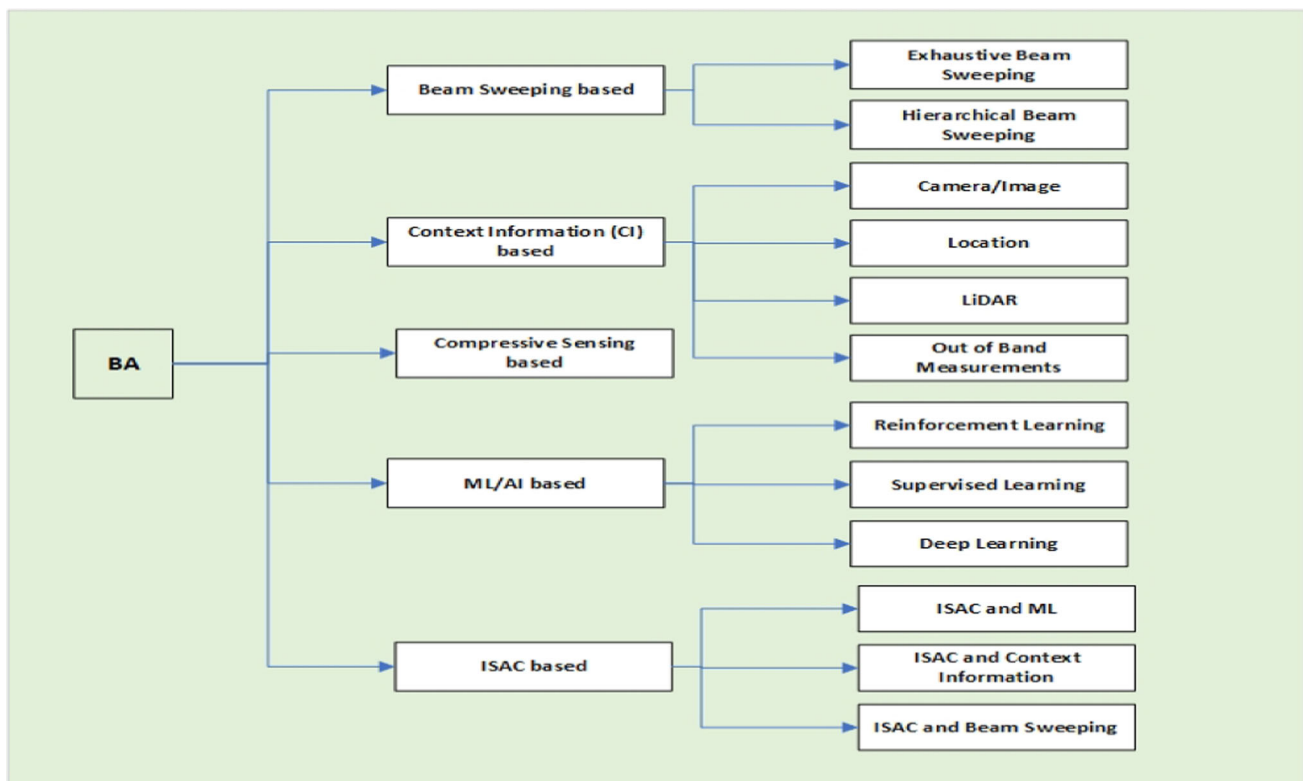


Fig. 4 Beam Alignment Taxonomy

station or mobile station derives the location information from GPS devices that are integrated into those entities. Once these entities obtain their positions, they beacon them towards the transmitter or receiver so that they know which area to search for suitable beams.

3.2.2 Camera-based alignment

The camera-based framework uses the camera as a sensor for images of objects in the environment of the transmitter or receiver to determine the object sending the signal and its direction [19].

3.2.3 Light detection and ranging

Light detection and ranging (LiDAR) technology is used to acquire the contextual information of the transmitter and receiver [19, 102]. The information is used to determine the direction of the beam.

3.2.4 Out-of-band measurements

Out-of-band measurements is any type of signal that can be sent to the transmitter or receiver to predict the direction of the source of the signal [20, 101].

Theoretically, a context information-based approach for beam alignment has a high potential to reduce latency, overhead, and energy consumption. However, the main shortcoming of such a framework is that the extra equipment needed for the in-band or out-of-band communication makes the equipment (base station and mobile station) more expensive. Hence, the industry may be reluctant to implement such an approach.

3.3 Compressive sensing (CS)

CS is a technique for signal processing that makes it possible to reconstruct images or signals from a comparatively small number of samples or measurements [103, 104]. CS relies on the sparsity principle and optimization algorithms for signal recovery. Sparse signals have a small number of non-zero components, while a significant number of the components are zeros or very close to zero. It is often quantified using the L1-norm of the signal, which is the sum of the absolute values of its components. Compressive sensing has applications in various fields, including image processing, medical imaging, and data compression. The equation below formalizes compressive sensing mathematically:

$$y = \Phi x = \Phi \Psi a = \Theta a \text{ (see [105] for details)}$$

Where y is the low dimensional measurements, Φ = random measurable matrix, Ψ = transform basis, a =sparse coefficients

The reconstruction of the signal problem will be solved as an optimization problem of the form:

$$\min \|a\|_{l_1}, \quad (1)$$

such that:

$$y = \Theta a \quad (\text{see [105] for details})$$

Compressive sensing reduces the training overhead for beam alignment by leveraging the spatial clustering of multipaths in the channel [20]. The best beam is selected by probing and measuring a small set of randomly selected beams from the whole codebook.

Although the compressive sensing technique may reduce overhead and energy consumption by probing fewer beams, it is complex due to the need for precise modelling and reconstruction algorithms and may face standardization and interoperability challenges.

3.4 Machine learning (ML) and artificial intelligence (AI) (ML/AI)

ML and AI are used to enhance initial beam alignment in wireless communication systems [106]. ML models are trained to estimate and predict wireless channel characteristics, such as signal strength, multipath propagation, and interference. These channel characteristics are critical for achieving optimal beam alignment. ML models learn from historical data, adapting to environmental factors like changes in surroundings, interference, or obstacles during wireless communication. ML/AI systems dynamically adjust beam parameters based on changing conditions, optimizing the initial alignment. Furthermore, weights and phase parameters can be adjusted for faster beam alignment. [107] presented the status quo, opportunities, and challenges for deep learning, including Convolutional Neural Networks (CNNs). Reinforcement learning trains systems to make decisions about initial beam alignment, learning optimal strategies through trial and error. ML and AI enable wireless communication systems to achieve faster, more accurate initial beam alignment, ensuring adaptability to diverse environmental conditions and enhancing overall reliability and performance. The machine learning and artificial intelligence (ML/AI) research work for beam alignment is further classified according to the machine learning model types, namely supervised, reinforcement, and deep learning, as depicted in figure 4.

3.4.1 Reinforcement Learning

According to [108], Reinforcement learning is a method within AI systems where the system learns from its experiences to improve its decision-making. This approach empha-

sizes learning through trial and error, marking a significant shift in the capabilities of artificial intelligence systems.

3.4.2 Supervised learning

Supervised learning involves using previously collected data, along with labeled information, to predict outcomes and through a training process, machine learning algorithms develop a function to anticipate output values. This system can then generate predictions for new input data after sufficient training, as defined by the authors of [109]. By comparing predicted outcomes with actual results, errors are identified and used to refine the model. In contrast, unsupervised learning is used when data lacks labels or classifications, aiming to uncover underlying patterns without predefined outputs by analyzing and deriving functions from unlabeled data, thus discovering hidden patterns through observation and analysis [109].

3.4.3 Deep learning

Deep learning uses computational models consisting of numerous layers to understand data by forming representations with various levels of complexity using neural networks [110].

The main drawback of the ML/AI approach is its high complexity due to the loads of data needed for training the models and the need for ongoing model improvements as the very expensive hardware necessary for running inference engines.

3.5 ISAC beam alignment frameworks

Integrated Sensing and Communication (ISAC) integrates wireless communication and sensing in one system. Its goal is to enhance efficiency by sharing spectrum, hardware, and signals between the two tasks. ISAC is particularly valuable in advanced networks like 5G and 6G beam alignment frameworks, where high data rates and real-time environmental awareness are crucial. ISAC can be combined with different other beam alignment frameworks to form subcategories. The three key subcategories of ISAC are ISAC and Machine Learning (ML), ISAC and Beam Sweeping, and ISAC and Context Information.

3.5.1 ISAC and machine learning

Machine Learning (ML) enhances ISAC by using data models to improve sensing and communication. For example, [31] integrates ISAC with computer vision and extended Kalman filters (EKF). Resulting in improved initial access (IA) and beam tracking in UAV networks The dual identity association (DIA) approach further enhances beam-tracking

accuracy and reduces delays. Similarly, [70], a deep learning method, reduces beam-training overhead in millimeter-wave (mmWave) systems. It uses partial codebook sweeping and neural networks to predict beamforming weights. This reduces overhead and increases achievable rates.

3.5.2 ISAC and beam sweeping

Beam sweeping plays a crucial role in ISAC systems operating in dynamic environments. Zhiqiang Xiao et al. [83] introduced a double-beam codebook specifically designed for millimeter-wave ISAC systems. This approach creates separate beams for sensing and communication, thereby enhancing performance while reducing overhead. Both single and double-beam methods facilitate simultaneous target sensing and communication with user equipment (UE). In [84], a Simultaneous Beam Training and Target Sensing (SBTTS) scheme uses reconfigurable intelligent surfaces (RIS). This method effectively reduces training overhead by distinguishing RIS from other targets.

3.5.3 ISAC and beam sweeping

Context information enhances ISAC optimize performance by using environmental data. For instance, [88] presents an ISAC-assisted approach specifically for Terahertz (THz) networks. Real-time environment perception, user tracking, and blockage prediction are used to manage narrow beams. This reduces beam misalignment and significantly increases coverage. Another approach, detailed in [87], introduces the Sense-Then-Train (STT) beam training scheme for near-field MIMO systems. It uses active sensing without codebooks and relies on neural networks for real-time alignment. While STT speeds up beam training, it faces challenges in dynamic settings due to high computational demands.

ISAC systems present a promising solution for future networks, combining communication and sensing. They offer benefits like better efficiency and performance. However, challenges such as computational complexity, infrastructure requirements, and real-time processing must be addressed. As research progresses, ISAC will likely play a major role in shaping 6G and other advanced networks.

4 Research discussions

4.1 Beam sweeping frameworks

Beam sweeping is used in wireless communication systems, particularly in beamforming and alignment within millimetre-wave (mmWave) and terahertz (THz) communication. This approach is necessary due to the narrow beamwidth and sensitivity to obstacles characteristic of high-

frequency bands. The process begins with an initial beam alignment, either derived from prior knowledge or a default configuration and then systematically scans transmit and receive beams over a range of directions. The transmitter sends a transmission for each direction, and the receiver evaluates the signal quality, providing feedback to the transmitter. This feedback informs the transmitter's adjustment of beam direction to optimize the communication link, considering factors such as signal strength or interference. The iterative process continues until an optimal alignment is achieved, with potential adaptations during communication sessions to address environmental changes. In dynamic environments, beam sweeping may be complemented with beam tracking, ensuring continuous monitoring and real-time adjustment of the beam direction to maintain optimal alignment amid obstacles or mobility-induced variations in link quality. Table 3 and 4 show the collected metadata of the selected beam-sweeping research studies that addressed our research questions: Reference, research objectives, methodology, beamforming architecture, beam alignment framework environment, mobility, number of beams, performance metrics, and more.

[10] identifies several challenges in the current beam-sweeping approach, particularly at higher carrier frequencies that necessitate narrower beams. The challenges include issues related to complexity, messaging overhead, and scalability. The authors also discuss UEs with multiple antenna panels, putting a focus on cooperative Tx/Rx optimization and efficient panel switching. One of the main drawbacks they pointed out was the dependence on DL/UL beam correspondence, which introduces inflexibility and blockage issues arising from mobility and device rotation, as these impact the efficient handovers and tracking heavily in high-speed scenarios like trains. The paper underscores the necessity for mmWave and THz codebook designs that are resilient and flexible, accommodating many frequency bands and deployment scenarios. Lastly, it emphasizes the absence of a useful framework for evaluation, calling for accurate channel models, as well as UE rotation and mobility models to meaningfully assess beam management solutions.

[32] addresses the challenges posed by millimetre-wave (mmWave) frequencies in 5G and anticipates the requirements of 5G-Advanced and 6G systems.

It introduces a novel signalling method for beam management (BM) that employs a hybrid analogue-digital (HAD) beamforming architecture. The proposed solution aims to parallelize the beam-sweeping procedure by transmitting spatially multiplexed synchronization signals with reduced overhead and latency. The paper evaluates the performance of this approach through Monte Carlo simulations, demonstrating its ability to reduce signal overhead and improve beam alignment. The key contribution lies in enabling the concurrent delivery of spatially multiplexed synchronization

Table 3 Beam Sweeping research studies

Ref	Objectives	Method	Architecture	Frame work	Environment	Mobility	Beam Nr.
[10]	Identifies the main challenges and future research directions of Beam management in 5G/6G	Survey	Analog BF	EBS	LOS and NLOS	Yes	64
[32]	Explores alternative signalling methods for managing beams by employing hybrid analogue-digital BF architecture to parallelize the beam sweeping process and enable mmWave signal multiplexing with a controllable overhead	Simulation	Hybrid BF	EBS	LOS	Yes	64
[33]	Provides an overview of the current 5G standards and support for mmWave beam management standardization	Survey	Hybrid BF	EBS	LOS and NLOS	N/A	equals SRS
[34]	Aims to achieve fast and efficient hierarchical beam selection for fixed wireless Xhaul mmWave through antenna switching to provide broader beams for samples and the coarse alignment stage.	Simulation	Hybrid BF	HB	LOS	N/A	8x8TRX

Table 3 continued

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[35]	Compares initial access measurement frameworks in mmWave cellular for accuracy, responsiveness, and overhead.	Simulation	Analog BF	EBS	NLOS	N/A	4,16, 64
[10]	SNR	Cellular, UAV	mmWave, THz	Gives Insight into 5G/6G challenges and possible solutions	Scalability issues and power consumption in beam management not extensively treated	Directional	
[32]	RSS, BPA, MDP	Cellular	mmWave	Significant improvement in beam alignment performance, reduced signalling overhead and latency	Some misdetections due to interference, performance is reduced for smaller arrays	Directional	
[33]	RSRP, RI, PMI, CQI	Cellular, V2X, UAV, FWA	mmWave	Scalable and flexible feedback, multi-panel support, joint beam management	High complexity in beam failure management, challenges in multi-panel operations, interference in multi-user MIMO scenarios	Directional	
[34]	SNR	FWA mmWave xHaul	mmWave	Low complexity, reduced measurements, and computational costs while maintaining satisfactory antenna gain performance	Beam alignment accuracy drops with larger scan intervals, the complex process requires tuning of several parameters for optimal performance	Hierarchical beam pattern	
[35]	SNR	Cellular	mmWave	Provides comprehensive evaluation for IA frameworks, includes 3GPP NR configurations	Overhead can increase with dense networks and high antenna elements	Directional	

BF= Beam Forming, RI=Rank indicator, PMI=precoding matrix Index, CQI =channel quality indicator, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, BPA = beam detection accuracy, MDP = miss detection probability, LOS = line of sight, NLOS = Non line of Sight, SNR = Signal to noise ratio, UAV = Unmanned aerial vehicle, FWA = fixed wireless access, V2X = Vehicle to anything, EBS = Exhaustive beam sweeping, HBS = Hierarchical beam sweeping, ABS= Adaptive beam Sweeping

Table 4 Continued Beam Sweeping research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[36]	Proposes a hierarchical codebook design for efficient beam alignment using bandit algorithms in mmWave systems	Simulation	Analog BF	HBS	LOS	N/A	Not Specified
[37]	Characterize radio propagation and assess beam management in a 5G FR2 network within an operational factory environment	Experimental	Hybrid BF	EBS	LOS, NLOS	Yes	32,27
[38]	Enhance security in mmWave communications by adapting beam management to avoid potential attacks	Experimental	Hybrid BF	ABS	LOS, NLOS	N/A	63
[39]	Optimize achievable data rates through an iterative adaptive beam alignment strategy in THz communication systems	Simulation	Hybrid - Digital BF	HBS	LOS, NLOS	Yes	Variable
[40]	To compare beam management procedures of Verizon and AT&T in 5G mmWave networks and assess their impact on performance	Experimental	Hybrid BF	EBS	LOS, NLOS	Yes	

Table 4 continued

Ref	metrics	Scenario	Frequen cy	Merits	Demerits	Beam Pattern
[36]	Probab ility of Success, Beam Gain	Cellular	mmWave	Reduces the search space for beam alignment, improving efficiency and reducing overhead	Complexity increases with the number of hierarchical levels and may require significant computational resources	Directional
[37]	RSRP, Path Gain, Beam Recovery	Industrial Automation (Factory)	mmWave	Real-world applicability, thorough beam management analysis	Limited generalizability, potential oversimplification of beam management	Directional
[38]	Covert Beam-Sweep Pressure (CBSP)	WLAN	mmWave	Improved security and adaptive management reduce eavesdropping and jamming risk	Increased complexity in real-time adaptive beam management	Directional
[39]	Throug hput, Beam Alignment Accuracy	Cellular, FWA	THz	High alignment accuracy, improved data rates, adaptive to dynamic channel conditions	High computational complexity, potential latency issues in real-time applications	Directional
[40]	48,24	SINR, Throu g hput, Beam Coherence Time, Beam Switching Delay	Cellular	mmWave	Higher SINR and throughput with narrow beams with wider beams	Frequent beam switching for narrow beams, suboptimal RSRQ selection in beam tracking

BF= Beam Forming, RI=Rank indicator, PMI=precoding matrix Index, CQI =channel quality indicator, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, BPA = beam prediction accuracy, MDP = miss detection probability, LOS = line of sight, NLOS = Non line of Sight, SNR = Signal to noise ratio, UAV = Unmanned aerial vehicle, FWA = fixed wireless access, V2X = Vehicle to anything, EBS = Exhaustive beam sweeping, HBS = Hierarchal beam sweeping, ABS= Adapbtive beam Sweeping

signals using a hybrid beamforming architecture, offering improvements in BM performance for future cellular systems operating at higher frequencies. [33] offers a comprehensive overview of beam management in mmWave communication, encompassing procedures from resource control to beam failure recovery and providing technical details on Release 15 and Release 16 enhancements. Specific scenarios and challenges in UL simultaneous transmission and interference-aware beam management are addressed, and the paper demonstrates a forward-looking approach by considering beyond the 5G evolution and acknowledging the role of artificial intelligence, particularly machine learning. However, it provides limited discussion on real-world implementation validation and insufficient exploration of standardization challenges. Opportunities lie in incorporating real-world examples, and recent developments, addressing the dynamic nature of technology.

