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6G PHY: Insights From 6G-ANNA Research Initiative

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ABSTRACT The sixth generation (6G) of wireless networks is envisioned to achieve far beyond the capabilities of fifth generation (5G), necessitating significant innovations at the physical layer (PHY). These include exploration of several fundamental trade-offs between spectral efficiency, reliability, and energy consumption, and enhancing the performance of key enablers for 6G PHY. This paper synthesizes key insights from the 6G-ANNA research initiative on emerging PHY technologies for 6G to provide a holistic exploration of the ongoing trends in the 6G research. The investigations span novel waveform and channel coding techniques for improved energy efficiency, the “Gearbox PHY” concept for adaptive transceiver operations, and optimized radio transceiver designs that balance complexity and power consumption. The study also examines advanced multiple access schemes and cell-free massive multiple-input multiple-output (MIMO) architectures to enhance spectral efficiency and uniform coverage. Integrated artificial intelligence (AI) solutions at the PHY layer and insights to security and trustworthiness challenges in 6G networks are also provided. The findings offer insights into the fundamental trade-offs and provide several key PHY innovations that address sustainability, capacity, and resiliency challenges of future 6G wireless systems.

INDEX TERMS 6G, PHY, energy efficiency, capacity, trustworthiness, AI integration.

I. INTRODUCTION

THE ADVENT of sixth generation (6G) wireless communication networks promises transformative advancements that extend far beyond the capabilities of their predecessors. While fifth generation (5G) networks are still being deployed globally, research and development efforts for 6G are intensifying to meet the anticipated demands of the future digital landscape. The ambitious vision of 6G relies on several core principles that will guide its development. *Sustainability* emphasizes minimizing environmental impact and ensuring efficient resource utilization throughout the network lifecycle [1]. *Trustworthiness* entails robust security mechanisms to protect user privacy and prevent cyberattacks in a world of ever-increasing interconnectedness [2]. *Digital inclusion* focuses on bridging the digital divide, ensuring equitable access to 6G's benefits for all, regardless of location or socioeconomic status [3]. These principles necessitate significant advancements in the physical layer (PHY) to meet diverse network requirements, support new use cases, and introduce new verticals. Consequently, there is a growing inclination towards flexible and reconfigurable radio designs [4], [5]. However, achieving such flexibility introduces considerable design and operational complexities, driven by several fundamental trade-offs.

1. Spectrum Scarcity vs High Data-rate Applications: With the rise of the tactile Internet and immersive applications such as virtual reality (VR) and augmented reality (AR), requirements for data rates, end-to-end latency, and reliability are increasing drastically [3]. One straightforward solution to enhance data rates is to expand the available spectrum. However, the spectrum scarcity persists even after the allocation of frequency range (FR) 1 and 2 bands in 5G. High-frequency bands in FR2 suffer from high path loss, making it a bigger challenge to provide coverage in macrocellular environments [6]. Moreover, expanding frequency bands is only part of the solution. Addressing the escalating data rate demand also requires introducing measures that target reduced data rate consumption, a concept referred to in sustainability contexts as sufficiency [7], [8]. Sufficiency involves optimizing network usage to prevent unnecessary data transmission and encourages efficient practices among users and applications. By implementing advanced data compression techniques, edge computing, and intelligent data management, networks can alleviate pressure on spectral resources while promoting energy efficiency (EE) [9].

2. Spectral Efficiency and Reliability vs Energy Efficiency: As mentioned previously, scarcity of spectrum forces wireless communications researchers to focus on increasing spectral efficiency (SE), to get the best out of the available spectrum resources. However, one of the primary challenges in mobile networks is managing the trade-off between SE and EE. SE, defined as the maximum data rate per unit bandwidth, is crucial for meeting the growing demand for high data-rate services. However, increasing SE often requires more sophisticated modulation schemes and higher power consumption, which can significantly impact EE [10]. Similar to spectral efficiency, reliability is also inversely related to EE. The most fundamental method of increasing reliability is to transmit redundant bits and increase the signal-to-noise ratio (SNR). Both of them come at the price of increased energy requirements. However, contradictory to this, in sub-THz bands, while they suffer even higher path loss than the rest of FR2, the availability of huge contiguous bandwidth means that even low-spectral-efficiency waveforms can still deliver multi-gigabit data rates over short, highly-directive links [11].

3. Network Densification vs Operational Cost: Network densification, which involves the deployment of a large number of small cells in a given area, is a possible way to meet the growing data traffic. In theory, an ultra-dense network (UDN) can boost throughput by cell-splitting gains and improved coverage. In practice, however, achieving UDN-scale densification has proven exceedingly difficult on a global scale. Most cellular networks today remain far from the UDN regime and are still largely coverage-limited rather than truly capacity-dense [12]. The main constraints to dense 6G and beyond deployments can be summarized as follows:

- Deploying a multitude of small cell sites is expensive. Crucially, small cells have not proven significantly cheaper per site than macrocells once all costs are factored in. Major expenses include site rental or leasing, backhaul provisioning, and the expenses for installation and integration. These expenses do not scale down proportionally with size and in many markets they are nearly as high as for a full macro tower [12], [13].
- Mobile network operators are also understandably reluctant to undertake another massive infrastructure overhaul so soon after the 5G roll-outs. They require a clear, near-term return on investment before immediately funding tens of thousands of additional small cells [14].
- There is a clear need for maximizing the use of existing macro sites (e.g., through spectrum refarming or tower colocation) over aggressive small-cell densification. Notably, interest in outdoor small cells has been muted in recent years – in the US, only about 198,000 outdoor small cells were operational by the end of 2024, far below early forecasts of 800,000 by 2026 [15].

To overcome these challenges and provide some key 6G features to the users, several technology drivers are currently being explored.

1. New waveforms and baseband processing: The evolution of waveforms and baseband processing is critical to meet the diverse requirements of 6G networks, especially in terms of flexibility, efficiency, and reliability. Unlike the traditional orthogonal frequency division multiplexing (OFDM), new waveforms aim to reduce further the limitations associated with spectral efficiency, latency, and power consumption. It is important to stress that the adoption of a new waveform is a major undertaking and hence requires a compelling justification in terms of improved key performance indicators and applicability to relevant use cases.

2. Cell-free massive MIMO (CF-mMIMO): One of the major limitations of this technology is the stringent information exchange requirements initially proposed for these distributed network architectures. Building on significant advancements in massive multiple-input multiple-output

TABLE 1. Synergies between Open RAN and 6G.