[34] presents a two-stage beam alignment method designed for mmWave and massive MIMO systems in fixed wireless communication settings. The primary aim is to enhance beam alignment efficiency in point-to-point mmWave radio links by addressing the elevated path loss associated with mmWave frequencies. The key contributions include the introduction of a hybrid analog-digital antenna array that enables steerable massive MIMO transmission and reception. The first stage involves a method for disabling some antennas to generate wider beams, facilitating coarse alignment, followed by a fine alignment stage utilizing theoretical beam patterns. Theoretical beam alignment techniques, including hard-alignment and soft-alignment algorithms, hierarchical codebook design, and wider beams for accelerated scanning, are discussed. The proposed methods aim to reduce complexity and measurement requirements compared to existing exhaustive methods, utilizing electromagnetic simulations of antenna arrays and free space propagation models. Numerical results illustrate the effectiveness of the approach in reducing complexity while maintaining performance, supported by simulations under experimental scenarios and the steerable hybrid antenna array architecture.

[35] addresses the challenges posed by mmWave frequencies in NR networks, focusing on the evaluation of various Initial Access (IA) schemes. It delves into analogue and digital beamforming strategies at UE and gNB sides, emphasizing the impact of antenna numbers on directional sweeping time during the Initial Access process.

Analog beamforming introduces significant delays, particularly if there are many directions to be searched, while digital beamforming improves performance by reducing sweeping time. The study identifies feasible configurations and discusses the delay in allocating resources for Implicit Beam Reporting in Standalone (SA) and Master Cell (MC) architectures. Overhead analysis considers time and frequency resources for Synchronization Signal (SS) Bursts,

exploring frequency diversity and repetition strategies. Practical recommendations include choosing configurations for single-burst sweeping and reporting to reduce SS block overhead. The paper provides a comprehensive analysis, highlighting trade-offs and suggesting future work on beam quality tracking and resilience in different scenarios, offering valuable insights for mmWave NR network deployment.

[36] introduces an approach to enhance beam alignment in millimetre-wave (mmWave) communication systems using a novel hierarchical codebook design to improve the performance of Multi-Armed Bandit (MAB) algorithms. This work's main contribution is designing a codebook that satisfies the unimodality property, which is crucial for the efficiency of the Hierarchical Optimal Sampling of Unimodal Bandits (HOSUB) algorithm. The authors propose a Max-Min criterion for designing beamformers using phase shifters and antenna deactivation, and they combine this with a subarray splitting technique to improve the coverage and gain of the beamformers. The performance of the proposed codebook is validated through simulations, showing that it outperforms existing designs, particularly in terms of the success rate of the HOSUB algorithm across varying signal-to-noise ratios (SNRs). In contrast, [37] conducts an experimental assessment of a 5G FR2 network deployed in a functioning factory environment for mmWave. The study's goal was to analyse radio propagation and evaluate beam management processes in a real-world industrial context, considering the presence of heavy machinery and autonomous mobile robots. Two different network configurations are examined, with an emphasis on coverage, path gain models, and beam management strategies, including beam sweeping, switching, and recovery. The paper offers practical insights into optimizing beam management to ensure reliable communication in highly dynamic industrial settings. The results reveal that beam recovery limits power loss while sweeping optimizes direct signals in challenging environments with significant scattering and Line-of-Sight conditions.

The study in [38] introduces a security-enhanced millimetre-wave (mmWave) adaptive beam management technique to counter threats during the Initial Access (IA) procedure. By using a Reinforcement Learning (RL) agent, the system dynamically adjusts beam sweeping to avoid insecure directions. A novel Covert Beam-Sweep Pressure (CBSP) metric measures secrecy capacity during beam sweeping. Experimental results show that focused, restrictive beam sweeps centred on the receiver enhance security, offering a practical solution for secure mmWave communications. [40] compares beam management strategies of Verizon and AT&T in 5G mmWave networks in Boston, MA. Verizon uses narrower beams for higher SINR but requires more frequent switches, while AT&T's wider beams offer stability with lower SINR. Despite frequent switches, Verizon's

shorter switch delays result in higher throughput. The study also suggests that the current RSRP-based beam selection might not always choose the best beam, indicating a need to reassess beam management criteria in 5G mmWave networks. Finally, [39] presents a beam alignment strategy for THz communication systems, using an iterative process to optimize beam directions and maximize data rates. It tackles challenges like severe path loss and the need for precise alignment in high-frequency environments. Despite its benefits in data rate and accuracy, the approach faces challenges with computational complexity and real-time feasibility. The study advances beam management in next-generation wireless networks, especially in the context of emerging THz technologies.

Beam sweeping exhibits various challenges and considerations. Firstly, it introduces latency, which, while tolerable in some applications, becomes critical in low-latency scenarios. This latency issue is compounded by the overhead incurred in terms of time and frequency resources, impacting the network's overall efficiency. Moreover, beam sweeping is sensitive to environmental changes, with factors like obstacles and interference affecting alignment accuracy and speed, potentially leading to suboptimal performance in dynamic settings. Scalability is a concern, particularly in scenarios with many users or devices, as managing multiple simultaneous beams and ensuring efficient alignment for each user poses challenges. Furthermore, the constant adjustment of beams through sweeping can contribute to increased energy consumption, raising concerns about the network's sustainability and energy efficiency.

Finally, the implementation and management of beam sweeping procedures, especially in millimetre-wave and THz frequencies, involve complexity, requiring sophisticated algorithms, signalling mechanisms, and hardware, which could escalate deployment and maintenance costs.

4.2 Context information frameworks

In wireless communication, context information encompasses details about the environment, including device locations, obstacle presence, device movement, and overall network conditions, which is valuable for optimizing communication parameters. Beam alignment is essential in millimetre-wave and THz communication, utilizing directional beams through beamforming to enhance signal focus and reliability. A context-aware beam alignment approach integrates additional contextual information, such as precise device locations, obstacle awareness, and device dynamics (especially for mobile devices), facilitating proactive adjustments for optimal beam direction and interference reduction. The context information approach often employs adaptive algorithms to monitor and analyze contextual factors, dynamically adjusting beamforming parameters for

better communication performance. Furthermore, contextual data plays a crucial role in Machine Learning (ML). It provides additional information that helps models make more accurate predictions. This enables informed decisions about beam alignment and adaptive responses to changing conditions. Tables 5 and 6 show the collected metadata of the selected Context Information frameworks research studies that addressed our research questions, which include year, title [Reference], Research objectives, Methodology, Beamforming Architecture, Beam Alignment frameworks Environment, Mobility, Number of beams, Performance metrics, etc.

[42] explains the transmission model for beamforming using a Butler matrix and parameters characterizing radio spatial propagation. It introduces the beam alignment problem as a multi-hypothesis testing issue, discussing various detection frameworks, including fixed-length detection and variable-length detection (SCET), with SCET presented as an adaptive and robust improvement over fixed-length methods. The paper details an experimental setup at TU Dresden for mmWave experimentation with hybrid beamforming, evaluating beam selection methods in different scenarios. The results demonstrated the adaptability and efficiency of SCET and SCT in single-path and multi-path scenarios compared to fixed-length methods. The paper also highlighted the adaptability and efficiency of the SCET framework in realistic mmWave scenarios. The study acknowledged its robustness and superiority over fixed-length methods. [41] addresses the beam alignment challenges in millimetre-wave (mmWave) communication, where high data transmission and reduced interference are crucial. The proposed algorithm leverages the location information of mobile users and potential reflectors to efficiently align beams in mmWave-band communications. The key idea is to enable the base station and mobile user to work together to scan a limited number of beams within the error boundary of the noisy location information. This initial set of beams guides the search for future beams, reducing alignment overhead, power consumption, and time resources. The algorithm's effectiveness is demonstrated through simulation results, demonstrating improved system performance even when dealing with noisy location data. The paper compares the proposed approach with existing methods, highlighting its adaptability, efficiency, and its reduced complexity. Overall, the research aims to enhance the beam alignment process in mmWave and THz communication, particularly in mobile environments, by exploiting location-aware coordination.

[43] explores "Frequency-Dependent Beamforming", leveraging fixed and variable length tests with a focus on mmWave communication systems. It introduces an exhaustive search (ES) based testing approach, including a Variable Length Testing Scheme (VLT) utilizing ES and a Generalized Likelihood Ratio Test (GLRT) considering cross-correlation values

and noise variance estimates, along with a termination threshold determined by the likelihood of a false alarm. The Frequency Dependent Beamforming (FDB) section employs a linear system model with Rician fading, adapting GLRT for hypothesis testing, and introducing a length-dependent threshold based on an F-distribution. Simulation results compare Fixed Length Testing (FLT) with true time delay for different scenarios, emphasizing the advantages of variable length testing, particularly in higher SNR regimes. The conclusion highlights the time efficiency of the proposed frequency-dependent beamforming, achieving power loss measures in medium to high SNR, and suggests further research for improving time efficiency and reducing power losses in challenging conditions.

[44] focuses on beam alignment strategies for mmWave massive MIMO systems to enhance communication performance, exploring various codebooks, including orthogonal, hierarchical, and frequency-dependent types. It discusses the optimal beamformer choice, focusing on the orthogonal codebook after a specific number of observations (N) and emphasizing the minimum required samples for the Least Squares (LS) solution. Simulations considered a channel with multiple paths and a receiver with a 64-element uniform linear array. The paper compares fixed and variable-length beam selection techniques using the Butler codebook and introduces the Sequential Competition and Elimination Test (SCET) for adaptive test length and robustness. The hierarchical codebook (MLVL) and Frequency-Dependent Beamforming (FDB) codebook are evaluated, showing that variable-length detection, especially with SCET, enhances adaptivity, resulting in rate gains and delay reduction. Different codebook types impact detection performance differently, with orthogonal codebooks benefiting from elimination mechanisms and frequency-dependent codebooks eliminating the need for beam switching. [45] investigated the initial beam acquisition/alignment in mmWave communication systems. The authors proposed a training protocol that uses a frequency-selective beam probing network to scan all beamformers from a particular codebook. This approach exploits the sparse nature of mmWave channels, mapping each beamformer to different frequencies. The paper compares two hardware designs for parallel beam training and evaluates their feasibility. The results demonstrated that frequency-selective beam probing outperforms exhaustive search in terms of effective transmission rates in rapidly changing environments, crucial for mmWave systems with large beamforming codebooks and short coherence times. The study highlights the importance of reducing timing overhead in communication systems, especially in scenarios with high mobility and spatial resolution. The proposed approach demonstrates advantages in time efficiency and transmission rates. It offers potential benefits in sparse scattering environments common in mmWave communications. The paper

suggests exploring continuous pilot subcarriers during data transmission for improved channel tracking for future work.

[46] introduces an innovative rapid access method for mmWave systems in cellular networks, aiming to reduce the complexity of beam training. This is achieved through the utilization of retro-directive arrays (RDA) and a Zadoff-Chu (ZC) sequence-based preamble. The proposed method involves two stages: in the first part, the base station (BS) performs transmit (Tx) beam sweeping with activated RDA, and if a mobile station (MS) is detected in any of the beam directions, the RDA retransmits the signal to the BS. In the second part, the BS transmits the preamble through the chosen Tx beam, and the MS performs Rx beam sweeping to measure the SNR. The paper demonstrated a notable decrease in complexity when compared to the traditional exhaustive search approach. Simulation results confirmed the technique's ability to accurately detect beam alignment parameters, highlighting its potential in addressing the complex challenges of beam training. The proposed approach, leveraging retro-directive arrays and Zadoff-Chu sequences, offers a promising solution for efficient initial access in mmWave networks.

[47] tackles the beam alignment challenge in mmWave communication networks by proposing a groundbreaking framework aided by Ultra-wideband (UWB). The innovation lies in integrating UWB technology to estimate optimal angles for beam alignment, eliminating the necessity for exhaustive space searching and addressing latency and complexity issues. The Multi-Frequency MUSIC (MF-MUSIC) algorithm expands the traditional MUSIC algorithm into the frequency domain, enabling accurate angle estimation with a small number of UWB antennas. The paper recognizes practical challenges with limited antennas on Commercial-Off-The-Shelf (COTS) devices and provides a solution, enhancing its real-world applicability. While comprehensive numerical evaluations and comparisons are strong, they lack real-world validation and rely on assumptions.

The main contributions of [48] include a novel approach to coordinate computation using accelerometer rotation angles, addressing azimuth errors. The paper proposes an efficient association of mobile stations (MS) with base stations (BS) through a transmitted uplink control signal, considering power, response vectors, and the geometric channel. Two broadcasting approaches, single and multi-broadcasting, facilitate data dissemination to multiple MS users. Performance evaluation indicates advantages such as significantly reduced access times, high success rates, and energy efficiency in comparison to existing schemes. Limitations include potential challenges in real-world implementation and the developmental stage of mmWave technology. In their future work, they suggest exploring outages caused by blockage and mobility.