Aspect	Open RAN Contribution	6G Vision	Intersection / Benefit
Enhanced flexibility and modularity	Promotes disaggregation of RAN components (e.g., RRU, DU, CU), allowing for more flexible and vendor-neutral deployment.	Anticipates diverse, flexible network architectures to handle varied use cases, such as ultrafast speeds, ultra-low latency, and massive device connectivity.	Open RAN can provide 6G with the flexibility required to handle the Network of Networks, seamlessly integrating diverse sub-networks and adapting to application-specific needs [20], [21].
AI integration	Supports AI-based applications like xApps and rApps in the RIC, to optimize network functions, manage traffic, and enhance EE.	6G is expected to leverage AI at all network layers to enable self-optimizing networks.	6G could significantly benefit from Open RAN's RIC and xApp, rApp frameworks to introduce data-driven intelligence, enabling near-real-time adjustments to changing network conditions [22].
EE	Provides a pathway for implementing energy-saving algorithms by separating hardware and software, thus allowing dynamic adjustment of resources.	Prioritizes green technologies and energy-efficient architectures as a core requirement.	Open RAN architecture can provide an alternative path for 6G to meet EE goals through energy-aware xApps, which could, for example, dynamically power down network elements based on traffic load [23].
Dynamic and heterogeneous networking	Facilitates integration of multiple types of RANs, allowing for more heterogeneous networks.	Anticipates a complex mix of terrestrial and non-terrestrial networks.	Open RAN can be the foundation for this dynamic mix in 6G by enabling different RAN types to coexist and collaborate efficiently in a unified architecture [24].
Security and privacy	Focuses on transparency and collaboration but raises concerns about security due to its open interfaces.	Demands ultra-secure networks to handle data privacy challenges, especially with the proliferation of IoT.	Open RAN can help realize 6G security objectives by allowing secure, fine-grained control through AI-driven applications, although there will be a need for strong security measures for these open interfaces [25].

(MIMO) systems, researchers have refined the concept of CoMP in recent years, leading to the modern view of cell-free systems. In these systems, signal processing tasks are divided between remote control units and multiple access points, aiming to minimize the required information exchange across the network. In particular, in ultra-dense cell-less systems, users are more likely to be located near an access point, offering opportunities to employ low-complexity and cost-effective hardware implementation compared to that used in base stations of traditional cellular networks. Combined with techniques to deactivate unused access points, cell-less systems have the potential to not only provide uniform quality-of-service to all users, but also to reduce the overall energy consumption. Despite these benefits, several challenges remain, including determining effective cooperative strategies among distributed units, addressing synchronization issues necessary for coherent combining, and implementing these solutions in open network architectures [12].

3. Deep artificial intelligence (AI) integration: The specific use cases of AI in the PHY layer still remain an evolving research area, but it is quite evident that AI-based methodologies hold significant promise for improving various aspects of PHY functionalities. This potential stems from AI‘s capacity to extract insights from large, complex datasets that will become increasingly abundant in 6G networks. For example, it is shown that data-driven approaches can be useful in mitigating hardware impairments in transceiver components [16], [17], [18]. Furthermore, the increasing scale and heterogeneity of network traffic data in 6G may offer an excellent opportunity for AI techniques to play an instrumental role in enabling proactive and adaptive strategies. These strategies could, in principle, address resource management challenges under diverse operational constraints [19].

4. Open-RAN: The typical RAN distribution mechanism consists of a single box with locked internal interfaces that are controlled by the vendor. The base station operations are divided into a centralized unit (CU), a distributed unit (DU), and a remote unit (RU) as we move toward Open RAN. These units are connected via open interfaces. Multiple manufacturers can utilize the Open RAN technique to build those entities because of the open interfaces (like open fronthaul) between them. The RAN intelligent controller (RIC), which is separated from the processing units and makes it possible to provide management functions like radio resource management and self-organizing networking, is also an essential part.

Open RAN and 6G share a common goal of creating more flexible, efficient, and intelligent wireless networks. A summary of how these two concepts intersect and support each other is provided in Table 1.

A. CONTRIBUTIONS

This paper synthesizes key technical outcomes and observations from the 6G-ANNA research project to identify PHY design directions for 6G. These span several critical aspects of PHY innovation for 6G wireless systems:

- Explores innovative waveform designs and advanced channel coding strategies tailored to significantly enhance EE in 6G networks. It highlights new waveform proposals beyond traditional OFDM, optimized for integrated communication and sensing, ultra-low-power IoT, and sub-THz frequency band applications.
- Provides a holistic assessment of energy-efficient designs across waveforms, transceiver architectures, and front-end hardware components.
- Analyzes multiple access techniques and CF-mMIMO, emphasizing their potential to support diverse quality of service requirements, enhance spectral efficiency, and handle massive connectivity scenarios typical in 6G environments.
- Provides strategies to optimize distributed beamforming and resource allocation using long-term channel statistics, significantly improving uniform user coverage and EE.
- Introduces innovative PHY security techniques, including the utilization of frequency-diverse arrays (FDA) and reconfigurable intelligent surface (RIS) to achieve robust confidentiality and protection against physical-layer threats.
- Explores several AI integrations at the physical layer, encompassing generative modeling for accurate channel estimations, predictive analytics for interference management, hybrid domain-aware machine learning, and reinforcement learning for adaptive parameter tuning.

The relationships among the key challenges and fundamental trade-offs for future PHY, the enabling technologies that require further investigation, and the practical constraints that limit their realization are summarized in Fig. 1. Building on this map, the rest of the paper presents promising research directions from the 6G-ANNA project, highlighting implementable pathways to translate these enablers into practical 6G PHY designs.

B. PAPER ORGANIZATION

The remainder of this article is organized as follows. Section II provides the practical challenges of key 6G techniques from a systems perspective. Section IV provides the findings on EE from the project perspective. Several promising techniques and findings on capacity and coverage enhancement are discussed in Section V. Methods to achieve a secure PHY are summarized in Section VI. AI algorithms for 6G and several use cases are studied in Section VII. Future research directions are provided in Section VIII, and finally, Section IX concludes the paper.

II. SYSTEM PERSPECTIVE FOR 6G PHY

The (cellular) communication networks form the core of the connection between users and the Internet, and, thus, play a key role in the deployment of current and new services [8]. A smooth introduction of 6G, enabling fast deployment of standalone 6G is of great practical importance because it eliminates the need to launch multiple versions of 6G. Therefore, as the foundation of the cellular network, PHY design must address several system-level trade-offs in evolving from 5G to 6G that will shape network capacity, efficiency, and complexity. This section outlines key challenges and design decisions from a systems perspective, highlighting open problems for 6G PHY.

A. D-MIMO VS. SMALL CELLS

Distributed MIMO (D-MIMO) - often realized as cell-free massive MIMO offers a new network paradigm for dense 6G deployments. Rather than splitting coverage into many small cells, D-MIMO uses geographically distributed antennas that jointly serve users without cell boundaries. This approach can significantly improve uniformity of service and capacity at the cell edges [26]. For instance, fully cooperative D-MIMO has been shown to boost edge user throughputs by 5$\times$ or more compared to a traditional uncoordinated small-cell network [27]. The network capacity in dense areas can therefore be increased via diversity and spatial multiplexing in D-MIMO.