Table 5 Context Information based Framework research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[42]	Evaluates the performance of a sequential competition and Elimination Test (SCET) - a variable length beam selection framework	Experimentally	Analog BF	Context information based	LOS and NLOS	N/A	64
[41]	Determines the optimal beams by utilising the user's position, the base station's location, or certain obstructions on the channel	Simulation	Analog BF	Context information based	NLOS	N/A	64
[43]	Achieves beam alignment by equipping the transmitter with a frequency-dependent beamformer that can simultaneously verify all spatial angles and, consequently, any beamformer that might come from a comparable codebook.	Simulation	Hybrid BF	Frequency-dependent beamforming	NLOS	N/A	16,32, 64
[44]	Compares the beam alignment accuracy and acquisition time of three types of orthogonal butler matrix strategy, hierarchical/multilevel search and frequency-dependent beamforming framework using both fixed and variable length	Simulation	Hybrid BF	Context information based	NLOS	N/A	8,16, 32,64

Table 5 continued

Ref	metrics	Scenario	Frequency	Merits	Demerits	Beam Pattern	
[45]	Used a strategy that simultaneously probes all beams from a codebook to determine AoA or AoD and exploits the sparsity of mmWave channels. The method maps every beamformer of the codebook to multiple frequencies using a frequency-selective beam probing network and spectral analysis at the receiver to determine favourable beamformers AoA or AoD	Simulation	Analog BF	Frequency-selective beam probing	NLOS	N/A	8
[46]	Proposed a retrodirective array (RDA)-based initial access method to lower overhead associated with the beam training overhead. The RDA transmits the incoming signal back to the source with a directivity that matches the size of the antenna array.	Simulation	Analog BF	Retrodirective array (RDA)	NLOS	N/A	BS:256, MS:8
[47]	Proposed a mmWave communication architecture with jointly situated UWB antennas to find the optimal angles for mmwave beam alignment.	Simulation	Analog BF	co-located UWB antennas	NLOS	N/A	-
[48]	When a new MS enters a cell, it scans the channel for a beacon indicating the bearing of the BS, broadcast by a nearby MS that has accomplished beam association. Then, using a digital compass, the location of the MS is reflected in the adjusted coordinates of the BS.	Simulation	digital BF	Probing beacon	NLOS	N/A	-
[42]	SNR and Latency	Cellular, UAV, FWA	mmWave	Reduces training overhead, adaptable to varying channel conditions	Computational complexity and hardware impairments impact accuracy	Orthogonal beams using a Butler Matrix setup	

Table 5 continued

Ref	metrics	Scenario	Frequen cy	Merits	Demerits	Beam Pattern
[41]	Through put	Cellular, V2X, UAV	mmWave	Reduced alignment overhead, enhanced alignment accuracy	Computational overhead requires precise location data	Adaptive beams based on location data
[43]	SNR	Cellular, UAV	mmWave, sub-THz	Reduces beam alignment time, higher SNR, adaptable to channel conditions	Computational complexity in multi-path scenarios, high hardware cost	Adaptive beam patterns based on time delay across different frequencies
[44]	SNR	Cellular, V2X	mmWave	Reduces beam-training overhead, adaptable to SNR conditions	Computational complexity, reliance on prior knowledge of SNR	Orthogonal beams via Butler Matrix, Frequency-dependent beams
[45]	SNR and throughput	Cellular, V2V, FWA	mmWave	Reduces beam alignment time, better performance in rapidly changing environments	Increased hardware complexity due to delay elements	Frequency-dependent beam patterns utilizing OFDM modulation
[46]	SNR, DP	Cellular	mmWave	Faster beam alignment with reduced complexity, accurate detection	Higher hardware cost, complexity in managing retrodirective arrays	Retrodirect ive beam patterns
[47]	SNR, Throughput, AC	Cellular	mmWave	Significant improvement in AoA estimation accuracy with fewer antennas, reduction of communication delays	Performance drops in NLoS scenarios, requires a calibration step for	Highly directional
[48]	SNR, EE, ST	Cellular	mmWave	Fast access times, high success rates, reduced energy consumption	Higher cost, complex beamforming structure, azimuth tilt errors	Omni-directional and directional

BF= Beam Forming, RI=Rank indicator, PMI=precoding matrix Index, CQI =channel quality indicator, RSSRP = Reference Signal Received Power, RSS = Received Signal Strength, BDA = beam detection accuracy, MDP = miss detection probability, DP = Detection Probability, C = complexity, LOS = line of sight, NLoS = Non line of sight, SNR = Signal to noise ratio, UAV = Unmanned aerial vehicle, FWA = fixed wireless access, V2X = Vehicle to anything, MS = mobile station, BS = basestation

Table 6 Continued Context Information based Framework research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[49]	The study used stochastic geometry and Student's t-distribution statistics analytical model to examine the effect of uplink power control on the downlink beam alignment errors in an mmWave network as they depend on several link factors	Analytical	Analog BF	Uplink power control	NLOS	N/A	-
[50]	The Authors proposed an energy-controlled THz pulse-level beam switching called TRPLE. The impulse radio, which emits pulses lasting femtoseconds, allows beam direction control at the pulse level rather than the packet level. TRPL framework solves the pulse-to-pulse and symbol-to-symbol separation parameters to maximize the data rate while meeting the interference requirements	Simulation	Analog BF	pulse-level beam switching	NLOS	N/A	-
[61]	The study evaluated the performance of beamforming leveraging space division multiple access (SDMA) depending on the design, i.e. array pattern, number of array elements and angle of separation. Signal of interest and signal of no interest scenarios were defined for different base stations' angles of separation and number of antenna elements.	Simulation	Analog BF	location-aware	LOS	N/A	128
[51]	Efficient initial access and wireless power transfer to energy-neutral devices	Simulation	Analog BF	Location	LOS, NLOS	N/A	variable
[52]	Reduce beam alignment time for mmWave communications using third-party camera data	Experimental	Analog BF	camera	LOS, NLOS	Yes	31
[53]	Reduce training overhead and enhance beamforming accuracy	Simulation, Experimental	Hybrid BF	Location	LOS, NLOS	Yes	Variable
[54]	Use CV and ML for beam management, reducing CSI reliance	Simulation	Hybrid BF	Camera	LOS	Yes	variable
[55]	Create a Digital Twin (DT) to improve beam management	Experimental, Simulation	Hybrid BF	Camera	LOS, NLOS	Yes	Not specified
[49]	SNR, CP	Cellular	mmWave	Reduces UE power consumption, maintains downlink SNR in NLOS	Degradation in LOS SNR with FPC, beam alignment errors in LOS	Directional, sector-based	

Table 6 continued

Ref	metrics	Scenario	Frequen cy	Merits	Demerits	Beam Pattern
[50]	DR, SNR	Small cells, WLAN	THz	High data rate (167 Gbps), effective for long distances (up to 20m), efficient multiplexing	High complexity in beam control, limited by pulse separation, molecular absorption	Highly directional with narrow beams
[61]	SNR	Cellular, D2D, 5G Ultra-Dense Networks	mmWave	Significant interference suppression, enhanced spatial multiplexing for ultra-dense networks	Requires accurate positioning, computational complexity increases with more dense environments	Directional with spatial separation
[51]	PG, Power Density	Indoor WPT	mmWave	Efficient power delivery using beam diversity; scalable for dense environments	Dependence on environment awareness; beam sweeping increases setup time and energy consumption	Directional
[52]	AC, Time Consumption	Indoor, Smart City	mmWave	Reduces beam alignment time by up to 1/50 compared to traditional methods	Reliance on camera availability and placement, processing overhead	Directional
[53]	Throughput, Training overhead	Cellular	mmWave	Reduces real-time channel training, improves communication rates even with moderate location errors	Relies on location accuracy, environmental changes affect performance	Directional
[54]	AC, Overhead	Cellular, UAV	mmWave	Reduces overhead and improves real-time beam alignment	Depends on camera data and environmental conditions	Directional
[55]	AC	Cellular	mmWave	Higher accuracy in beam alignment reduces overhead	Camera dependency, high computational overhead	Digital twin with adaptive mapping

BF= Beam Forming, RI=Rank indicator, PMI=precoding matrix Index, CQI =channel quality indicator, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, BDA = beam detection accuracy, MDP = miss detection probability, DP = Detection Probability, C = complexity, LOS = line of sight, NLOS = Non line of Sight, SNR = Signal to noise ratio, UAV = Unmanned aerial vehicle, FWA = fixed wireless access, V2X = Vehicle to anything, MS = mobile station, BS = base station, AC = accuracy, PG = path gain, WPT = wireless power transfer

[49] investigates the impact of uplink power control on downlink beam alignment errors in mmWave cellular networks, employing stochastic geometry and Student's *t*-distribution statistics. The authors created an analytical framework that considers link parameters, uplink power control, and SNR coverage. The results demonstrate a substantial reduction in user equipment (UE) power consumption through effective uplink power control without compromising downlink SNR coverage. The study highlights fractional power control for uplink pilot signal transmission, an underexplored area in mmWave systems. Key contributions include exploring the influence of uplink power control on downlink beam alignment errors, introducing an analytical model, and showcasing significant UE power consumption reduction with minimal effects on downlink SNR coverage. Acknowledging limitations related to assumptions, the paper suggests future research directions involving real-world validation, dynamic power control strategies, and extensions to additional scenarios for a comprehensive understanding of power control mechanisms in emerging wireless communication technologies. In summary, the research provides valuable insights into optimizing power consumption in mmWave cellular networks while ensuring satisfactory downlink SNR coverage.

[50] focuses on advancing Terahertz (THz) communication by developing and optimizing a Medium Access Control (MAC) protocol framework. The authors aim to tailor the MAC framework for the downlink in THz networks, considering THz channel characteristics and emphasizing pulse-level beam-switching using large antenna arrays based on graphene for macro-scale communication. The proposed framework aims to establish a "pseudo wired" wireless link through focused transmission via line-of-sight or reflected paths. The paper explores key components, including the optimization of Inter-Pulse Separation (IPS) and Inter-Symbol Separation (ISS), revising transmission scheduling, discussing beam acquisition strategies, addressing beam switching delay, and presenting numerical results for both LOS and NLOS.

[61] investigates the application of beamforming and spatial multiplexing in the context of 5G Ultra-Dense Networks (UDN), particularly emphasizing the transition to mmWave. The study highlights adaptive beamforming (AB) and spatial signal processing as crucial elements in overcoming mmWave limitations. The paper explores adaptive beamforming scenarios, addressing challenges like beam alignment and presenting analog, digital, and hybrid methods. The research evaluates spatial multiplexing performance through simulations employing the Least Mean Squares (LMS) algorithm. It focuses on the interference suppression rate (ISR) under various conditions. Key contributions include assessing location-aware beamforming and developing a simulation model to understand the impact of angular

separation and antenna elements on interference suppression. In conclusion, the research significantly advances the understanding of beamforming and spatial multiplexing in 5G UDN, providing valuable insights for further exploration and practical implementation.

Context-based beam alignment is an optimization technique in wireless communication systems that utilizes contextual information such as user locations, environmental conditions, interference levels, and network dynamics to dynamically adjust beam parameters. While this approach aims to enhance system performance, reliability, and efficiency, it faces several common limitations. These include the complexity introduced to system design, challenges in achieving real-time adaptation, reliance on accurate contextual information, concerns regarding interoperability across diverse systems, and potential security and privacy issues associated with sensitive contextual data.

To address these challenges, common recommendations include the development of robust algorithms, integration with artificial intelligence and machine learning for improved adaptability, and collaborative standardization efforts to ensure consistency, real-world validation to assess effectiveness in various environments, and the implementation of strong security measures, such as encryption and authentication, to safeguard sensitive information.

4.3 Compressive sensing (CS) frameworks

CS is employed to take advantage of the mmWave channels' intrinsic sparsity. The sparsity characteristics allow for the accurate recovery of dominant paths with fewer training resources. It also reduces the training overhead by providing a means to recover essential channel information with a sparse set of measurements. Additionally, compressive sensing can be combined with other techniques (e.g., Kalman Filtering [25]) to adapt to the dynamic nature of time-varying channels, ensuring accurate beam alignment over changing conditions. Tables 7 and 8 show a list of studies included in this section. The selected studies in Tables 7 and 8 collectively provide a contemporary understanding of the status quo in Compressive Sensing (CS) beam alignment. These studies showcase the potential of CS-based frameworks in addressing challenges associated with mmWave communication. Notably, the integration of CS with Kalman Filtering, as demonstrated by Kun-Hsien Lin, presents a promising approach for accurate channel recovery with reduced overhead. Erfan Khordad's exploration of beam alignment in dynamic environments emphasizes the importance of adaptability and a switching mechanism between beam training and tracking to balance accuracy and overhead.

[25]'s work further underscores the potential of CS-Kalman Filtering integration in achieving accurate beam alignment with significantly lower Mean Squared Error

(MSE) compared to traditional methods. However, the status quo also reveals critical aspects that warrant attention. The impact of CS-based frameworks in highly mobile scenarios and their robustness under extreme channel dynamics require further investigation. Real-world deployment challenges, such as hardware constraints and synchronization issues, are recognized but not extensively discussed. Adaptability to diverse environments and comprehensive analysis of CS performance under varying signal-to-noise ratios (SNR) remain areas for more in-depth investigation. The trade-off between accuracy and overhead reduction, as well as comparative assessments with alternative beam alignment techniques, need more detailed consideration. In conclusion, the status quo of CS-based beam alignment is promising, with notable advancements in integration strategies and performance improvements. Yet, there exists a need for continued research to address challenges in mobility, real-world implementation, environmental adaptability, SNR sensitivity, and a comprehensive understanding of trade-offs in practical mmWave communication scenarios.

4.4 ML/AI frameworks

The application of machine learning (ML) and artificial intelligence (AI) principles in beam alignment involves a data-driven approach, utilizing historical data to train models on relevant features, such as signal strength and environmental factors. Supervised learning is employed for tasks with labelled datasets, while unsupervised learning aids in understanding data patterns. Reinforcement learning trains systems to make beam alignment decisions through trial and error. ML models adapt in real time to dynamic environmental changes, and optimization algorithms adjust beamforming parameters for optimal performance. Deep learning, particularly Convolutional Neural Networks (CNNs), may be used for image processing and pattern recognition. The principles also include the creation of adaptive systems that dynamically adjust beam parameters based on changing conditions and predictive analytics for forecasting potential misalignments. Together, these principles enhance the automation, optimization, and adaptability of beam alignment processes, improving efficiency and reliability in various technologies.

Tables 9, 10, 11 and 12 show the collected metadata of the selected ML/AI framework-based research studies that addressed our research questions, which include year, [Reference], Research objectives, Methodology, Beamforming Architecture, Beam Alignment frameworks Environment, Mobility, Number of beams, Performance metrics, etc. The work of [56] explores beam alignment in mmWave massive MIMO systems using ML. The proposed framework using ML, introduces a neural network (NN) trained offline in simulated environments that uses partial beams to forecast the beam distribution vector. Based on the NN predic-

tions, all users' beams are then simultaneously aligned. The framework demonstrated superior overall performance, considering total training time slots and

spectral efficiency. The approach eliminates the need for historical user location data during NN training, contributing to reduced system overhead. The research indicates that ML techniques can significantly enhance beam alignment by improving efficiency and reliability.

[57] proposes a new approach to overcome the challenges of beam alignment in mmWave systems, which are crucial for addressing propagation issues at high frequencies. The paper introduces a distributed beam-alignment strategy utilizing an adversarial multi-armed bandits (MAB) approach, leveraging a single bit of feedback indicating whether the SINR surpasses a predetermined cutoff. The main breakthrough is a redesigned reward function that draws inspiration from the mmWave channels' sparse structure, efficiently reinforcing good beam directions and penalizing poor ones. The proposed algorithm, MEXP3, builds upon the exponential weights (EXP3) algorithm, demonstrating theoretical guarantees for regret. The results of the mmWave numerical simulations with user mobility showcase the superior performance of MEXP3 when compared to EXP3 and other policies, emphasizing its adaptability to dynamic wireless environments.

[58] suggests BsNet, a deep learning-based beam selection technique. The motivation stems from the challenges posed by the narrow and highly directional beam characteristics of mmWave bands, making beam alignment costly and challenging. BsNet addresses this by treating beam alignment as an image reconstruction problem, leveraging deep neural networks (DNNs) for beam domain image reconstruction. The approach involves offline training and online prediction stages, significantly decreasing the online beam selection overhead. The paper introduces the concept of eigen-beam extraction and uses a learning-based method for BsNet training, achieving remarkable results in terms of scalability, robustness, and performance. Simulation results demonstrate BsNet's superiority over existing methods, such as Modified Rosenbrock's Direct Search (MRDS) and local learning-based clustering algorithm with feature selection (LLCfs), offering high spectral efficiency while minimizing the search overhead. The proposed approach exhibits promising potential for efficient beam selection in mmWave communication scenarios, demonstrating adaptability to various environments and scenarios. [59] proposes a machine learning solution for beam management in 5G NR using geolocation side information. The method models the mapping between the geolocations of user equipment (UE) and the beams or cells that serve them in a multiuser, multi-cell environment by using support vector machines (SVMs). Furthermore, a multiuser scheduling approach is shown that reduces real-time channel state information (CSI) feedback

Table 7 Compressive Sensing Framework research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[22]	Demonstrated that limiting randomness in compressed sampling to local sets achieves robustness to structured errors due to carrier frequency offset	Simulation	Analog BF	Compressive sensing	LOS	N/A	64
[23]	Aims to optimize beam alignment in multiuser mmWave MIMO systems under practical low SNR conditions by investigating compressive sensing techniques, proposing a trial-based protocol and a novel deterministic construction for the CS sensing matrix, and demonstrating superior performance compared to existing methods.	Simulation	Analog BF	Compressive sensing	LOS, NLOS	Yes	Variable
[24]	Develop a deterministic sensing matrix for millimeter-wave beam alignment using a Kronecker-based structure, exploiting the sparse nature of mmWave channels.	Simulation	Analog BF	Compressive sensing	NLOS, LOS	N/A	variable
[25]	Aimed to address the challenges of tracking and training beams in a time-varying millimetre-wave channel while minimizing overhead by combining Compressed Sensing (CS) and Kalman Filtering.	Simulation	Analog BF	Compressive sensing	NLOS, LOS	N/A	Variable
[26]	To reduce overhead in beam alignment for mmWave/THz systems using compressive sensing.	Simulation	Hybrid BF	Compressive Sensing	LOS	N/A	32
[27]	To reduce computational complexity in mmWave beam alignment using a deterministic, sparse sensing matrix	Simulation	Hybrid BF	Compressive Sensing	LOS	N/A	variable

Table 7 continued

Ref	metrics	Scenario	Frequen cy	Merits	Demerits	Beam Pattern
[22]	SNR	Cellular, WiFi	mmWave	Reduces beam misalignment, robust to CFO, fewer measurements than exhaustive search methods	Limited evaluation in highly dynamic environments, complexity in beam broadening	Adaptive, multi-resolutional
[23]	SNR	Cellular	mmWave	Reduces beam alignment overhead, handles time-varying channels, robust in low SNR environments	Increased hardware complexity for Symbol-based Beam Switching (SBBS)	Adaptive
[24]	SNR	Cellular, WiFi	mmWave	Reduces computational complexity, deterministic approach guarantees sparse recovery, robust to low SNR	Increased complexity when extended to larger antenna arrays	Structured, sparse beam pattern using Kronecker product
[25]	SNR	Cellular, UAV	mmWave	Improved tracking in mobile scenarios	Complexity in integrating Kalman filters	Directional beam patterns
[26]	Beam forming gain, SNR, Success Rate	WLAN	mmWave, THz	Efficient beam alignment, higher beamforming gain, compatible with low-resolution phased arrays	May require complex optimization and implementation	Sectoral, comb-like, non-overlapping
[27]	PCA, SNR	Cellular	mmWave	Reduced computational complexity, efficient in low SNR scenarios, guarantees sparse recovery	Requires deterministic matrix design, limited to sparse channels	Kronecker-based sparse

BF= Beam Forming, RI=Rank indicator, PMI=precoding matrix Index, CQI =channel quality indicator, RSSRP = Reference Signal Received Power, RSS = Received Signal Strength, BDA = beam detection accuracy, MDP = miss detection probability, DP = Detection Probability, C = complexity, PCA = Probability of Correct Alignment, LOS = line of sight, NLOS = non line of sight, SNR = signal to noise ratio

Table 8 Continued Compressive Sensing Framework research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[28]	To develop a fast, robust, and low-complexity beam alignment algorithm effective in the presence of CFO.	Simulation	Analog BF	Compressive Sensing	LOS, NLOS	N/A	variable
[29]	To enhance beam alignment efficiency in time-varying and low SNR mmWave channels using compressive sensing techniques	Simulation	Hybrid BF	Compressive Sensing	LOS, NLOS	Yes Implied by time-varying channels	Variable
[30]	To reduce latency and overhead in initial access and beamforming training for mmWave cellular systems using compressive sensing techniques	Simulation	Hybrid BF	Compressive Sensing	LOS, NLOS	N/A	Variable
[31]	To develop an efficient and accurate channel estimation method for mmWave systems with limited measurements, using spectral profiles and multi-resolution compressive sensing	Simulation	Hybrid BF	Compressive Sensing	LOS, NLOS	Not explicitly	Variable

Table 8 continued

Ref	metrics	Scenario	Frequen cy	Merits	Demerits	Beam Pattern
[28]	Beam forming gain, Success rate	Cellular	mmWave	Reduces training overhead and complexity, robust against CFO, adaptable to different architectures	Potential complexity in extending to high mobility scenarios, reliance on accurate CFO estimation	Randomized, Zadoff-Chu (ZC) sequence-based
[29]	accuracy	Cellular	mmWave	Improves alignment accuracy in low SNR and time-varying channels, robust to challenging conditions	Increased complexity and feedback overhead, requires more advanced hardware for SBBS	Kronecker product-based
[30]	Access latency, Overhead, accuracy	Cellular	mmWave	Reduces latency and overhead, robust to synchronization errors, mitigates beam squint, suitable for large bandwidths	Implementation complexity, limited focus on high mobility scenarios	Quasi-omnidirectional
[31]	CSI estimation error, Gain, efficiency	Cellular, WiFi	mmWave	Reduces CSI estimation error, adaptive resolution, robust to non-low-rank matrices, improves beamforming performance	Implementation complexity, performance in highly dynamic environments not fully explored	Adaptive

BF= Beam Forming, RI=Rank indicator, PMI=precoding matrix Index, CQI =channel quality indicator, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, BDA = beam detection accuracy, MDP = miss detection probability, DP = Detection Probability, C = complexity, PCA = Probability of Correct Alignment, LOS = line of sight, NLOS = non line of sight, SNR = signal to noise ratio

by using local beam assignment information from neighbouring cells. Simulations demonstrated that the proposed multiuser scheduler achieves high performance with low algorithmic complexity, resulting in an initial access latency decrease of 50% and a 34% reduction in signalling overhead compared to conventional exhaustive beam sweeping approaches. The paper addresses the challenges posed by mmWave propagation and emphasizes the importance of efficient beam management for 5G NR deployment in scenarios like vehicle-to-everything (V2X) communication. However, it is important to remember that the suggested solution assumes an idealized training scenario without interference and relies on a specific communication protocol for geolocation information transfer, which can restrict its practicality in the actual world, interference-prone environments. Further investigation and validation in diverse scenarios are necessary to evaluate the robustness and scalability of the solution.

[60] introduces an innovative machine learning (ML) approach for beam selection in mmWave communication systems, a crucial aspect of modern wireless networks. The proposed method utilizes a Multi-Layer Perceptron (MLP) classifier to predict optimal access points (APs) and beams based solely on user equipment (UE) locations, overcoming challenges in dynamic environments and imperfect location data. Through extensive evaluations, the paper demonstrates that the MLP classifier consistently outperforms traditional techniques and other ML models, showcasing its robustness and efficiency. The study explores the model's sensitivity to UE location noise and training dataset size, revealing that the MLP classifier excels in performance with minimal training data. The findings highlight the significant contributions of the ML-assisted approach, offering a hopeful solution for improving beam alignment and providing valuable insights for future research in wireless communication. [62] proposes a clever algorithm for beam training using a deep convolutional neural network (DCNN). The algorithm capitalizes on the deep CNN's feature extraction capabilities and the spatial correlation between several beams to select a subset of beams for training. To measure the correlation, the spatial mutual information is defined, and the probing beams are selected based on a weighted combination of average correlation with the remaining beams and correlation with the optimal beam. The deep CNN is trained with offline data collected using exhaustive beam sweeping. Simulation findings show that the suggested technique considerably lowers beam training overheads and leads to improved throughput performance compared to state-of-the-art methods.

[63] The study suggested a beam selection framework for 6G communication networks that is based on deep learning. Large antenna arrays at base stations are essential in 6G, where very high frequencies are used to form directional beams to overcome path losses encountered by such signals. Conventional methods for beam selection suffer from high

training overhead, leading to increased computational complexity and power consumption. The paper introduces a data-driven neural network framework using a CNN trained from simulator-generated beam datasets. To balance accuracy and computational complexity, the model uses hyperparameter optimization and skip connections approach. With the proposed strategy, computational complexity can be reduced by up to 15 percent and accuracy can be increased to over 70 percent. The main contributions include generating datasets using simulators and designing a less-complex CNN model for beam selection. The outcomes show that the suggested model is effective when compared to traditional and machine learning-based methods. The computational complexity is also reduced, making the solution suitable for 6G systems. [64] introduces an ML-based blind beam alignment approach tailored for mmWave massive MIMO setups with a single RF chain. Leveraging Matrix Factorization (MF) and Non-negative Matrix Factorization (NMF), the method optimally exploits Line-of-Sight channel characteristics to mitigate signalling overhead. The study conducts a comprehensive Train/Test performance analysis, showcasing the swift adaptation of the model parameters, particularly in NMF, resulting in rapid error reduction. Notably, the proposed strategy achieves accurate predictions with just 10% of beams in massive MIMO configurations, emphasizing its efficiency. The paper contributes valuable insights into the trade-offs between ALS calculus and Gradient Descent, emphasizing the former's faster convergence. The findings affirm the proposed ML-based Blind Beam Alignment as a compelling solution for mmWave Massive MIMO, with future work recommended to explore alternative ML frameworks. [65] introduces a beam alignment framework leveraging machine learning to predict directional beams for communication in challenging environments. The proposed method involves training an NN network to learn a site-specific codebook and optimizing its beam patterns to capture environmental characteristics. Through extensive evaluations in various environments, including Rosslyn and DeepMIMO scenarios, the paper demonstrates that the learned probing codebook consistently outperforms predefined codebooks, achieving superior beam alignment accuracy. The key contributions include the reduction of beam sweeping complexity, especially in scenarios with NLOS users, and the provision of an insightful explanation of the learned codebook's effectiveness by using data clustering and representation learning. The findings highlight the potential of the solution to outperform state-of-the-art beam search approaches, making it a promising solution. [66] addresses the critical challenges of beam selection in mmWave systems.

Unlike conventional approaches that rely on predefined codebooks, the proposed method introduces a grid-less and one-shot beam alignment technique. The method employs unsupervised machine learning to train a neural network,

enabling the synthesis of analogue beamforming weights directly without sweeping through a set of candidates. Through experiments, the paper demonstrates the method's ability to achieve remarkable performance, with a reduction of over 20 times in beam sweeping latency and an improvement of about 0.32 dB below the theoretical maximum. The key contributions include the elimination of the grid-based codebook constraint, scalability to multiple devices, and integration inside the architecture for 5G NR beam alignment.

[67] presents an algorithm for beam training based on Deep Reinforcement Learning (DRL) for mmWave MIMO communication systems, specifically addressing user mobility effects. The algorithm dynamically selects techniques for training beams using past channel measurements, finding a balance between training overhead and energy efficiency (EE) or spectral efficiency (SE) performance. Through extensive simulations, the proposed DRL algorithm outperforms the baseline Multi-Armed Bandit (MAB) approach, attaining a higher SE with a 10% decrease in measurements or a comparable EE with 20% less beam measurements. The study introduces an EE/SE maximization strategy and evaluates the impact of factors such as the trade-off parameter, state vector size, and random blockages. Noteworthy contributions include the development of an intelligent, adaptable beam training framework and insights into optimizing performance and computational complexity. The paper discusses limitations, such as the assumption of equal power allocation, and suggests avenues for future research, emphasizing practical implications for mmWave systems.

[68] proposes an advanced K-means (KM) learning algorithm for optimizing beam alignment for MIMO channels. The study employs Detection-Modified Orthogonalization (DMO) to significantly enhance the computational speed of the algorithm compared to conventional KM

learning methods, showcasing over 100-fold improvement. Notably, the paper introduces a novel application of the Kolmogorov-Smirnov (KS) test to address uncertainty arising from Feature Extraction (FE) and obtain the training set's empirical probabilities, thereby improving the ability of the KM algorithm to learn. Experimental results indicate that the suggested KM learning algorithm, incorporating DMO and the KS test, outperforms traditional KM algorithms in terms of beamforming gains, especially in scenarios with reduced computational complexity. The research contributes a valuable advancement in beam alignment techniques for mmWave MIMO channels, demonstrating superior performance and efficiency.

In [69], the authors address the beam alignment (BA) problem by proposing a novel learning algorithm called Hierarchical Beam Alignment (HBA). The algorithm uses past knowledge of channel variations and the intrinsic correlation structure between beams to speed up the BA process. Through extensive simulations and evaluations, the study

demonstrates that HBA outperforms existing benchmarks, significantly reducing the quantity of measurements needed for BA. The algorithm proves effective in various scenarios, including multipath channels and under different channel fluctuation distributions. Notably, HBA exhibits robustness and scalability, achieving high beam detection accuracy even in the case of many beams. The research further explores the impact of transmission distance and coarse prior knowledge on performance, highlighting the algorithm's effectiveness in practical scenarios. The key contributions include the development of HBA, a machine learning-based approach, and a comprehensive evaluation demonstrating its superiority in terms of regret performance, scalability, and beam alignment latency, ultimately providing valuable insights for optimizing mmWave communication systems. [70] introduces the Extreme-Beam Management (X-BM) framework. This approach uses machine learning to optimize beam management in 6G networks, especially for large MIMO systems. The X-BM framework improves initial access and spectral efficiency, achieving an 8dB boost in signal quality. It outperforms traditional methods across different scenarios. The system handles CSI acquisition with less feedback and adapts well to various environments and antenna arrays.

However, it adds computational challenges, particularly for real-time operations, despite its high adaptability and efficiency.

[71] The paper presents a restless, multi-armed bandit (MAB) framework named MAMBA for optimizing beam tracking and rate adaptation. MAMBA uses reinforcement learning for beam tracking and rate adaptation in mmWave systems. It leverages Adaptive Thompson Sampling (ATS) and HARQ feedback to optimize beam and MCS selection. This reduces control overhead and improves efficiency. MAMBA improves throughput by up to 182% compared to static methods. The system is robust in both LOS and NLOS environments and handles high mobility well. However, real-time use is challenged by computational complexity.

[72] proposes a deep-learning approach to improve beam alignment and security in 5G. It uses a Deep Neural Network (DNN) to rank beam pairs efficiently. This reduces the need for exhaustive beam searches. The method also minimizes signal leakage to eavesdroppers. It cuts the beam search space by 75% while maintaining 99.66% accuracy. The approach improves secure communication probability by 68.12%. Though signal strength drops by 6.5 dB, the method is highly accurate. It also reduces energy use and overhead, making it ideal for future wireless networks.

[73] presents beam training algorithms for THz communication, which is important for beam training 6G networks. The authors propose three algorithms—UCB, Loc-LinUCB, and Probing-LinUCB—using a Multi-Armed Bandit (MAB) framework. The contextual algorithms (Loc-LinUCB and Probing-LinUCB) use location and probing data to improve

beam selection. The findings show that these algorithms improve spectral efficiency and adapt faster to changes compared to UCB. Probing-LinUCB performs best but has higher complexity. Limitations include increased computational demands and hardware needs for the contextual algorithms. UCB struggles in dynamic environments, and Probing-LinUCB introduces latency due to its added complexity, making it less ideal for ultra-low latency needs.

[74] explores how AI and ML can improve beam management in 5G-Advanced. These technologies boost beam prediction accuracy, reduce latency, and improve performance, especially in high-mobility areas. Two key methods are discussed. Spatial Beam Prediction (SBP) uses location data to find the best beam. Temporal Beam Prediction (TBP) uses past beam data to predict future beams over time. Both methods outperform traditional techniques. They increase prediction accuracy by up to 63.5% and reduce signal differences and overhead. However, challenges remain. These include high computational demands, difficulties in generalizing models, privacy concerns, and the lack of standard protocols. Solving these will be key for AI/ML's success in future 5G networks. [75] presents a deep learning-based hierarchical framework for beam alignment in mmWave systems. The Hierarchical Beam Alignment Network (HBAN) uses a two-tier probing process to optimize beam selection. This reduces the number of measurements and improves accuracy for both MISO and MIMO systems. The method achieves higher accuracy with fewer measurements. It also enhances spectral efficiency and reduces overhead compared to traditional methods. However, there are some limitations. The system has high computational complexity and requires extensive training data. Real-time deployment can be challenging, especially in resource-constrained environments. The framework may also need frequent retraining to adapt to different environments, and the MIMO-specific design adds complexity. Both [70] and [75] use hierarchical approaches and machine learning to enhance beam management. However, they focus on different areas. [75] targets beam alignment in mmWave systems, while [70] focuses on codebook design for X-MIMO. Both aim to reduce overhead and improve performance. [75] emphasizes beam search and probing, whereas the [70] concentrates on optimizing the feedback process and CSI-based beamforming for larger arrays and wider frequency ranges.

[76] introduces a reinforcement learning framework. It optimizes beam selection and transmission power to improve energy efficiency in mmWave networks. The approach uses the Advantage Actor-Critic (A2C) method. It reduces overhead and energy consumption while maintaining coverage. Key findings show that the A2C method more than doubles energy efficiency compared to traditional methods. It is suitable for high-mobility and dense user scenarios. The method adapts well to different network conditions. It can

also be integrated into Service Management and Orchestration (SMO) platforms like Open RAN. However, the model has high computational complexity. It requires extensive training data and faces challenges in scalability for multi-base stations or multi-user environments. [77] proposes a deep learning framework to enhance beam selection efficiency in mmWave MIMO systems by modelling it as a contextual multi-armed bandit (MAB) problem. Using neural network algorithms like Neural Epsilon-Greedy and Neural Network Committee (NNC), the system makes real-time decisions to optimize beam selection and maximize throughput while reducing the need for exhaustive search methods. The approach shows significant improvements in beam selection efficiency and performance in dynamic environments. However, the method introduces computational complexity, requires substantial training data, and its adaptability to diverse real-world scenarios may need further validation.