However, these gains come with significant system-level trade-offs. D-MIMO relies on phase-synchronous joint transmission from many access points, demanding rigorous time/frequency synchronization and calibration across the

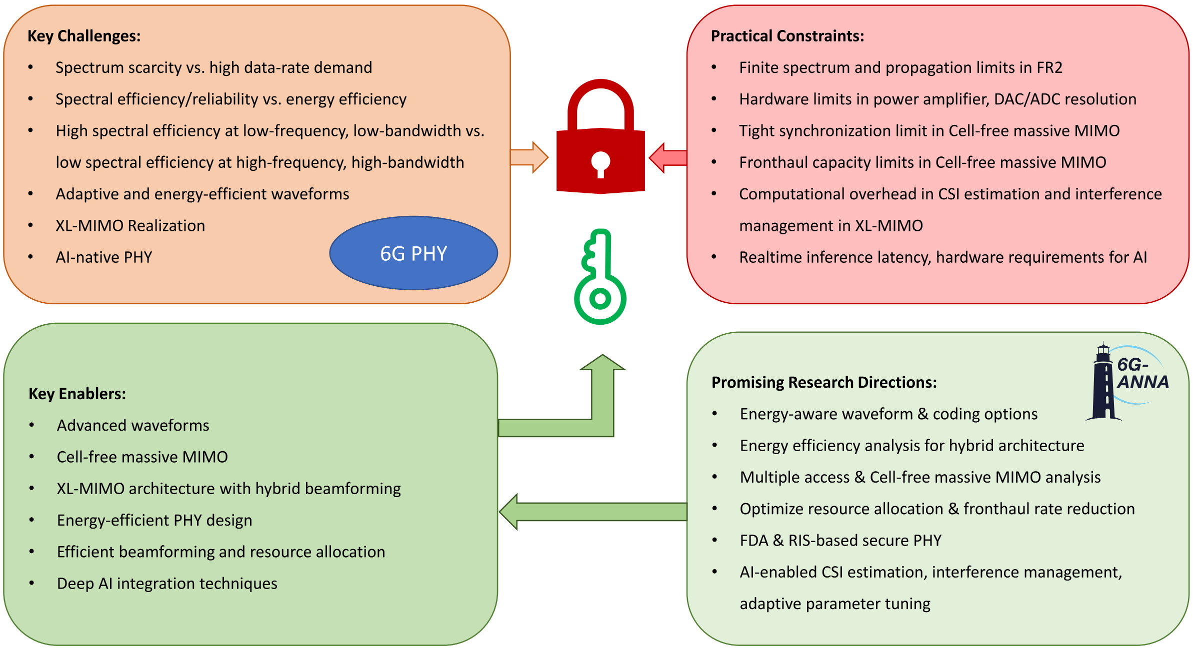


FIGURE 1. **Mapping of key challenges and fundamental trade-offs for 6G PHY, technology enablers requiring further investigation, practical constraints limiting their adoption, and promising research directions derived from the 6G-ANNA outcomes synthesized in this manuscript.**

network [28]. It also requires a high-bandwidth, low-latency fronthaul network to connect distributed antennas to a CU for coordination [26]. In practice, deploying fiber or equivalent fronthaul to numerous distributed radios can be expensive, and any fronthaul latency or capacity limitations directly degrade the D-MIMO benefits. Cost and complexity are thus major concerns – each additional distributed antenna adds not only hardware cost but also overhead for coordination algorithms (e.g., joint precoding and interference cancelation) and channel state exchange. Moreover, the synchronization requirements pose challenges in real deployments, as any timing error or phase noise can degrade the joint beamforming gains. In contrast, ultra-dense small cells (each serving its own users independently) are simpler to deploy incrementally, but suffer inter-cell interference and handover overhead in dense scenarios. Users at cell edges experience highly variable performance in such networks. D-MIMO essentially generalizes the small-cell concept by adding strong cooperation to mitigate inter-cell interference and eliminating edge effects [12]. The trade-off is that D-MIMO shifts complexity from the devices to the network infrastructure. Ongoing 6G research is coming up with efficient solutions for these challenges [29].

B. HIGH SPECTRAL EFFICIENCY VS LARGER BANDWIDTH

A fundamental design question for the 6G physical layer is whether to seek capacity gains through higher spectral efficiency, much larger bandwidths, or both. On one hand, advanced multi-user MIMO and massive MIMO techniques can multiply spectral efficiency by serving many users and streams concurrently in the same band. Massive MIMO in 5G has already demonstrated spectral efficiency improvements on the order of $10 - 20\times$ over single-antenna systems, and even larger gains are expected in the 6G by scaling up the number of antennas and spatial multiplexing layers [30]. This approach makes the most of scarce spectrum below 6 GHz, squeezing more bits per Hz through spatial processing and higher-order modulation. Extremely large antenna arrays, also known as XL-MIMO or Extreme MIMO, are a research direction to further boost spectral efficiency in 6G, potentially operating in near-field regimes and supporting more simultaneous beams [31]. However, pushing spectral efficiency to extreme levels runs into diminishing returns and practical issues: channel hardening and multiplexing gains plateau if user channels become correlated or if channel state information is imperfect. Moreover, achieving very high per-user spectral efficiencies demands very high SNR and linearity. For example, operation at 4096-quadrature amplitude modulation (QAM) would require more than 30 dB SNR in practice, which is unrealistic in many mobile channels due to propagation loss and device power limits [32]. Thus, purely pursuing spectral efficiency with massive MIMO and high-order modulation can be impractical beyond a point, and it also entails significant signal processing complexity and overhead for channel estimation or feedback to manage a large number of antenna ports.

On the other hand, tapping into wider bandwidths offers an orthogonal path to higher capacity. By moving into higher frequency bands, 6G can access new spectrum—for example, the emerging FR3 between 7–24 GHz is expected to provide abundant new bandwidth for 6G. Early 6G visions also foresee combining low/mid bands (for coverage) with mmWave/sub-THz bands (for capacity bursts). The trade-off is that at very high frequencies, propagation is challenging (higher path loss, susceptibility to blockages), and the coverage area of each cell shrinks. Thus, leveraging large bandwidth often requires deploying many small cells or narrow beams, which circles back to the densification issue [32]. Additionally, very wide bandwidth signals demand high-performance RF front-ends and analog-to-digital (ADC), digital-to-analog (DAC) converters; the hardware complexity and power consumption grow with bandwidth. Channel estimation across wide bandwidths can also become difficult if channel frequency selectivity is high or if the receiver must process gigantic fast Fourier transform (FFT) sizes in an OFDM system. These issues necessitate careful standardization – for instance, 5G NR already introduced scalable numerologies up to 960 kHz subcarrier spacing to support 2 GHz-wide channels in FR2. For 6G, even larger FFT sizes (e.g., 8k FFT) and new numerologies are being considered to handle multi-GHz bandwidth carriers [33].

Overall, 6G radio access should be able to utilize the entire spectrum range available for 5G, including new 3GPP frequency ranges. In particular, it is desirable to extend legacy spectrum assets in FR1/FR2 with the new FR3 so that a 6G-connected user equipment (UE) may have better performance than a 5G UE at the same location. This means that 6G must be able to use new FR3 bands together with the legacy frequency division duplex (FDD) and time division duplex (TDD) bands below 7 GHz to improve throughput aggregation and performance for 6G UEs [34]. During the period of migration from 5G to 6G, a radio network may run several radio access technologies (RAT) on the same carrier and thereby make it accessible to both legacy and new 6G UEs. Thus, efficient spectrum sharing between 5G and 6G in low and mid-bands is essential. In particular, a 6G PHY supporting multi-RAT deployment should have the following characteristics:

1) It should be transparent to legacy UEs so that they can operate as intended.
2) It should have a minor impact on the new 6G UEs so that the cost and complexity increases required to support multi-RAT deployments are low.
3) It should allow largely independent evolution of the 5G and 6G RATs to avoid cross-dependencies that imply additional cost and complexity.
4) It must support high spectrum efficiency, given that spectrum is a scarce and very valuable resource.
5) It should enable partial re-use of the FR1/FR2 baseband processing in the new 6G frequency bands, especially in the centimeter-wave bands, to reduce the cost and time to market.

C. ENERGY EFFICIENCY TRADE-OFFS IN THE PHY

Energy performance is key in 6G and must be considered for the design of the 6G PHY. Optimizing energy performance means minimizing the energy consumption for a set of performance requirements (throughput, capacity, latency, etc.). An energy-efficient standard can enable low energy-consuming operation by creating opportunities to deactivate hardware components in the radio transceivers. In this regard, it is important to observe that the 5G standard differs from earlier generations in that the physical layer is designed to enable very low energy consumption when the traffic is low. It utilizes a so-called lean design [35], [36] of the physical layer, where as few broadcast signals as possible are transmitted when there is no data. Hence, 5G transceivers can enter low-energy-consuming modes when there is low traffic in the network. The lean design has been a great success, and therefore it is natural to build on that success. Hence, a pragmatic approach to EE in 6G is based on protocols and physical channels that enable abundant silent periods by means of the following design principles.

1) The necessary control and signaling information broadcasted by the network, such as synchronization signals, must be as sparse as possible, in the temporal, frequency and spatial domains. We stress the fact that 5G has a lean design that already fulfils the criterion of sparse essential signaling in the time domain, and 6G should further make the signals sparse in the frequency domain (e.g., minimize the number of carriers used to broadcast essential signals) and in the spatial domain (e.g., minimize the number of beams or number of transmission points used to broadcast essential signals).
2) Enhance discontinuous reception (DRX) and discontinuous transmission (DTX) to increase the duration of silent periods, without sacrificing QoS.
3) The physical channels utilize a PHY with high spectrum efficiency that enables the transmission of uplink (UL) and downlink (DL) data at the highest possible rate.

D. XL-MIMO: DIGITAL VS PRACTICAL IMPLEMENTATIONS

Massive MIMO has been a cornerstone of 5G, and 6G is expected to push antenna counts even higher, entering the regime of XL-MIMO. From a systems perspective, the key question is how to implement these large antenna arrays in a practical, cost-effective, and energy-efficient way. In theory, the most flexible approach is fully digital beamforming, where each antenna element has its own RF chain (DAC/ADC, up/down-conversion, etc.), allowing independent control of amplitude and phase per antenna. Fully digital massive MIMO enables optimal spatial multiplexing and precise beamforming (including null-forming to suppress interference). However, as antenna numbers grow into the hundreds or thousands, fully digital architectures become prohibitively expensive and power-hungry. Each RF chain contributes to power consumption (from mixers, frequency synthesizers, data converters, etc.), and having one per antenna can drive the front-end power to impractical levels. The cost scales similarly – hundreds of transceiver chains drastically increase hardware cost and complexity for calibration [31].

For these reasons, current mmWave massive MIMO systems rarely use fully digital beamforming. Instead, they resort to hybrid beamforming architectures, where a smaller number of digital RF chains feed a larger number of analog phase shifters or passive elements. Advances in semiconductor technology (e.g., integrated antenna-on-chip, optical RF interconnects, etc.) may push the boundary of feasible RF chain counts upward, but power dissipation constraints will still play a major role. Researchers are exploring analog beamforming, lens arrays, and even metasurface antennas as means to implement very large apertures more passively. For example, an emerging concept is holographic MIMO or intelligent surfaces, where a continuous surface with many tiny radiating elements is driven by a limited set of feeds [37], [38]. In such cases, the element count can be huge (to get extreme aperture gain), but not every element is independently controlled.

Along this line, severable flexible antenna technologies are proposed in recent times. Notable examples include movable antennas, which enable the physical repositioning of antenna elements in three-dimensional continuous space to optimize channel conditions, providing additional spatial degrees of freedom that can be utilized for diversity and multiplexing in XL-MIMO systems [39]. Fluid antennas, leveraging software-controlled fluidic materials like liquid metals, allow dynamic reconfiguration of shape, size, and radiation patterns, and have the potential to adapt according to 6G scenarios and complexity issues in traditional MIMO setups [40]. Another innovative setup, named pinching antennas, utilizes small dielectric particles placed along waveguides to create controllable radiation points, facilitating strong line-of-sight links [41]. However, all these setups require extensive studies and physical measurements before employing them in 6G. Their inclusion in radio transceivers hinges on the trade-off between implementation complexity and performance gains.

E. WAVEFORMS: OFDM BACKWARD COMPATIBILITY VS. NEW WAVEFORM PROPOSALS

Cyclic prefix-OFDM (CP-OFDM), with a numerology aligned to that of 5G in FR1 and FR2, is a modulation scheme that serves as a foundation for the 6G PHY and fulfills the characteristics mentioned in Sections II-B and II-C. Indeed, by aligning the 5G and 6G numerologies in FR1/FR2, highly efficient 5G-6G sharing is possible, where the scheduler in the network may allocate radio resource elements and coordinate the concurrent operation of 5G and 6G UEs in a manner that is transparent to 5G UEs while only imposing minor constraints on 6G UEs and eliminating complex interdependencies between 5G and 6G. Furthermore, CP-OFDM yields high spectrum efficiency when combined with advanced channel coding, and would facilitate the reuse of baseband processing, such as FFT and demapping modules in 6G baseband units supporting both legacy and new frequency bands.

TABLE 2. Example of 6G OFDM numerology compatible with 5G.

Spectrum range	subcarrier spacing
Low band	15 kHz
Mid-band	30 kHz
6G mid-band (7-15 GHz)	30/60/120 kHz
mmWave	120 kHz
60 GHz	120/480 kHz

Based on the characteristics 1-5 and design principles 1-3 listed in Sections II-B and II-C, both the UE and the network may save power by either turning off or setting to a low power mode their analog and/or digital transceiver circuitry during the silent periods. In other words, based on these principles, 6G would create more opportunities than 5G to deactivate hardware components, which is a proven and effective method to increase the EE of the network without sacrificing network capacity [36].