[78] introduces an LSTM-based approach to optimize beam tracking in millimeter-wave (mmWave) wireless systems, particularly in multi-cell environments. The method reduces power consumption and signalling overhead while maintaining high beam tracking accuracy by selectively tracking beams based on channel quality predictions. The approach reduces overhead by up to 85% and predicts the best beam within 2 dB of the optimal SNR 95% of the time. It is adaptable to both analog and digital architectures and is suitable for real-time deployment. However, the method introduces computational complexity and relies heavily on training data, which can be challenging in data-scarce environments. Further optimization is required to balance performance under different network conditions.

[79] presents a two-stage prediction-based beam selection (TS-PBBS) algorithm that improves beam selection efficiency in urban vehicular scenarios. It uses a deep neural network (DNN) to predict optimal beams and a local search method to refine them, reducing overhead and enhancing accuracy in dynamic environments with frequent blockages. The TS-PBBS algorithm achieves 90% accuracy even in low SNR conditions, reducing beam search overhead by up to 86.4%. It performs well in urban settings with blocked line-of-sight, making it promising for 6G systems. However, the algorithm introduces computational complexity due to DNN training and prediction, requires high-quality training data, and its performance may vary with different environment configurations, necessitating parameter fine-tuning.

[80] investigates using ML to optimize beam management in mmWave D-MIMO systems by reducing the need for exhaustive beam measurements across multiple Access Points (APs). ML algorithms such as Random Forest (RF), MissForest (MF), and c-GAN are used to predict the best beam and AP with minimal measurements, significantly lowering overhead. RF and MF provide the highest accuracy and efficiency, while c-GAN performs well but requires

more data. However, the approach is heavily reliant on high-quality training data, and its computational complexity may limit real-time applications in resource-constrained environments. Additionally, scaling to larger networks with more APs and users presents challenges in managing multiple beams simultaneously. [81] presents a deep learning method called deep regularised waveform learning (DRWL) to improve beam prediction in non-cooperative mmWave systems, addressing the challenge of limited training data. Using data augmentation techniques like cyclic time shift (CTS) and signal splicing, DRWL predicts optimal beams without coordination between transmitter and receiver, reducing the need for exhaustive beam sweeping. The method improves beam prediction accuracy even with fewer training samples, maintaining high performance by leveraging waveform characteristics. However, the model introduces computational complexity, making real-time deployment difficult in resource-constrained environments, and its performance depends on input signal quality. Further testing is needed to confirm its effectiveness in dynamic, real-world scenarios.

[82] explores using computer vision (CV) and machine learning (ML) to improve mmWave beam management. Traditional systems rely on channel state information (CSI), leading to high overhead and delays. This new approach uses camera data to select beams without needing CSI. The framework focuses on improving efficiency, robustness, and scalability with ML models. Simulations show better beam alignment and reduced computational costs. However, the system depends on reliable camera data, which may be impacted by blocked views or poor conditions. Labeling data for ML training is also challenging. The system faces further issues with multiuser environments, integration complexity, and environmental sensitivity.

The research papers spanning [56–60, 62–69], [70–82] collectively provide a thorough examination of ML/AI-based beam alignment techniques. These methodologies, exemplified by innovations like HBA (Hierarchical Beam Alignment), are designed to optimize beamforming for improved communication performance, demonstrating promising outcomes in terms of regret performance, scalability, and beam alignment latency reduction. However, the papers identify several

limitations, including reliance on specific channel models that may not fully represent real-world mmWave complexities, posing challenges for generalization to diverse scenarios. The impact of mobility, dynamic obstacles, and environmental changes on beam alignment is also insufficiently addressed. Practical implementation aspects, such as computational complexity and energy efficiency, are often overlooked, with deployment challenges needing more attention. The trade-off between exploration and exploitation in learning algorithms, especially in dynamic mmWave channels, requires further exploration. In essence, while ML/AI-

based beam alignment techniques exhibit significant progress in optimizing mmWave communication, challenges persist in generalization, practical implementation, and adaptability to dynamic scenarios, necessitating future work to address these limitations and explore real-world deployment challenges, mobility, and energy efficiency for a more holistic solution in mmWave communication systems.

4.5 ISAC beam alignment frameworks

Integrated Sensing and Communication (ISAC) is an emerging technology. It combines wireless communication and sensing within one system. ISAC offers new ways to optimize beam alignment. Which is essential for efficient data transmission and environmental awareness. Machine Learning (ML), beam sweeping, and context information frameworks can enhance ISAC. These methods boost performance in dynamic environments. The following research highlights advancements and innovations in ISAC, providing an overview of key efforts driving this field forward, see Tables 13 and 14.

In [83], Zhiqiang Xiao et al. presented a beamforming technique for mmWave integrated sensing and communication (ISAC) systems, aiming to create a cost-effective analog beamforming approach that enables a MIMO ISAC system to simultaneously sense targets and communicate with user equipment (UE). Their research introduces a flexible double-beam codebook to create separate beams for sensing and communication. They also propose simultaneous beam-sweeping schemes. These include single and double-beam methods to optimize the process and reduce overhead.

[84] presents an ISAC system using Reconfigurable Intelligent Surfaces (RIS). It improves communication and target sensing efficiency. The authors propose a Simultaneous Beam Training and Target Sensing (SBTTS) scheme. This scheme distinguishes RIS from targets by accumulating energy in different domains. It reduces training overhead. A Positioning and Array Orientation Estimation (PAOE) scheme further improves efficiency with a fast search algorithm. The system performs well in both line-of-sight and non-line-of-sight scenarios. However, it faces complexity, noise sensitivity, and pilot overhead challenges. Deployment is also difficult due to large networks' hardware needs, real-time control, and scalability. [85] introduces the Integrated Sensing and Communication (ISAC) beam alignment method for Terahertz (THz) networks. The method, called Joint Synchronization Signal Block (SSB) and Reference Signal (RS)-based Sensing (JSRS), reduces line-of-sight (LoS) blockages and corrects beam misalignment caused by user mobility. With high-resolution THz sensing, JSRS detects and prevents misalignment early, improving network coverage. The paper shows JSRS enhances beam alignment and coverage, especially in urban vehicle-to-everything

Table 9 ML/AI based Framework research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[56]	The article suggested a method for beam alignment with partial beams that uses machine learning and doesn't require any prior knowledge, like user location data.	Simulation	Hybrid BF	ML-NN	NLOS	N/A	5
[57]	To be considered aligned, a signal must reach a certain SINR threshold before it can be considered aligned by a distributed beam alignment scheme.	Simulation	Hybrid BF	ML-RL	NLOS	Yes	32
[58]	Proposed a deep neural network (DNN) solution that required no knowledge of the channel but treated the beam selection as an image reconstruction problem and the DNN is used to construct a beam domain image. The solution consists of offline training and online prediction. Eigen-beam theorem entry treated as starting value for beam domain image reconstruction (BDIR). The off-line Eigen-beam extraction reduces the overhead of online-beam alignment.	Simulation	Analog and Hybrid BF	ML-DNN	NLOS	N/A	32,64, 128,256
[59]	Proposed a mmWave beam alignment solution that uses geolocation side information and leveraging Support Vector Machine (SVM) model for mapping UE location and covering beam in a multi-user multi-cell scenario. Subsequently, the beam assignment information from user-adjacent cells helps to reduce the latency for channel state information (CSI) feedback.	Simulation	Analog and Hybrid BF	ML- Supervised	LOS	N/A	8
[60]	Proposed ML-based beam alignment framework that is trained to forecast the best access point (AP) and the most suitable beam choice given an UE's GPS coordinates. Whereby the GPS coordinates are reported by the UE or by some other technique.	Simulation	Hybrid and Analog BF	ML-DCNN	NLOS	N/A	64
[62]	The authors derived an AP beam-training framework by using the spatial correlation between various beams in addition to the ability of the Deep Convolutional Neural Network (DCNN) to retrieve features. The AP framework only probes a fixed set of the entire beam space and determines the best	Simulation	Analog BF	DCNN framework	NLOS	N/A	128
[63]	The authors proposed a CNN strategy for performing beam selection between the transmitter and receiver. The employed CNN skip connections and hyperparameter optimization to balance between accuracy and computational complexity.	Simulation	Analog BF	CNN framework	NLOS	Yes	61

Table 9 continued

Ref	metrics	Scenario	Frequency	Merits	Demerits	Beam Pattern
[56]	SNR, SE	Cellular	mmWave	Reduces training time, does not require user location data, efficient beam alignment	High computational complexity, requires simulated training environments	Directional
[57]	SNR	Cellular	mmWave	Low-latency beam alignment, optimal performance in sparse mmWave channels	High computational complexity, requires tuning of reward parameters for varying conditions	Directional Beam Pattern
[58]	SNR	Cellular	mmWave	Reduces beam search overhead by up to 90%, maintains 99% of spectral efficiency compared to exhaustive search	Requires extensive training, potential computational complexity in real-time applications	Directional Beam Pattern
[59]	SNR	Cellular, V2X	mmWave	Reduces latency by up to 50%, decreases signaling overhead by 34%, and improves beam pairing accuracy.	High reliance on geolocation data, complexity in multi-cell scenarios, computational overhead in training	Directional Beam Pattern
[60]	BPA	Cellular	mmWave	Reduces search space for optimal AP and beam alignment, robust against dynamic scatters and location uncertainty	High computational complexity, only considers MISO scenario, requires more development for UE-side beam training.	Directional Beam Pattern
[62]	SNR, BPA, Latency	Cellular, V2X	mmWave	Reduces computational complexity by 15%, high accuracy (70.4%) in beam selection	Requires extensive training dataset, computational complexity in real-time deployment	Directional, Adaptive
[63]	SNR	Cellular	mmWave	Reduces signaling overhead by 90%, high prediction accuracy with 10% beam soundings	Computational complexity, requires careful model tuning to prevent over fitting	Direction

BF= Beam Forming, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, BPA = beam Prediction accuracy, SE = Spectral Efficiency, ML = Machine Learning, RL = Reinforced Learning, SNR = Signal to Noise Ratio, NN = neural Networks, DNN= Deep NN, DCNN Deep Convolutional NN, EE =Energy Efficiency, UDN =Ultra-Dense Networks (UDN), D2D = Device-to-Device (D2D), SBP =Spatial Beam Prediction, TBP=Temporal Beam Prediction, DL = Deep Learning, L-STM = Long and Short Memory, SL=supervised Learning

Table 10 Continued ML/AI based Framework research studies - continued

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[64]	The authors proposed to train Matrix factorization ML and Nonnegative Matrix factorization models by probing a tiny subset of a massive beam's codebook of TX and RX to predict the SNRs of the beams of the codebook. Subsequently, they derived equations for optimizing the matrix factorization method	Simulation	Analog BF	ML-NN	NLOS	N/A	1024
[65]	The authors studied a site-specific-sounding codebook and designed a NN frame that uses measurements from the sounding codebook to predict the best beam. The NN framework model captured the site-specific beams that are associated with the particular characteristics of the propagation environment.	Simulation	Analog BF	ML-NN	NLOS	N/A	128
[66]	The authors proposed a gridless beam alignment framework that predicts near-optimal beam weights from a continuous beam set using unsupervised training that uses few beams for channel sounding.	Experimental	Analog BF	ML-NN	NLOS	N/A	variable
[67]	Proposed a deep reinforcement learning-based beam alignment framework that can switch between different beam alignment methods depending on the radio channel thereby achieving good power and spectral efficiency by using channel circumstances to regulate active RF chains	Simulation	Hybrid BF	ML-DRL	NLOS	Yes	64

Table 10 continued

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[68]	Improved the Kolmogorov model (KM) by introducing discrete monotonic optimization to reduce complexity and improve scalability. Furthermore, testing advanced hypotheses can also be conducted using the Kolmogorov-Smirnov (KS) criterion, which requires no subjective threshold setting compared to frequency estimation used in KM	Simulation	Analog BF	ML-KM	NLOS	N/A	16
[69]	The authors proposed a hierarchical beam alignment algorithm by using knowledge about the inter-beam correlation structure and channel variation. The authors conceptualised the beam alignment problem as a "multi-armed bandit" problem and solved by characterizing the beam correlation structure in the multi-channel as a multimodal function. Additionally, use the previously gained knowledge of the channel fluctuations to properly consider reward uncertainty	Simulation	Analog BF	ML-MAB	NLOS	N/A	512
[70]	Optimize beam management and CSI acquisition using ML in X-MIMO systems for 6G networks	Simulation	Hybrid BF	ML-NN	LOS, NLOS	Yes	8, 16, 32

Table 10 continued

Ref	metrics	Scenario	Frequency	Merits	Demerits	Beam Pattern
[64]	SNR	Cellular	mmWave, THz	Reduces beam sweeping overhead by 3x, achieves over 90% alignment accuracy	High training complexity, dependent on site-specific training data	Directional Beam Pattern
[65]	SNR	Cellular	mmWave	Reduces sweeping overhead by 21x, achieves 0.32 dB of the theoretical upper bound	High computational complexity, requires site-specific training	Directional
[66]	SNR	Cellular	mmWave	Reduces training overhead, adapts to environmental changes, maximizes both EE and SE	High computational complexity, sensitive to changes in real-world environments, relies on deep learning	Adaptive
[67]	EE, SE	Cellular	mmWave	Reduced computational complexity, improved beam alignment performance	High complexity in previous KM models, computational limitations	hierarchical beam pattern
[68]	SNR	Cellular, WLAN, FWA, UAV	mmWave	Significantly reduced computational complexity, improved beam alignment performance	High computational complexity with larger antenna arrays	Overlapping, hierarchical
[69]	SNR	UDN, D2D	mmWave	Improved interference suppression, location-aware communication, optimized beamforming for spatial multiplexing in dense environments	Requires accurate positioning and synchronization, computational complexity in high-density environments	Directional
[70]	RSRP, SNR, SE	Cellular	mmWave	Significant gains in spectral efficiency, reduced adaptability, reduced feedback requirements	Increased computational complexity, challenges in real-time operations and generalization.	Dynamic and Adaptive

BF= Beam Forming, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, BPA = beam Prediction accuracy, SE = Spectral Efficiency, ML = Machine Learning, RL = Reinforced Learning, SNR = Signal to Noise Ratio, NN = neural Networks, DNN= Deep NN, DCNN Deep Convolutional NN, EE =Energy Efficiency, UDN =Ultra-Dense Networks (UDN), D2D = Device-to-Device (D2D), SBP =Spatial Beam Prediction, TBP=Temporal Beam Prediction, DL = Deep Learning, L-STM = Long and Short Memory, SL=supervised Learning

Table 11 Continued ML/AI based Framework research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[71]	Optimize beam tracking and rate adaptation in mmWave systems using reinforcement learning	Simulation	Hybrid BF	ML-RL	LOS, NLOS	Yes	VARIABLE
[72]	Optimize initial access and beam alignment for security and efficiency using deep learning	Simulation Real-world data	Hybrid BF	ML-DL	LOS, NLOS	Yes	Limited set
[73]	Optimize beam training at THz frequencies using MAB algorithms for fast and adaptive beam selection	Simulation	Hybrid BF	ML-RL	LOS, NLOS	Yes	VARIABLE
[74]	Enhance beam management with AI/ML to improve prediction accuracy, reduce latency, and optimize performance in 5G-Advanced	Simulation	Survey	Hybrid BF	ML-SBP ML-TBP) LOS, NLOS	Yes	VARIABLE
[75]	Optimize beam alignment in mmWave systems using a deep learning-based hierarchical framework	Simulation	Hybrid BF	ML-DL	LOS, NLOS	Yes	VARIABLE
[76]	Improve energy efficiency in mmWave networks using the A2C learning framework for beam selection and power optimization	Simulation	Hybrid BF	ML-RL	LOS, NLOS	Yes	VARIABLE