Another learning from 5G is that there is no need to support multiple subcarrier spacings on the same carrier for data transmission. With this simplification, in 6G only one numerology is used in any given frequency band. The numerology is determined by the deployment scenario.

5G currently supports a 4096-point FFT. 6G could also implement an 8192-point FFT to support larger bandwidths. In 5G the basic time-domain transmission structure is the so-called slot, which comprises 14 OFDM consecutive symbols. Mini-slots were also introduced in 5G to better support low-latency services, analog beamforming, and operation in unlicensed spectrum. A mini-slot transmission occupies only a part of a slot comprising 2, 4 or 7 consecutive OFDM symbols. To simplify and to add more granularity and flexibility to the scheduler, 6G should use one OFDM symbol as its basic time-domain transmission structure. Table 2 gives an example of OFDM numerology for 6G.

Despite the versatility of CP-OFDM, there are 6G innovations for which it may not be suitable, or for which some modifications are desirable. These innovations include integrated communications and sensing (ISAC), ultra-low power IoT, wake-up radios and communications in sub-THz frequency bands. OFDM is not well suited for low-cost, ultra-low-power devices. The large dynamic range, accuracy of the ADC and DAC, and linearity required for an OFDM radio result in both relatively high cost and power consumption. Further, ISAC is another 6G innovation that may benefit from waveforms specially designed for radar. This means that some 6G innovations will require non-OFDM waveforms or modifications to OFDM waveforms. Since OFDM is the foundation of the 6G PHY it is highly desirable to be able to transmit and receive needed non-OFDM or modified OFDM waveforms using radios optimized for OFDM. This reduces the cost and time to market of network equipment, making these innovations more attractive and affordable.

One non-OFDM waveform proposal is orthogonal time frequency space (OTFS) modulation, which places information symbols in the delay-Doppler domain to transform time-varying channels into a quasi-static representation, offering superior robustness to Doppler shifts and delay spreads in high-mobility scenarios such as vehicular or space-air-ground networks [42]. Compared to OFDM, OTFS is particularly suitable for ISAC applications where delay-Doppler representations align with radar sensing [43]. Similarly, there are several other linear waveforms that have gained attention, such as affine frequency division multiplexing (AFDM) [44] and orthogonal chirp division multiplexing (OCDM) [45]. However, most of these can be generated using OFDM, like OTFS, which is a two-dimensional Fourier transform operation over OFDM. This increases computational and equalization complexity, so their trade-off with performance needs to be extensively studied from a systems perspective.

F. RECONFIGURABLE INTELLIGENT SURFACE (RIS)

RIS have emerged as a tantalizing 6G physical layer technology, offering the possibility to engineer the propagation environment itself. An RIS typically consists of a large array of passive reflecting elements whose reflective properties (phase, and sometimes amplitude) can be electronically controlled. By appropriately tuning these elements, an RIS can steer or shape incident electromagnetic waves to, for example, create a strong beam towards a receiver or null out interference. The promise of RIS is to improve coverage and capacity without significantly increasing the power consumption and noise amplification of traditional active nodes [46].

In current networks, coverage in difficult areas (e.g., mmWave dead zones or inside buildings) is often improved by using repeaters or relays. A common solution in 5G mmWave deployments is the use of network-controlled repeaters (NCRs), which are simple active devices that receive, amplify, and forward the signal. Repeaters can be strategically placed to fill coverage holes, but they come with drawbacks: they add noise (since they amplify noise along with signal), consume power for the RF amplification, and can potentially cause feedback or oscillation if not properly isolated. RIS, being mostly passive, introduces no thermal noise of its own and can be almost power-neutral (aside from the minimal power for its control circuitry). In theory, an RIS could achieve similar effects to a repeater without the noise amplification and with very low energy use [47]. Nonetheless, repeaters have the advantage of being relatively straightforward to integrate and were standardized as part of 5G-Advanced (Release 18) to help extend mmWave range.

Simulations and early experiments have shown that RIS can significantly enhance received SNR and even capacity when properly configured. Moreover, RIS can perform more complex wavefront transformations than a simple mirror, potentially focusing signals or even imparting different phases to serve multiple users [48]. Recent works have further underscored the promise of RIS in addressing coverage challenges in dead zones, particularly in challenging environments with signal blockages. For instance, in mmWave integrated sensing and communication networks, it was analyzed through stochastic geometry analysis that deploying distributed RIS can substantially mitigate blockage effects by establishing virtual line-of-sight paths, elevating the joint coverage rate from 67.1% to 92.2%, and providing valuable deployment guidelines for base station densities [49]. Similarly, authors in [50] introduced a RIS-enhanced dual-functional radar-communication system framework, explicitly utilizing RIS to create virtual LoS links in dead zones, thereby enhancing both communication coverage and sensing performance under imperfect channel state information (CSI). In industrial factory settings, ray-tracing models to evaluate RIS-assisted coverage at sub-6 GHz and mmWave frequencies are studied, revealing marked improvements in non-line-of-sight scenarios and affirming RIS's relevance for 5G industrial networks [51]. These advancements collectively position RIS as a compelling, passive technology for extending reliable service into shadowed or obstructed regions.

Despite these theoretical advantages, RIS is still in an early stage of practical development and standardization. In fact, recent 3GPP discussions reveal a cautious approach: RIS was proposed as a study item in Releases 18 and 19, but ultimately it was not taken forward to full specification in those releases. Instead, the focus remained on the simpler NCRs, which were standardized in Rel-18 as they are more mature and immediately needed [52]. Another challenge is how to integrate RIS into the network architecture. Standardization would need to specify how RIS are discovered, how they are coordinated by the base stations (or perhaps a new network entity), and how channel state involving RIS is estimated (possibly new reference signal designs). Currently, there is no consensus yet, which is why RIS remains at a pre-standardization research stage. Researchers have pointed out several practical issues - from the impact of RIS element quantization and narrowband response (many RIS designs work well only for a narrow frequency band) to the need for line-of-sight between transmitter-RIS and RIS-receiver for best results. These must be mitigated or carefully engineered before RIS can deliver robust gains in a cellular setting [53]. To summarize, the key limitations and trade-offs RIS need to overcome are integration challenges, standardization gaps, and trading theoretical capacity gains for added deployment complexity and infrastructure investment. Additional trade-offs include channel estimation and energy consumption overhead vs performance gains.

However, for 6G, the potential of RIS remains significant. If the open problems are solved, RIS could offer a highly cost-effective way to create programmable propagation channels. An RIS panel might be much cheaper and consume orders of magnitude less power than deploying an active small cell, which aligns with 6G principles of EE and cost-effectiveness. Some envisioned use cases include dynamically mitigating interference between links by adjusting reflections, providing PHY security by nulling signals toward potential eavesdroppers, or even combining communication and sensing, where an RIS could be configured to assist localization by focusing signals at objects for radar-like operation [54]. The systems perspective here is that any gains from RIS must justify the added deployment complexity. Rolling out RIS in large numbers means infrastructure investment and a new layer of network control – operators will demand a significant return on investment in terms of capacity or coverage improvement for this to materialize.

G. AI INTEGRATION

6G is treated as the first AI-native wireless generation, where AI and machine learning (ML) are deeply integrated into network design and operation [55]. From a systems perspective, incorporating AI at the PHY offers a way to handle high complexity and non-linear optimizations that are difficult to tackle with traditional analytic methods [56]. However, the integration of AI into 6G PHY is not without challenges. Real-time inference on the edge (e.g., baseband units) requires efficient hardware (ASICs or GPUs) and low latency [57]. There is also the question of reliability – learned components might not have guaranteed worst-case behavior, which is problematic for services like ultra-reliable low-latency communications (URLLC). Therefore, standardization will tread carefully, likely incorporating AI first in non-critical optimization loops or as assistive technology. Indeed, 3GPP has initiated study items on AI for network automation and air interface in Release 18, but mostly focusing on higher-layer aspects [58].

Nonetheless, the vision of an AI-native air interface is strongly advocated by many in the industry. This means the 6G air interface should be designed from the outset to accommodate learning – for example, by exposing radio measurements to learning algorithms, enabling data collection for training, and allowing AI-driven reconfiguration of PHY parameters. Ericsson's design principles for 6G RAN explicitly include "AI-native design" so that AI can be easily applied where it is beneficial [59]. Overall, a truly AI-native PHY demands efficient edge hardware and low-latency inference, with reliability concerns for URLLC due to a lack of worst-case guarantees. Further trade-offs encompass AI performance gains versus explainability for debugging, energy savings against user experience, computation latency vs performance gain, and integration challenges versus broader applications like predictive analytics and non-linear optimization.

III. COMPARISON WITH EXISTING RESEARCH INITIATIVES

Since 2020, the vision for 6G and the concept of key enablers for beyond-5G networks started to emerge. At the same time, regulators started to consider spectrum for 6G experiments; notably, the FCC opened frequencies from 95 GHz to 3 THz for experimental use, paving the way for terahertz communication research. By 2019, the first academic 6G conference had been held and produced a preliminary 6G vision white paper, foreshadowing the direction of future networks. Various research groups worldwide also began publishing "6G vision" papers around 2020–2021, discussing ambitious ideas for the next generation of wireless technology [1], [20], [33], [60], [61], [62], [63], [64], [65], [66], [67]. These early visions highlighted key trends and technical challenges that define the 6G agenda. In academia, multi-institution labs and consortia were formed, such as the 6G Flagship program in Finland, which published a series of thematic white papers in 2020 on topics ranging from machine learning in networks to remote area connectivity and security/privacy in 6G [68].

Industry and government involvement in 6G accelerated quickly after these initial academic moves. Throughout 2020 and 2021, several countries launched formal national 6G programs and public-private partnerships. For instance, Japan convened a governmental 6G strategy panel in early 2020. Europe also ramped up efforts: the European Union's flagship Hexa-X project was kicked off in 2021 as a collaborative platform to develop key 6G technologies [72]. This was soon followed by the Hexa-X-II project [73], and over 30 other EU-funded 6G research projects. The United States formed the Next G Alliance in late 2020, and by 2022–2023, this alliance had released several 6G white papers on themes such as sustainability, new use cases, and technological roadmaps [74]. Several specialized projects were also launched, 6G BRAINS targets AI-driven resource allocation in an industrial cell-free MIMO network, and RISE-6G focuses on RIS for adaptive coverage and localization. While each yields detailed results in its niche, they do not encompass the full breadth of PHY challenges. From 6G ANNA, two recent publications covered the aspects of AI in 6G [75] and the network architecture for 6G [76] and provided a broad overview on these topics, but they did not focus on all the aspects of PHY.

Recent surveys in 2023-2024, such as [69], [70], [71], continue the broad mapping of 6G technologies and use cases, but largely at a conceptual level: they list waveforms, KPIs, sustainability, integrated sensing and communication (ISAC), AI, distributed MIMO systems, and security as priorities—without a unifying, hardware-aware, PHY-level design and evaluation framework. As summarized in Table 3, most existing works address only subsets of these physical-layer domains, often at a high level or in isolation. They identify these elements as important research directions and enumerate potential solutions (e.g., mentioning rate-splitting multiple access and cell-free MIMO as promising for capacity), yet do not provide detailed models or quantitative system evaluations. In other words, even the recent surveys compile individual insights from literature but fall short of integrating them into a unified design.

TABLE 3. Comparison of this work's scope against recent survey papers and flagship EU projects that are active in the same timeframe, showing whether each topic is addressed and the depth of coverage is labeled as conceptual, detailed, or system-level (integrated modeling/prototyping). A cross (✗) means it is largely out of scope.

Technical Category	Recent 6G Surveys e.g., [69], [70], [71]	Hexa-X [72]	6G BRAINS	RISE-6G	This Paper
Waveform design	*conceptual*	*detailed/architectural*	✗	✗	*system-level*
Energy efficiency optimization	*conceptual*	*detailed/architectural*	✗	*detailed*	*system-level*
Adaptive PHY architecture	✗	*conceptual*	✗	✗	*detailed*
End-to-end transceiver modeling	✗	*architectural*	✗	✗	*system-level*
AI/ML in PHY	*conceptual*	*detailed/architectural*	*system-level*	✗	*system-level*
PHY-layer security	*conceptual*	*conceptual*	✗	✗ / *limited*	*detailed*
Sensing-aided PHY (ISAC; RIS-aided sensing)	*conceptual*	*detailed/architectural*	*system-level*	*detailed*	*system-level*
Capacity/coverage enhancement	*detailed-review*	*detailed/architectural*	*system-level*	*RIS-centric*	*system-level*

Notes: "Recent 6G surveys (2023–2024)" refers to representative works such as [69], [70], [71]. Hexa-X and Hexa-X-II operate under the SNS JU umbrella [72], [73]. Depth tags indicate whether coverage is primarily high-level (*conceptual*), provides in-depth technical treatment (*detailed*), or demonstrates integrated modeling (*system-level*). A cross (✗) means it is largely out of scope.

IV. ENERGY-EFFICIENT PHY DESIGN

The global energy consumption of Information and Communication Technology (ICT) is responsible for 4% of electricity usage and 1.4% of GHG emissions in 2020 [77]. Out of this, communication networks are responsible for 1% of the global electricity usage and 0.34% of global annual GHG emissions. Mobile communication networks account for 161 TWh of electricity use, which is 0.7% of global electricity, and 118 MT CO_2 emissions, which are equivalent to 0.22% of the global emissions. Moreover, the trend of power consumption and carbon footprint shows an upward trajectory, and this problematic growth in energy consumption poses a significant environmental and economic challenge. While efficiency, sufficiency, and consistency strategies are needed jointly to address this issue, within the PHY optimization of the EE is most relevant. The EE in communication systems is typically defined as the number of bits transmitted per energy unit. One possible way of mathematically expressing it is SE/power consumption.