Table 11 continued

Ref	metrics	Scenario	Frequency	Merits	Demerits	Beam Pattern
[71]	Throughput, Outage duration	Cellular	mmWave	182% throughput gain, reduced outage duration, low overhead, adaptable to mobility	Computational complexity in real-time operations, tuning of ATS parameters for performance.	Dynamic and Adaptive
[72]	BPA, RSRP	Cellular	mmWave	75% reduction in beam search space, 99.66% accuracy, improved security, energy efficiency	Reduced RSRP by 6.5 dB for security, trade-off between signal strength and security	Dynamic and Adaptive
[73]	Adaptation Speed, SE	Cellular	THz	Improved spectral efficiency, faster adaptation, and superior performance with contextual data.	Higher complexity for contextual algorithms, latency trade-offs with Probing-LinUCB	Dynamic and Adaptive
[74]	BPA RSRP Latency	Cellular	mmWave	63.5% increase in prediction accuracy, reduced overhead, and better high-mobility performance	High computational complexity, difficulties with model generalization, privacy concerns	Dynamic and Adaptive
[75]	BPA, SE, Overhead	Cellular	mmWave	Higher accuracy with fewer measurements, reduced overhead, enhanced spectral efficiency	High computational complexity, need for extensive training data, challenges in real-time deployment	Dynamic and Adaptive
[76]	EE, Overhead, SNR	Cellular	mmWave	More than doubles energy efficiency, adapts to various conditions, and integrates into Open RAN	High computational complexity, extensive training data, scalability issues in multi-user environments	Dynamic and Adaptive

BF= Beam Forming, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, SE = Spectral Efficiency, ML = Machine Learning, RL = Reinforced Learning, SNR = Signal to Noise Ratio, NN = neural Networks, DNN= Deep NN, DCNN Deep Convolutional NN, EE =Energy Efficiency, UDN =Ultra-Dense Networks (UDN), D2D = Device-to-Device (D2D), SBP =Spatial Beam Prediction, TBP=Temporal Beam Prediction, DL = Deep Learning, LSTM = Long and Short Memory, SL=supervised Learning, BPA=Beam Prediction Accuracy

Table 12 Continued ML/AI based Framework research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[77]	Optimize beam selection in mmWave MIMO systems using a deep contextual bandit learning framework	Simulation	Hybrid BF	ML-DL	LOS, NLOS	Yes	Variable
[78]	Improve beam tracking efficiency and reduce overhead using LSTM in multi-cell mmWave environments	Simulation	Analog and Digital BF	ML-DL and -LSTM	LOS, NLOS	Yes	Variable
[79]	Improve beam selection efficiency and reduce overhead in dynamic, blockage-prone environments	Simulation	Hybrid BF	ML-NN	LOS, NLOS	Yes	Variable
[80]	Use ML algorithms to optimize beam management in D-MIMO systems and reduce measurement complexity	Simulation	Hybrid BF	ML-SL	LOS, NLOS	Yes	Variable
[81]	Improve beam prediction with limited data using deep learning in non-cooperative mmWave environments	Simulation	Hybrid BF	ML-DL	LOS, NLOS	Yes	variable
[82]	Use CV and ML for beam management, reducing CSI reliance	Simulation	Hybrid BF	ML-SL	LOS	Yes	variable

Table 12 continued

Ref	metrics	Scenario	Frequen cy	Merits	Demerits	Beam Pattern
[77]	Throug hput, Overhead	Cellul ar	mmWa ve	Improved beam selection efficiency, reduces exhaustive search, adaptable to dynamic environments	High computational complexity, requires significant training data, limited real-world validation	Dynamic and Adaptive
[78]	Power Consumption, Overhead, BPA	Cellul ar	mmWa ve	Reduced power consumption and overhead, high accuracy in beam tracking, adaptable to environments	Computational complexity, reliance on training data, fixed vs adaptive constraint complexities	Dynamic and Adaptive
[79]	Over head, SNR, BPA	Cellul ar	mmW ave	90% accuracy, reduces beam search time by 86.4%, performs well in dynamic environments like urban V2X	Computational complexity, data dependency, parameter optimization for various environments.	Dynamic and Adaptive
[80]	Over head, BPA	Cellul ar	mmW ave	Reduces measurement overhead, improves beam selection accuracy, efficient in dynamic environments	Data dependency, computational complexity, challenges in scaling to large networks	Dynamic and Adaptive
[81]	BPA, Overhead	Cellul ar	mmWa ve	High prediction accuracy with limited training samples, reduced beam sweeping overhead	High computational complexity, performance dependent on signal quality, limited real-world testing	Dynamic and Adaptive
[82]	BPA, Overhead	Cellul ar UAV	mmWa ve	Reduces overhead and improves real-time beam alignment	Depends on camera data and environmental conditions	Predefined beam codebook (YOLO, etc.)

BF= Beam Forming, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, SE = Spectral Efficiency, ML = Machine Learning, RL = Reinforced Learning , SNR = Signal to Noise Ratio, NN = neural Networks, DNN= Deep NN, DCNN Deep Convolutional NN, EE =Energy Efficiency, UDN =Ultra-Dense Networks (UDN), D2D = Device-to-Device (D2D), SBP =Spatial Beam Prediction, TBP=Temporal Beam Prediction, DL = Deep Learning, LSTM = Long and Short Memory, SL=supervised Learning, BPA=Beam Prediction Accuracy

(V2X) scenarios. However, challenges include managing sensing resources, upgrading infrastructure, ensuring real-time performance, and handling environmental changes and LoS blockages in dynamic settings.

[86] addresses reliable beamforming in high-speed environments like vehicle networks. Traditional methods struggle with misalignment and channel fading. The authors propose a transformer-based solution that combines data from sensors like vision, radar, LiDAR, and position information. A 3D ResNet-18 model extracts features, and a transformer fuses them. The system achieves over 91% top-3 accuracy in fast environments. Key findings show improved accuracy and reliability through multimodal fusion. Limitations include increased complexity, sensitivity to weather, and dependence on high-quality sensor data. Deployment challenges involve real-time processing, expensive infrastructure, and scalability in dense networks.

[87] introduces the Sense-Then-Train (STT) beam training scheme for near-field MIMO. It improves performance by using active sensing and eliminating the need for codebooks. The approach is tailored for near-field MIMO, where spherical-wave propagation is key, unlike far-field methods. STT works for both single and multi-beam scenarios, using neural networks for real-time alignment. Key findings show that STT provides faster, low-complexity beam training without full channel state information (CSI). However, it faces challenges like high computational complexity, limited flexibility in dynamic environments, and underused degrees of freedom (DoFs). Deployment challenges include real-time processing, infrastructure upgrades, and scalability in larger networks. [88] suggests using Integrated Sensing and Communication (ISAC) to improve beam management in Terahertz (THz) networks. THz networks offer high data rates for 6G but face severe propagation loss and line-of-sight (LoS) blockages. The ISAC-assisted approach addresses these issues by enabling real-time environment perception, user tracking, and blockage prediction. Sensing technologies help manage narrow beams and maintain communication in complex environments. ISAC reduces beam misalignment by 70% and increases coverage by 36.4%. However, the system needs complex infrastructure upgrades, relies on precise environmental data, and has high computational demands. Deployment challenges include hardware upgrades, scalability, and ensuring real-time adaptation in dynamic conditions.

[89] introduces a hybrid quantum-transformer network (QTN) for better beam prediction in ISAC systems. It focuses on millimeter-wave (mmWave) communications in Vehicle-to-Infrastructure (V2I) scenarios. The QTN model uses multimodal data, like vision and position information, to improve accuracy. It also leverages quantum computing to lower complexity. Key findings show that QTN outperforms traditional models in accuracy and robustness, especially with data from sensors like LiDAR. However, challenges

include sensitivity to quantum noise, data dependencies, and the need for infrastructure upgrades and real-time processing in large networks. [90] suggests a new way to improve beam management for UAV networks using mmWave communication. The system combines sensing and communication (ISAC) with computer vision. It uses an extended Kalman filter (EKF) and dual identity association (DIA) to enhance initial access (IA) and beam tracking. The goal is to reduce delays and improve accuracy in high-mobility UAV situations. The system shows better performance with faster and more accurate beam tracking. However, it depends on camera-based sensing, requires infrastructure upgrades, and has high computational complexity. Challenges for deployment include real-time processing, scalability, and the need for hardware upgrades to integrate sensors. [91] presents a deep learning solution to lower beam-training overhead in mmWave systems. It uses partial codebook sweeping and neural networks to predict optimal beamforming weights. This improves accuracy and performance in massive MIMO setups. The model increases the signal-to-noise ratio (SNR) and cuts beam-training overhead by 75%. Achievable rates rise by 60%. However, the system has challenges like higher computational complexity and reliance on quality training data. Integrating it into existing systems is also difficult. Deployment faces issues with real-time processing, infrastructure needs, and scalability in larger networks.

[92] presents a new way to improve beam alignment in mmWave systems. The method uses a ping-pong pilot scheme, where the transmitter and receiver take turns sending pilots. This removes the need for feedback, making the system simpler. The paper also includes reconfigurable intelligent surfaces (RIS) to help in multipath environments. The approach reduces pilot overhead and improves signal-to-noise ratio (SNR), beating traditional methods. However, deep learning, especially LSTM networks, adds complexity. Real-world deployment needs infrastructure upgrades and fast processing. Aligning beams in noisy, multipath channels remains difficult.

[93] shows how SLAM can improve ISAC systems. SLAM enhances localization and environmental mapping in wireless networks. It introduces multi-domain SLAM using cross-sensing, cross-user, cross-frequency, and cross-device techniques. These methods improve mapping accuracy and beam management. The study shows SLAM's ability to boost communication strategies with decimeter-level accuracy. However, challenges include high computational complexity and

the need for infrastructure upgrades. Environmental factors like multipath propagation also affect accuracy. Deployment issues include real-time processing, scalability, and the need for advanced hardware.

Table 13 ISAC Beam Alignment Frameworks Research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.
[83]	To develop and evaluate a multi-beam sweeping approach for integrated sensing and communication in mmWave MIMO systems	Simulation, Experimental	Hybrid BF	ISAC-Beam sweeping	LOS, NLOS	Yes	16
[84]	Improve beam training and sensing using RIS	Simulation	Hybrid BF	ISAC-ML	LOS, NLOS	Yes	Not specified
[85]	Reduce LoS blockages and beam misalignment using ISAC	Analytical	Hybrid BF	ISAC-Beam Sweeping	LOS, NLOS	Yes	Not specified
[86]	Improve beamforming accuracy in dynamic environments	Simulation, Experimental	Hybrid BF	ISAC-ML	LOS, NLOS	Yes	Not specified
[87]	Improve beam training in near-field MIMO systems	Simulation	Hybrid BF	ISAC-ML	LOS, NLOS	Yes	Not specified
[88]	Improve beam management using ISAC to enhance THz coverage	Simulation	Hybrid BF	ISAC-Context Information	LOS, NLOS	Yes	Not specified

Table 13 continued

Ref	metrics	Scenario	Frequen cy	Merits	Demerits	Beam Pattern
[83]	BPA, SNR, Latency	Cellul ar, V2X, UAV	mmWa ve	Reduces beam alignment time, supports multi-beam sweeping, improves sensing and communication integration	Potentially complex implementation, increased processing requirements	Simultaneous multi-beam patterns
[84]	sensing accuracy	Cellul ar, V2X, Radar	mmWa ve THz	Reduces training overhead, enhances beam alignment	Complexity with RIS implementation, sensitive to environment	RIS-aided beam sweeping
[85]	CP, BM	V2X, Urban	THz	Early detection of misalignment, improved network coverage High complexity,	Real-time processing challenges	Adaptive beam patterning with sensing
[86]	BA, BPA	Vehicle networks	mmWa ve	High beam accuracy, early misalignment detection	High computational complexity, data dependency	Adaptive beamforming using sensor data
[87]	BA, SE	Near-field MIMO	mmWa ve	Fast beam training, low-dimensional subspace for training	High computational complexity, underused Degrees of Freedom	Adaptive
[88]	BM	Cellul ar, V2X, Urban	THz	Reduces beam misalignment by 70%, increases coverage by 36.4%	Complex infrastructure requirements, environmental sensitivity	Adaptive, narrow beam with sensing integration

BF= Beam Forming, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, ISAC = integrating sensing and communication, SA = sensing accuracy, RIS = Reconfigurable Intelligent Surface, ML = Machine Learning, RL = Reinforced Learning , SNR = Signal to Noise Ratio, NN = neural Networks, DNN= Deep NN, DCNN Deep Convolutional NN, EE =Energy Efficiency, UDN =Ultra-Dense Networks (UDN), DL = Deep Learning, LSTM = Long and Short Memory, SL=supervised Learning, BPA=Beam Prediction Accuracy CP = coverage probability, BM = beam misalignment, BA =beam accuracy

Table 14 Continued ISAC Beam Alignment Frameworks Research studies

Ref	Objectives	Method	Architecture	Framework	Environment	Mobility	Beam Nr.	Metrics	Scenario	Frequency	Merits	Demerits	Beam Pattern
[89]	To improve beam prediction in V2I ISAC scenarios using quantum-transformer networks	Simulation	Hybrid BF	ISAC-ML	LOS, NLOS	Yes	Not specified	BPA, power loss	V2I, Cellular	mmWave, THz	Reduced complexity, improved prediction accuracy using multimodal data	High computational complexity	Adaptive
[90]	To enhance beam management for UAVs using mmWave communication through sensing assistance	Simulation	Hybrid BF	ISAC-ML	LOS, NLOS	Yes	Not specified	BTA, IA delay	UAV, Cellular	mmWave	Improved tracking accuracy and beam alignment using sensing	High computational complexity, dependency on sensing accuracy	Adaptive, based on real-time sensing
[91]	Improve beam management in mmWave systems by reducing beam-training overhead	Simulation	Hybrid BF	ISAC-ML	LOS, NLOS	Yes	variable	Achievable rate, BG	Cellular, Urban	mmWave	Increases rates by 60%, Reduces beam sweep overhead by 75%	High computational complexity, dependency on training data	Adaptive

Table 14 continued

Ref	Objectives	Method	Architecture	Frame work	Environment	Mobility	Beam Nr. metrics	Scenario	Frequency	Merits	Demerits	Beam Pattern
[92]	To improve beam alignment and RIS reflection design	Simulation	Hybrid - BF	ISAC-ML	LOS, NLOS	Yes	Multiple	Cellular	mmWave	Reduces pilot training overhead, improves multiple RF beamforming gain, enables RIS reflection optimization.	High complexity, requires multiple RF chains, sensitive to channel variations	Adaptive
[93]	To enhance ISAC systems through cooperative SLAM	Simulation, Experimental	Hybrid BF	ISAC-ML	LOS, NLOS	Yes	Not specified	Cellular, V2X, UAV	mmWave, THz	Improved localization, better environmental awareness	High computational complexity, infrastructure upgrades needed	Adaptive, environment-aware beam patterns

BF= Beam Forming, RSRP = Reference Signal Received Power, RSS = Received Signal Strength, ISAC = integrating sensing and communication, SA = sensing accuracy, RIS = Reconfigurable Intelligent Surface, ML = Machine Learning, RL = Reinforced Learning, SNR = Signal to Noise Ratio, NN = neural Networks, DNN= Deep NN, DCNN Deep Convolutional NN, EE =Energy Efficiency, UDN =Ultra-Dense Networks (UDN), DL = Deep Learning, LSTM = Long and Short Memory, SL=supervised Learning, BPA=Beam Prediction Accuracy CP = coverage probability, BM = beam misalignment, BA =beam accuracy, BTA = Beam tracking accuracy, IA = initial access, BG = Beamforming gain

Table 15 The comparison of the four Frameworks

Feature/ Framework	Beam Sweeping	Context Information	Compressive Sensing	ML/AI	ISAC Frameworks
Method	Systematically adjusting the direction of the beam across predefined angles to find the optimal alignment	Considers additional information about the environment, such as user location or obstacles, to enhance beam alignment decisions	Utilizes a small number of measurements to reconstruct the complete beam information, exploiting the sparsity of the channel	Utilizes machine learning algorithms to learn and adapt beamforming strategies based on historical data or real-time feedback.	use jointly sensing and communication in combination with non ML and ML beam alignment frameworks
Implementation Complexity	Simple	Complexity depends on the methods used for context data collection and interpretation.	Complex due to the need for precise modelling and reconstruction algorithms	Complexity in designing and training the model	High, requires dual modes communication and sensing and potential deployment challenges
Computational Complexity	Low	Varies, depends on the methods used to gather and process context data.	Moderate to high, depending on the reconstruction algorithm chosen	High but better inference	Medium -High, matrix-vector dominate and optimized for GPUs and FPGA hardware
Resource Requirements	Low	Resource Requirements	Moderate to high	High resource requirements for training data, computational power, and memory during learning	High, requires RIS infrastructure and in some cases quantum devices
Latency	higher latency in finding optimal alignment	It depends on the time required to collect and process context data.	It depends on the algorithm and the number of measurements taken	Quick Inference, but training introduces latency, and real-time adaptation may require fast computation	Low.