A. ENERGY EFFICIENT WAVEFORMS

Phase-modulated continuous wave (PMCW) is a waveform specially designed for radar systems and thus benefits from inherent favorable sensing performance. The modulation scheme is based on direct-sequence spread spectrum (DSSS) with pseudo-random binary sequences (PRBSs) and thus has a low peak-to-average power ratio (PAPR) and higher power efficiency. However, PMCW suffers from shortcomings in communication capability, especially from the aspect of throughput. To solve this issue, a code-orthogonal PMCW (CO-PMCW) approach was proposed in [78], [79]. In the CO-PMCW ISAC systems, the data and pilot are spread by two orthogonal codes and transmitted simultaneously. The pilot sequence can be used at the communications receiver for channel estimation and at the radar receiver for sensing estimation, while the data sequence is independent of radar parameterization, enabling a flexible data sequence design and a higher data rate. In addition, the continuous transmission of the pilot allows the communications receiver to track the channel condition in time, enhancing reliability in dynamic environments. However, the simultaneous transmission scheme inevitably leads to interference between the two sequences, especially for the radar functionality, where a high dynamic range is required. The result in [79] shows a reduction of radar dynamic range and increased sidelobe power, which limits the maximum applicable range of CO-PMCW radar if no further mitigation methods are applied. In conclusion, the CO-PMCW scheme significantly improves the communications performance in throughput and reliability at the expense of radar dynamic range.

B. ENERGY EFFICIENT CHANNEL CODING

In 5G, the channel coding for the shared data channels is based on low-density parity check (LDPC) codes. The data to be transmitted (a so-called transport block) is split into one or more code blocks (CB), a cyclic redundancy check is appended, and each code block is encoded using LDPC. Optionally, CBs are grouped into code block groups (CBG), and feedback indicating whether the decoding is error-free is provided for each CBG. The 5G LDPC decoders employed in both UE and base stations are typically tailor-made hardware accelerators. The 5G LDPC codes could be reused in 6G, due to their excellent performance, and to avoid the need to introduce yet another type of hardware accelerator in communications equipment supporting both 5G and 6G. However, since 6G is expected to support higher data rates than 5G, and at high data rates the power consumption of the LDPC decoders typically increases super-linearly with the clock frequency, it is desirable to design the 6G physical layer processing in a manner that enables parallelism of the decoding as an alternative, or a complement, to increased clock frequency. In this way, the power consumption can be made to scale linearly with the data rate. The 5G protocol stack is already very flexible and enables a degree of

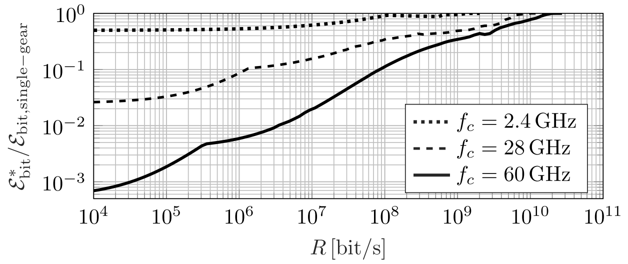


FIGURE 2. Minimum Energy of Gearbox-PHY relative to single-gear QAM [80].

parallelization. For example, in 5G, it is possible to configure the data transmission so that the CBs are mapped to the space-frequency-time radio resources first to a MIMO layer, then in frequency, and last in time, to facilitate prompt decoding of the CBs at the receiver. Further optimizations of the decoding pipeline could be made in 6G. For example, using rate matching if necessary, CBs could be mapped to only one OFDM symbol. The 6G receiver could then start decoding in parallel CBs as soon as each OFDM symbol is received and equalized.

C. ADAPTIVE TRANSCEIVER OPERATION—GEARBOX PHY

Recent studies on data rate distributions have shown that low data rate demands dominate mobile traffic, whereas peak rates occur only rarely [81], [82]. This dominance of low-rate scenarios highlights a promising opportunity to reduce energy consumption by targeting system design towards these more frequent operating conditions through adaptive transceiver operations.

A concept that aims to exploit this variability in data rate demands through adaptive transceiver operation to increase EE is the Gearbox-PHY, introduced in [83]. The Gearbox-PHY dynamically switches between different modulation schemes and their corresponding analog front ends, which are referred to as "gears", based on the current data rate requirements and available system resources. This switching allows the transceiver to operate more efficiently across a wide range of data rate requirements, rather than being optimized solely for peak throughput.

The Gearbox-PHY concept can be formulated as a constrained optimization problem [84], where the objective is to minimize the total energy per successfully transmitted bit, considering both the transmitter and receiver. The primary optimization variables include the transmit power P_{T}, the system bandwidth B, the duty cycle γ (i.e., the ratio of active transmission time to total available transmission time), and the gear selection. Given a required data rate R, the system selects the optimal parameter set that minimizes energy consumption while satisfying all transmission constraints.

To assess the EE of the Gearbox-PHY, the main energy consumers in the analog front end must be considered. These include the power amplifier (PA), the local oscillator (LO), the mixer, the ADC, the DAC, and the low noise amplifier (LNA). The relationship between these components' power consumption and the optimization variables is described in detail in [85] and [80].

The most comprehensive evaluation of the EE gains achievable with the Gearbox-PHY is provided in [80], where the trade-off between oscillator power consumption and phase noise, as modeled in [86], was incorporated into the optimization framework. In this study, the energy per bit achievable with a Gearbox-PHY, capable of switching between different impulse radio schemes and QAM with varying constellation sizes, was compared to a single-gear approach, where the analog front end remains fixed and is optimized for the highest considered QAM constellation size, specifically $M = 256$ QAM. The resulting energy savings are illustrated in Figure 2, demonstrating that the Gearbox-PHY can achieve energy reductions of up to three orders of magnitude at high carrier frequencies, particularly for low data rates at $f_c = 60\,\mathrm{GHz}$. However, at lower carrier frequencies, such as $f_c = 2.4\,\mathrm{GHz}$, the achievable savings are marginal, indicating that a Gearbox-PHY is less necessary for low carrier frequencies.

These findings suggest that while Gearbox-PHY is not essential for lower frequency bands, it becomes increasingly beneficial as mobile networks include higher frequencies in 6G and beyond. This approach offers a solution for meeting EE targets in future networks, ensuring that energy consumption remains manageable while maintaining performance.