Table 15 continued

Feature/ Framework	Beam Sweeping	Context Information	Compressive Sensing	ML/AI	ISAC Frameworks
Robustness	Limited robustness in dynamic environments	Can enhance robustness by considering environmental factors	Robust in sparse channel conditions but may struggle in highly dynamic scenarios	Can adapt and improve robustness over time with continuous learning	High, sensitive to environment but improved beamforming accuracy and highly adaptable
Standardization Potential	Generally simpler and widely used, making it easier to standardize across different systems	Standardization may be feasible for certain aspects, but context information can be diverse and application-specific	May face challenges in standardization due to variations in algorithms and reconstruction methods.	Standardization is challenging due to the diversity of machine learning models and the need for tailored solutions	Moderate to High, reliant on 5G like standards and unlikely to be adopted in RIS aided 6G Standards
Interoperability	Generally, more interoperable as it relies on basic beam adjustment mechanisms	Interoperability can be a challenge if different systems use diverse context information sources and processing methods	Interoperability challenges may arise due to variations in sensing hardware and algorithms.	Interoperability is a concern due to variations in machine learning models, architectures, and training data	High, scales to large networks with multiple reflecting surfaces and UEs
Scalability	Highly scalable as it involves basic beam adjustments, suitable for various deployment scales	Scalability challenges may arise if context information sources become too complex or diverse	Scalability depends on the efficiency of sensing hardware and algorithms, potentially facing limitations in large-scale deployments	Scalability can be an issue due to the computational demands, especially during the training phase	High asit integrates well with existing mmWave setups in large scale systems
Network Scenarios	All	All	All	All	All

5 Comparison and limitations of existing frameworks

In this section, RQ2 is addressed. Table 15 shows a qualitative analysis of performance metrics used to compare all the frameworks identified in this review. In comparing the frameworks for beam alignment, each framework offers distinct advantages and challenges.

Beam Sweeping, characterized by its systematic adjustment of beam direction, is simple to implement and widely used, making it easily scalable and interoperable. However, its limited robustness in dynamic environments and higher latency in finding optimal alignment may be drawbacks.

Context Information, which incorporates additional environmental data, enhances robustness but may suffer from complexity and interoperability challenges, particularly with diverse sources of context information.

Compressive sensing, relying on sparse channel exploitation, offers robustness in certain conditions but requires complex algorithms and may face challenges in standardization and interoperability due to variations in hardware and methods.

ML/AI-based approaches leverage machine learning for adaptive strategies, promising improved robustness over time. Still, they demand high computational resources and may struggle with standardization and interoperability due to diverse models and training data.

ISAC systems present a promising solution for future networks, combining communication and sensing. They offer benefits like better efficiency and performance. However, challenges such as computational complexity, infrastructure requirements, and real-time processing must be addressed. As research progresses, ISAC will likely play a major role in shaping 6G and other advanced networks. Machine learning-based and ISAC-based frameworks are both scalable and interoperable with other frameworks, however, they are heavy in terms of computation. Despite heavy computational resource requirements and complexity, they have a potential for standardization.

In essence, while each framework presents unique strengths, they also pose distinct complexities and limitations that are shown in Table 16.

6 Future directions and research opportunities

This section will address RQ4. The 3GPP Release 15 introduced the beam sweeping-based protocol for 5G to address the beam alignment [10, 94]. However, as a higher frequency spectrum and larger antenna arrays are deployed in 5G and 6G, this approach won't be adequate. The beam-sweeping approach won't address all the challenges that are associated

with beam alignment. Instead, the overhead, complexity and latency associated with beam sweeping scale up with the size of the beam space [10]. Some of the challenges and gaps that need to be solved in addressing beam alignment were identified in [10, 111–113] and can be summarized as follows:

6.1 Dynamic and mobile environments

Many existing beam alignment frameworks primarily focus on static scenarios and may not adequately address the challenges posed by dynamic environments and mobile users. Research is needed to develop beam alignment techniques that can efficiently track and adapt to Fast-moving users or changing environmental conditions, ensuring continuous and reliable connectivity [10, 112, 113].

6.2 Robustness against environmental factors

Environmental factors, such as blockages, reflections, diffraction, and atmospheric conditions, can significantly impact the performance of beam alignment frameworks. Developing robust beam alignment techniques that can handle varying environmental conditions, including adverse weather conditions, dense urban environments, and indoor scenarios, is an important research area [113].

6.3 Interference mitigation

Interference from neighbouring systems or coexisting networks can hinder beam alignment performance. Research is needed to develop interference-aware beam alignment frameworks that can effectively mitigate interference effects and maintain high-quality communication links in crowded spectrum environments [94], [111].

6.4 Energy efficiency considerations

Beam alignment techniques often involve energy-intensive operations, such as beam training and tracking. Considering the energy constraints of battery-powered devices and the growing demand for energy-efficient communication systems, research is needed to explore energy-efficient beam alignment methods and protocols without compromising the performance and reliability of the communication links [112].

6.5 Standardization and interoperability

While several beam alignment frameworks have been proposed, there is a lack of standardization and interoperability across different systems and vendors. Efforts are required to develop common standards and protocols for beam align-

ment, facilitating seamless integration and interoperability among different devices, networks, and technologies [113].

6.6 Real-world deployment and validation

Many existing beam alignment frameworks have been evaluated through simulations or limited experimental setups. More research is needed to validate these frameworks in real-world deployments, considering practical constraints, real-life channel conditions, and diverse deployment scenarios. This would provide valuable insights into the actual performance, limitations, and scalability of beam alignment techniques [10].

6.7 Security and privacy considerations

Beam alignment frameworks may be vulnerable to security threats, including eavesdropping, spoofing, or unauthorized beam manipulation. Further research is needed to investigate security and privacy aspects related to beam alignment and develop robust mechanisms to ensure secure and private communication in beamforming-based systems [111], [113].

Addressing these research gaps will contribute to the development of more efficient, reliable, and adaptive beam alignment frameworks, paving the way for the successful deployment of mmWave and THz communication systems in various scenarios and applications.

7 Conclusion

The SLR was conducted on published research focusing on beam alignment and initial access frameworks for mmWave and THz. The SLR identified the most relevant 73 research papers according to the author's knowledge during the review period. 596 papers were initially selected using the defined search strings from digital libraries such as IEEE, Springer, Elsevier, and Francis & Taylor. Subsequently, a three-stage filtering mechanism was applied to the title, abstract, and full text, including the assessment of paper quality. The chosen studies were then explored, sorted and evaluated according to the defined RQs.

In this study, we presented state-of-the-art frameworks for beam alignment in mmWave and THz, and we explained the taxonomy of the beam alignment frameworks by classifying them into beam sweeping-based, context information-based, compressive Sensing-based machine Learning/Artificial Intelligence (ML/AI) -based and ISAC-based frameworks. To improve beam alignment in terms of latency reduction, energy consumption reduction and overhead, the existing literature body was explored to identify the most common beam alignment frameworks. While each framework presents unique strengths, they also pose distinct complex-

ities and limitations. Beam Sweeping and Context Information offer simplicity and robustness enhancements but may struggle with dynamic environments and interoperability issues. Compressive sensing provides robustness in sparse channels but demands complex algorithms and faces standardization challenges. ML/AI approaches promise continuous improvement in robustness but come with high computational demands and potential interoperability hurdles. ISAC systems present a promising solution for future network beam management, combining communication and sensing. They offer benefits like better efficiency and performance. However, challenges such as computational complexity, infrastructure requirements, and real-time processing must be addressed. Thus, the choice among these frameworks hinges on factors such as deployment environment, computational resources, and the need for adaptability and standardization.

In addition, we presented research gaps by identifying and analyzing the limitations of the current frameworks. Lastly, challenges and possible opportunities for future research were highlighted.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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References

1. Uwaechia, A. N., & Mahyuddin, N. M. (2020). A comprehensive survey on millimeter wave communications for fifth-generation

- wireless networks: Feasibility and challenges. *IEEE Access*, 8, 62367–62414.
2. Xue, Q., Ji, C., Ma, S., Guo, J., Xu, Y., Chen, Q., & Zhang, W. (2024). A survey of beam management for mmwave and thz communications towards 6g. *IEEE Communications Surveys & Tutorials.*, 26(3), 1520–1559.
 3. Zhang, J., Björnson, E., Matthaiou, M., Ng, D. W. K., Yang, H., & Love, D. J. (2020). Prospective multiple antenna technologies for beyond 5g. *IEEE Journal on Selected Areas in Communications*, 38(8), 1637–1660.
 4. Ning, B., Tian, Z., Mei, W., Chen, Z., Han, C., Li, S., Yuan, J., & Zhang, R. (2023). Beamforming technologies for ultra-massive mimo in terahertz communications. *IEEE Open Journal of the Communications Society*, 4, 614–658.
 5. Al-Falahy, N., & Alani, O. Y. (2019). Millimetre wave frequency band as a candidate spectrum for 5g network architecture: A survey. *Physical Communication*, 32, 120–144.
 6. Petrov, V., Pyattaev, A., Moltchanov, D., & Koucheryavy, Y. (2016). Terahertz band communications: Applications, research challenges, and standardization activities. In: 2016 8th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), pp. 183–190. IEEE.
 7. Wang, X., Kong, L., Kong, F., Qiu, F., Xia, M., Arnon, S., & Chen, G. (2018). Millimeter wave communication: A comprehensive survey. *IEEE Communications Surveys & Tutorials.*, 20(3), 1616–1653.
 8. Narengerile, N. (2022). Channel estimation and beam training with machine learning applications for millimetre-wave communication systems.
 9. Attaoui, W., Bouraqia, K., & Sabir, E. (2022). Initial access i& beam alignment for mmwave and terahertz communications. *IEEE Access*, 10, 35363–35397.
 10. Heng, Y., Andrews, J.G., J., M., V., V., A., A., L., N.B., & Zhang, J.C. (2021). Six key challenges for beam management in 5.5 g and 6g systems. *IEEE Communications Magazine* 59(7).
 11. Ning, B., Mei, W., Zhu, L., Chen, Z., & Zhang, R. (2024). Codebook design and performance analysis for wideband beamforming in terahertz communications. *IEEE Transactions on Wireless Communications*.
 12. Ning, B., Wang, T., Huang, C., Zhang, Y., & Chen, Z. (2023). Wide-beam designs for terahertz massive mimo: Sca-atp and s-sarv. *IEEE Internet of Things Journal*, 10(12), 10857–10869.
 13. Duan, Q., Kim, T., & Ghauch, H. (2021). Km learning for millimeter-wave beam alignment and tracking: Predictability and interpretability. *IEEE Access*, 9, 117204–117216.
 14. Ning, B., Chen, Z., Tian, Z., Han, C., & Li, S. (2021). A unified 3d beam training and tracking procedure for terahertz communication. *IEEE Transactions on Wireless Communications*, 21(4), 2445–2461.
 15. Ning, B., Chen, Z., Chen, W., Du, Y., & Fang, J. (2021). Terahertz multi-user massive mimo with intelligent reflecting surface: Beam training and hybrid beamforming. *IEEE Transactions on Vehicular Technology*, 70(2), 1376–1393.
 16. Giordani, M., Mezzavilla, M., & Zorzi, M. (2016). Initial access in 5g mmwave cellular networks. *IEEE communications Magazine*, 54(11), 40–47.
 17. Tataria, H., Shafi, M., Molisch, A. F., Dohler, M., Sjöland, H., & Tufvesson, F. (2021). 6g wireless systems: Vision, requirements, challenges, insights, and opportunities. *Proceedings of the IEEE*, 109(7), 1166–1199.
 18. Yi, W., Zhiqing, W., & Zhiyong, F. (2024). Beam training and tracking in mmwave communication: A survey. *China Communications*.
 19. Zecchin, M., Mashhadi, M. B., Jankowski, M., Gündüz, D., Kountouris, M., & Gesbert, D. (2022). Lidar and position-aided mmwave beam selection with non-local cnns and curriculum training. *IEEE Transactions on Vehicular Technology*, 71(3), 2979–2990.
 20. Ali, A., González-Prelcic, N., & Heath, R. W. (2017). Millimeter wave beam-selection using out-of-band spatial information. *IEEE Transactions on Wireless Communications*, 17(2), 1038–1052.
 21. Li, X., Fang, J., Duan, H., & Li, H. (2019). A sparse encoding and phaseless decoding approach for fast mmwave beam alignment. *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE.
 22. Myers, N.J., & Heath, R.W. (2019). Localized random sampling for robust compressive beam alignment. *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE.
 23. Khordad, E., Collings, I.B., Hanly, S. V., & Caire, G. (2022). Compressive sensing-based beam alignment schemes for time-varying millimeter-wave channels. *IEEE Transactions on Wireless Communications*, 22(3), 1604–1617.
 24. Khordad, E., Collings, I.B., & Hanly, S.V. (2019). A kronecker-based sparse compressive sensing matrix for millimetre wave beam alignment. 2019 13th International Conference on Signal Processing and Communication Systems (ICSPCS). IEEE.
 25. Lin, K. H., & Liu, K. H. (2022). A novel beam alignment scheme for mobile millimeter-wave communications based on compressed sensing aided-kalman filter. *IEEE Open Journal of the Communications Society*, 3, 1515–1527.
 26. Masoumi, H., Verhaegen, M., & Myers, N.J. (2023). In-sector compressive beam alignment for mmwave and thz radios. arXiv preprint [arXiv:2308.13268](https://arxiv.org/abs/2308.13268)
 27. Khordad, E., Collings, I.B., & Hanly, S.V. (2019). A kronecker-based sparse compressive sensing matrix for millimeter wave beam alignment. In: 2019 13th International Conference on Signal Processing and Communication Systems (ICSPCS), pp. 1–5. IEEE.
 28. Myers, N. J., Mezghani, A., & Heath, R. W. (2018). Swift-link: A compressive beam alignment algorithm for practical mmwave radios. *IEEE Transactions on Signal Processing*, 67(4), 1104–1119.
 29. Khordad, E., Collings, I.B., Hanly, S. V., & Caire, G. (2022). Compressive sensing-based beam alignment schemes for time-varying millimeter-wave channels. *IEEE Transactions on Wireless Communications*, 22(3), 1604–1617.
 30. Yan, H., & Cabric, D. (2019). Compressive initial access and beamforming training for millimeter-wave cellular systems. *IEEE journal of selected topics in signal processing*, 13(5), 1151–1166.
 31. Song, Y., Ge, C., Qiu, L., & Zhang, Y. (2023). 2ace: Spectral profile-driven multi-resolutional compressive sensing for mmwave channel estimation. In: Proceedings of the Twenty-fourth International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing, pp. 41–50.
 32. Fernandes, F., Rom, C., Harrebek, J., & Manchón, C.N. (2022). Improving beam management signalling for 5g nr systems using hybridbeamforming. *IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE.
 33. Li, Y. N. R., Gao, B., Zhang, X., & Huang, K. (2020). Beam management in millimeter-wave communications for 5g and beyond. *IEEE Access*, 8, 13282–13293.
 34. Qian, J., Masouros, C., Tanabe, K., Sasaki, E., Zein, N., & Marumoto, T. (2022). Beam-pattern assisted low-complexity beam alignment for fixed wireless mmwave xhaul. *ICC 2022-IEEE International Conference on Communications*. IEEE.
 35. Giordani, M., Polese, M., Roy, A., Castor, D., & Zorzi, M. (2018). Initial access frameworks for 3gpp nr at mm-wave frequencies. 17th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net). IEEE.

36. Khirwadkar, P., Shahsavari, S., Hücümenoğlu, M.C., & Pal, P. (2023). Max-min hierarchical codebooks for millimeter-wave channel sensing with bandit algorithms. In: 2023 57th Asilomar Conference on Signals, Systems, and Computers, pp. 387–392. IEEE.
37. Ram, A., López, M., Rodr, I., Sørensen, T. B., Barrio, S. C., Padilla, P., Valenzuela-Valdés, J. F., Mogensen, P., et al. (2024). Fr2 5g networks for industrial scenarios: Experimental characterization and beam management procedures in operational conditions. *IEEE Transactions on Vehicular Technology*, 73(9), 13513–13525.
38. Baron-Hyppolite, A., Abreu, J.V., Santos, J.F., DaSilva, L.A., & Kibilda, J. (2023). Adaptive beam management for secure mmwave communications using software-defined radios. In: MILCOM 2023-2023 IEEE Military Communications Conference (MILCOM), pp. 243–244. IEEE.
39. Huang, W., Zhang, W., & Wang, C. (2023). Iterative achievable rate adaptive beam alignment for thz communication systems. In: 2023 8th International Conference on Communication, Image and Signal Processing (CCISP), pp. 450–456. IEEE.
40. Feng, Y., Wei, J., Dinh, P., Ghoshal, M., & Koutsonikolas, D. (2023). Beam management in operational 5g mmwave networks. In: Proceedings of the 7th ACM Workshop on Millimeter-Wave and Terahertz Networks and Sensing Systems, pp. 13–18.
41. Orikumhi, I., Kang, J., Park, C., Yang, J., & Kim, S. (2018). Location-aware coordinated beam alignment in mmwave communication. 2018 56th Annual Allerton Conference on Communication, Control, and Computing (Allerton). IEEE.
42. Marandi, M.K., Wei, S., Khodapanah, B., Rave, W., & Fettweis, G. (2022). Experimental evaluation of a variable length beam selection framework in a usrp based testbed with mmwave frontends and butler matrices. IEEE International Symposium on Phased Array Systems I& Technology (PAST). IEEE.
43. Jans, C., Rave, W., & Fettweis, G. (2022). Fast beam alignment via true time delay frequency dependent beamforming using fixed and variable length tests. IEEE International Symposium on Phased Array Systems I& Technology (PAST). IEEE.
44. Marandi, M.K., Jans, C., Rave, W., & Fettweis, G. (2021). Evaluation of detection accuracy and efficiency of considered beam alignment strategies for mm-wave massive mimo systems. 55th Asilomar Conference on Signals, Systems, and Computers. IEEE.
45. Jans, C., Song, X., Rave, W., & Fettweis, G. (2020). Frequency-selective analog beam probing for millimeter wave communication systems. IEEE Wireless Communications and Networking Conference (WCNC). IEEE.
46. Kim, Y., Lee, H., & Cho, Y.S. (2020). Fast initial access technique for millimeter-wave systems using retrodirective arrays. International Conference on Information and Communication Technology Convergence (ICTC).
47. Wang, J., Chen, X., Liu, X., & Dudek, G. (2021). Uwb-assisted fast mmwave beam alignment. ICC 2021-IEEE International Conference on Communications. IEEE.
48. Aldabahi, A., Siasi, N., Mazin, M.A. A. & Jasim. (2022). Digital compass for multi-user beam access in mmwave cellular networks. Digital Communications and Networks.
49. Zia, M.S., Blough, D.M., & Weitnauer, M.A. (2022). Uplink power control and snr-dependent beam alignment errors in mmwave cellular networks. IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC). IEEE.
50. Lin, J., & Weitnauer, M. A. (2019). Pulse-level beam-switching for terahertz networks. *Wireless Networks*, 25(6), 3047–3062.
51. Deuschmann, B.J., Wilding, T., Larsson, E.G., & Witrisal, K. (2022). Location-based initial access for wireless power transfer with physically large arrays. In: 2022 IEEE International Conference on Communications Workshops (ICC Workshops), pp. 127–132. IEEE.
52. Zhang, T., Wang, Y., Ouyang, M., Xing, L., & Gao, F. (2024). Third-party camera aided beam alignment real-world prototype for mmwave communications. In: 2024 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–6. IEEE.
53. Wu, D., Zeng, Y., Jin, S., & Zhang, R. (2023). Environment-aware hybrid beamforming by leveraging channel knowledge map. *IEEE Transactions on Wireless Communications*, 23(5), 4990–5005.
54. Zheng, K., Yang, H., Ying, Z., Wang, P., & Hanzo, L. (2023). Vision-assisted millimeter-wave beam management for next-generation wireless systems: Concepts, solutions, and open challenges. *IEEE Vehicular Technology Magazine*, 18(3), 58–68.
55. Arnold, M., Major, B., Massoli, F.V., Soriaga, J.B., & Behboodi, A. (2024). Vision-assisted digital twin creation for mmwave beam management. arXiv preprint arXiv:2401.17781.
56. Ma, W., Qi, C., & Li, G. Y. (2020). Machine learning for beam alignment in millimetre wave massive mimo. *IEEE Wireless Communications Letters*, 9(6), 875–878.
57. Chafaa, I., Belmega, E.V., & Debbah, M. (2020). Exploiting channel sparsity for beam alignment in mmwave systems via exponential learning. IEEE International Conference on Communications Workshops (ICC Workshops). IEEE.
58. Lin, C.H., Kao, W.C., Zhan, S.Q., & Lee, T.S. (2019). Bsnnet: A deep learning-based beam selection method for mmwave communications. IEEE 90th Vehicular Technology Conference (VTC2019-Fall). IEEE.
59. Arvinte, M., Tavares, M., & Samardzija, D. (2019). Beam management in 5g nr using geolocation side information. 53rd Annual Conference on Information Sciences and Systems (CISS). IEEE.
60. Heng, Y., & Andrews, J. G. (2021). Machine learning-assisted beam alignment for mmwave systems. *IEEE Transactions on Cognitive Communications and Networking*, 7(4), 1142–1155.
61. Lazarev, V., & Fokin, G. (2020). Beamforming and spatial multiplexing performance evaluation in 5g ultra-dense networks. In: International Youth Conference on Electronics, Telecommunications and Information Technologies: Proceedings of the YETI 2020, St. Petersburg, Russia, pp. 709–717. Springer.
62. Wang, Z., Shan, W., Zhang, L., Ma, S., Xiao, M., Wei, N., & Li, S. (2022). Intelligent beam training with deep convolutional neural network in mmwave communications. GLOBECOM 2022-2022 IEEE Global Communications Conference. IEEE.
63. Vankayala, S.K., Kumar, S., Thirumulanathan, D., Mathur, A., Yoon, I. S., & Kommineni. (2022). Deep-learning based beam selection technique for 6g millimeter wave communication. IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC). IEEE.
64. Ktari, A., Ghauch, H., & Rekaya, G. (2022). Matrix factorization for blind beam alignment in massive mmwave mimo. IEEE Wireless Communications and Networking Conference (WCNC). IEEE.
65. Heng, Y., Mo, J., & Andrews, J. G. (2022). Learning site-specific probing beams for fast mmwave beam alignment. *IEEE Transactions on Wireless Communications*, 21(8), 5785–5800.
66. Heng, Y., & Andrews, J.G. (2022). Grid-less mmwave beam alignment through deep learning. GLOBECOM 2022-2022 IEEE Global Communications Conference. IEEE.
67. TNarengerile, T.J., Patras, P., & Ratnarajah, T. (2022). Deep reinforcement learning-based beam training with energy and spectral efficiency maximisation for millimetre-wave channels. *EURASIP Journal on Wireless Communications and Networking* 2022(1), 110
68. Duan, Q., Kim, T., Ghauch, H., & Wong, E.W. (2020). Enhanced beam alignment for millimeter wave mimo systems: A kolmogorov model. GLOBECOM 2020-2020 IEEE Global Communications Conference. IEEE.

69. Yang, P., Wu, W., Zhang, N., Shen, X., Yang, P., Wu, W., & Shen, X. (2021). Machine learning-based beam alignment in mmwave networks. *Millimeter-Wave Networks: Beamforming Design and Performance Analysis*, 37–71.
70. Dreifuerst, R.M., & Heath, R.W. (2024). Hierarchical ml codebook design for extreme mimo beam management. *IEEE Transactions on Machine Learning in Communications and Networking*.
71. Krunz, M., Aykin, I., Sarkar, S., & Akgun, B. (2023). Online reinforcement learning for beam tracking and rate adaptation in millimeter-wave systems. *IEEE Transactions on Mobile Computing*, 23(2), 1830–1845.
72. Ozmat, U., Yazici, M. A., & Demirkol, M. F. (2023). Secure initial access and beam alignment using deep learning in 5g and beyond systems. *IEEE Access*, 12, 46–59.
73. Dinh-Van, S., Mo, Y.K., Zidan, J., Fowler, D.S., Evans, A., Higgins, M.D., et al. (2024). Rapid beam training at terahertz frequency with contextual multi-armed bandit learning. In: 2024 IEEE International Conference on Industrial Technology (ICIT), pp. 1–7. IEEE.
74. Xue, Q., Guo, J., Zhou, B., Xu, Y., Li, Z., & Ma, S. (2023). Ai/ml for beam management in 5g-advanced. arXiv preprint [arXiv:2309.10575](https://arxiv.org/abs/2309.10575)
75. Yang, J., Zhu, W., Tao, M., & Sun, S. (2023). Hierarchical beam alignment for millimeter-wave communication systems: A deep learning approach. *IEEE Transactions on Wireless Communications*, 23(4), 3541–3556.
76. Dantas, Y., Iturria-Rivera, P.E., Zhou, H., Bavand, M., Elsayed, M., Gaigalas, R., & Erol-Kantarci, M. (2023). Beam selection for energy-efficient mmwave network using advantage actor critic learning. In: ICC 2023–IEEE International Conference on Communications, pp. 5285–5290. IEEE.
77. Mohsenivatani, M., Ali, S., Rajatheva, N., & Latva-Aho, M. (2023). Deep contextual bandits learning-based beam selection for mmwave mimo systems. In: 2023 IEEE International Mediterranean Conference on Communications and Networking (MeditCom), pp. 211–216. IEEE.
78. Shah, S. H. A., & Rangan, S. (2023). Lstm-aided selective beam tracking in multi-cell scenario for mmwave wireless systems. *IEEE Transactions on Wireless Communications*, 23(2), 890–907.
79. Sheng, Y., Xu, J., & Tao, X. (2023). A two-stage prediction-based beam selection algorithm in mmwave massive mimo systems. In: 2023 IEEE 34th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), pp. 1–6. IEEE.
80. Hegde, D.N., Sarajlic, M., Sarkar, A., et al. (2023). Machine learning (ml)-assisted beam management in millimeter (mm) wave distributed multiple input multiple output (d-mimo) systems. arXiv preprint [arXiv:2401.05422](https://arxiv.org/abs/2401.05422)
81. Huang, H., Gui, G., Gacanin, H., Yuen, C., Sari, H., & Adachi, F. (2023). Deep regularized waveform learning for beam prediction with limited samples in non-cooperative mmwave systems. *IEEE Transactions on Vehicular Technology*, 72(7), 9614–9619.
82. Zheng, K., Yang, H., Ying, Z., Wang, P., & Hanzo, L. (2023). Vision-assisted millimeter-wave beam management for next-generation wireless systems: Concepts, solutions, and open challenges. *IEEE Vehicular Technology Magazine*, 18(3), 58–68.
83. Xiao, Z., Chen, S., & Zeng, Y. (2024). Simultaneous multi-beam sweeping for mmwave massive mimo integrated sensing and communication. *IEEE Transactions on Vehicular Technology*, 73(6), 8141–8152.
84. Chen, K., Qi, C., Dobre, O. A., & Li, G. Y. (2023). Simultaneous beam training and target sensing in isac systems with ris. *IEEE Transactions on Wireless Communications*, 23(4), 2696–2710.
85. Chen, W., Li, L., Chen, Z., Liu, Y., Ning, B., & Quek, T. (2024). Isac-enabled beam alignment for terahertz networks: Scheme design and coverage analysis. *IEEE Transactions on Vehicular Technology*.
86. Cui, Y., Nie, J., Cao, X., Yu, T., Zou, J., Mu, J., & Jing, X. (2024). Sensing-assisted high reliable communication: A transformer-based beamforming approach. *IEEE Journal of Selected Topics in Signal Processing*.
87. Jiang, H., Wang, Z., & Liu, Y. (2024). Sense-then-train: A novel beam training design for near-field mimo systems. arXiv preprint [arXiv:2402.15634](https://arxiv.org/abs/2402.15634)
88. Li, L., Chen, W., Chen, Z., Hu, T., Mei, W., & Ning, B. (2024). Enhancing terahertz communications coverage with isac-assisted beam management. *IEEE Wireless Communications*, 31(1), 34–40.
89. Tariq, S., Arfeto, B.E., Khalid, U., Kim, S., Duong, T.Q., & Shin, H. (2024). Deep quantum-transformer networks for multi-modal beam prediction in isac systems. *IEEE Internet of Things Journal*.
90. Yanpeng, C., Qixun, Z., Zhiyong, F., Wen, Q., Ying, Z., Zhiqing, W., & Ping, Z. (2024). Sensing-assisted accurate and fast beam management for cellular-connected mmwave uav network. *China Communications*.
91. Chen, H., Liu, L., Xue, S., Sun, Y., & Pang, J. (2023). Active sensing for beam management: A deep-learning approach. In: 2023 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–6. IEEE.
92. Jiang, T., Sohrabi, F., & Yu, W. (2023). Active sensing for two-sided beam alignment and reflection design using ping-pong pilots. *IEEE Journal on Selected Areas in Information Theory*, 4, 24–39.
93. Yang, J., Wen, C.-K., Yang, X., Xu, J., Du, T., & Jin, S. (2023). Multi-domain cooperative slam: The enabler for integrated sensing and communications. *IEEE Wireless Communications*, 30(1), 40–49.
94. Li, Y. N. R., Gao, B., Zhang, X., & Huang, K. (2020). Beam management in millimeter-wave communications for 5g and beyond. *IEEE Access*, 8, 13282–13293.
95. Wang, X., Kong, L., Kong, F., Qiu, F., Xia, M., Arnon, S., & Chen, G. (2018). Millimeter wave communication: A comprehensive survey. *IEEE Communications Surveys & Tutorials*, 20(3), 1616–1653.
96. Yi, W., Zhiqing, W., & Zhiyong, F. (2024). Beam training and tracking in mmwave communication: A survey. *China Communications*.
97. Khan, M. Q., Gaber, A., Schulz, P., & Fettweis, G. (2023). Machine learning for millimeter wave and terahertz beam management: A survey and open challenges. *IEEE Access*, 11, 11880–11902.
98. Khan, M. Q., Gaber, A., Schulz, P., & Fettweis, G. (2023). Machine learning for millimeter wave and terahertz beam management: A survey and open challenges. *IEEE Access*, 11, 11880–11902.
99. Häger, S., Sabbah, B., & Wietfeld, C. (2024). Design aspects for efficient beam training in 6g millimeter-wave networks with mobile users. cni.etit.tu-dortmund.de.
100. Ning, B., Wang, P., Li, L., Chen, Z., & Fang, J. (2022). Multi-ris-aided multi-user mimo in mmwave/thz communications: A space-orthogonal scheme. *IEEE Transactions on Communications*, 70(12), 8138–8152.
101. Heng, Y., & Andrews, J.G. (2022). Grid-less mmwave beam alignment through deep learning. *GLOBECOM 2022–2022 IEEE Global Communications Conference*. IEEE.
102. Klautau, A., González-Prelcic, N., & Heath, R. W. (2019). Lidar data for deep learning-based mmwave beam-selection. *IEEE Wireless Communications Letters*, 8(3), 909–912.
103. Jain, J.K., & Chauhan, D. (2023). Innovative model of internet of things for industrial applications. In: *Opportunities and Chal-*

- lenges of Industrial IoT in 5G and 6G Networks, pp. 95–118. IGI Global, ???.
104. Myers, N. J., Mezghani, A., & Heath, R. W. (2018). Swift-link: A compressive beam alignment algorithm for practical mmwave radios. *IEEE Transactions on Signal Processing*, *67*(4), 1104–1119.
 105. Candès, E. J. (2006). Compressive sampling. *Proceedings of the International Congress of Mathematicians.*, *3*, 1433–1452.
 106. Cousik, T.S., Shah, V.K., Erpek, T., Sagduyu, Y.E., & Reed, J.H. (2022). Deep learning for fast and reliable initial access in ai-driven 6g mm wave networks. *IEEE Transactions on Network Science and Engineering*.
 107. Ma, K., Wang, Z., Tian, W., Chen, S., & Hanzo, L. (2021). Deep learning for beam-management: State-of-the-art, opportunities and challenges. arXiv preprint arXiv:2108.04551.
 108. Sutton, R.S., & Barto, A.G. (2018). Reinforcement Learning: An Introduction. MIT press, ???.
 109. Saravanan, R., & Sujatha, P. (2018). A state of art techniques on machine learning algorithms: a perspective of supervised learning approaches in data classification. In: 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 945–949. IEEE.
 110. LeCun, Y., Bengio, Y., & Hinton, G. (2015). *Deep learning. nature*, *521*(7553), 436–444.
 111. Chowdhury, M.Z., Shahjalal, S., Ahmed, M., & Jang, Y.M. (2020). 6g wireless communication systems: Applications, requirements, technologies, challenges, and research directions. *IEEE Open Journal of the Communications Society*, *1*, 957–975
 112. Huang, C., Hu, S., Alexandropoulos, G. C., Zappone, A., Yuen, C., Zhang, R., & Debbah, M. (2020). Holographic mimo surfaces for 6g wireless networks: Opportunities, challenges, and trends. *IEEE Wireless Communications*, *27*(5), 118–125.
 113. Khan, M. Q., Gaber, A., Schulz, P., & Fettweis, G. (2023). Machine learning for millimeter wave and terahertz beam management: A survey and open challenges. *IEEE Access*, *11*, 11880–11902.

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