D. END-TO-END MODELING OF THE TRANSCEIVER

The EE of massive MIMO systems is closely tied to the total power consumption of various hardware components, with the PA being the primary contributor at the transmitter and ADC at the receiver [87]. Besides PAs, other hardware components like DACs and ADCs also play a pivotal role in reshaping the EE of massive MIMO systems. These components introduce nonlinearities and quantization noise, which hinder system performance and reduce the system EE. This becomes more pronounced in hybrid analog/digital transceiver architectures where multiple radio frequency (RF) chains are implemented to multiplex the signal over the wireless channel [88]. Thus far, recent literature has primarily focused on examining the impact of PAs [89], [90], [91] or DACs/ADCs [92], [93], [94] on massive MIMO systems. However, to fully capture the dynamics of EE in massive and extremely large-scale MIMO systems, it is imperative to study the joint impact of PAs, DACs, and ADCs in an end-to-end (E2E) system model. Such a strategy allows for an accurate assessment of the system performance in terms of SE and EE, facilitating the development of robust solutions to meet the demands of next-generation wireless networks. This E2E system model is illustrated in Figure 3, and based on the SE requirements of the system, different transceiver configurations can be selected. Overall, the Gearbox-PHY approach can be further extended to the whole transceiver, where dynamically switching between different configurations depending on SE requirements in the network can result in significant energy savings.

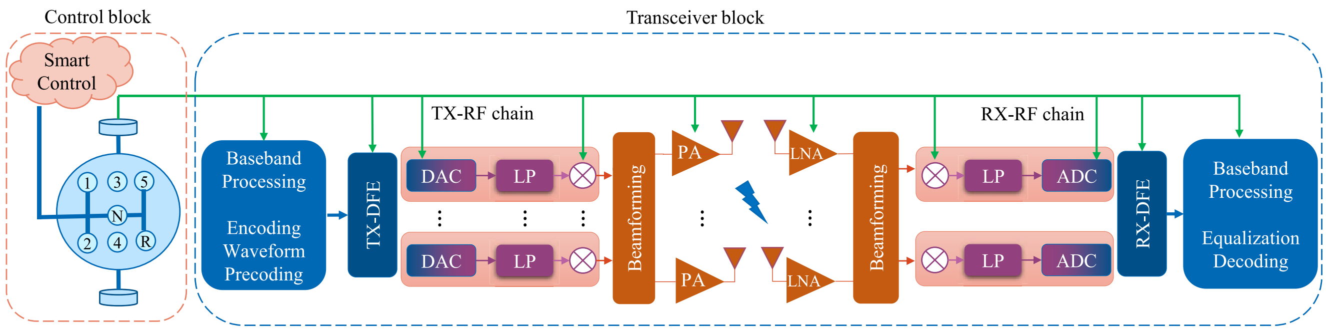


FIGURE 3. End-to-end model of a generic radio transceiver.

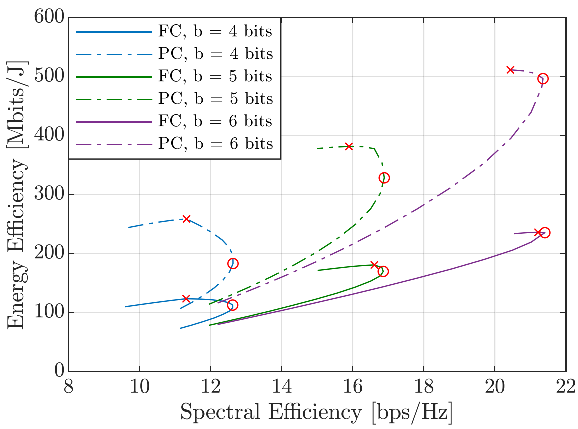


FIGURE 4. EE-SE curves for varying IBO values. (P_s= 10 dBm). The red crosses and circles denote the maximum EE and maximum SE, respectively.

A possible solution to the EE vs SE trade-off can be obtained by selecting the optimal transceiver configurations in terms of the least energy consumption for a spectral efficiency requirement. For this, analytical expressions of EE and SE as a function of DAC and ADC resolution and input back-off (IBO) of PA are derived in [95]. Figure 4 depicts the EE-SE curves as a function of varying IBO values for both partially connected (PC) and fully connected (FC) architectures with input signal power set to 10 dBm. The red crosses and circles denote the maximum EE and SE, and the DAC and ADC resolution is denoted by b. The results indicate that the PC architecture achieves higher EE compared to the FC architecture due to its reduced number of phase shifters, which results in less power consumption. Additionally, it can be observed that the EE initially increases with higher IBO levels but subsequently decreases as the PA output power diminishes. The PC architecture demonstrates higher EE due to its reduced power consumption, attributed to the smaller number of phase shifters compared to the FC structure. This plot effectively portrays the EE-SE tradeoff in massive MIMO systems. According to this plot, not necessarily an arbitrary IBO results in high EE. Depending upon the DAC/ADC resolution, the IBO point leads to maximum SE and EE changes. Moreover, it can be observed that for a specific SE, there can be several configurations, including fully connected and partially connected architectures, and the optimal configurations can be considered as the gears of the transceiver.

V. CAPACITY AND COVERAGE ENHANCEMENT

Studies in 6G-ANNA concentrate on three complementary techniques that jointly boost capacity and coverage:

1) Advanced multiple access (MA) schemes that flexibly share time–frequency resources and cope with heterogeneous QoS targets.
2) Cell-free massive-MIMO architectures that turn dense access-point deployments into a user-centric distributed antenna system.
3) Fronthaul-aware compression techniques that reduce the backhaul load of cell-free networks without sacrificing user data fidelity.

The following subsections summarize the key ideas and results obtained so far.

A. MULTIPLE ACCESS

Multiple access techniques in 5G networks face several challenges in meeting the demands for high spectral efficiency and massive connectivity. Traditional orthogonal multiple access (OMA) schemes, such as orthogonal frequency division multiple access (OFDMA), may not suffice due to their limited capacity to support a large number of users simultaneously. Non-orthogonal multiple access (NOMA) has been proposed to address these limitations by allowing multiple users to share the same frequency resources, thereby enhancing spectral efficiency. However, implementing NOMA introduces complexities, including the need for sophisticated receiver designs capable of handling increased interference and ensuring fairness among users with varying channel conditions. Additionally, the integration of NOMA with existing technologies like MIMO systems presents further challenges, such as managing the trade-offs between system complexity and performance gains. Addressing these issues is crucial for the successful deployment of 5G networks that can meet the diverse requirements of modern wireless communication systems. In 6G networks, addressing the limitations of traditional multiple access techniques is

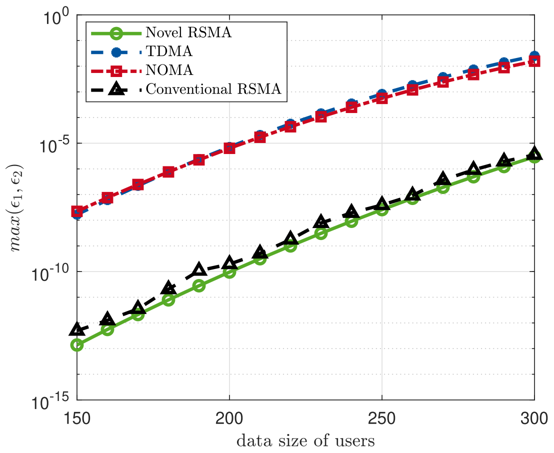


FIGURE 5. Min-max error probability vs. data size of users. The green line indicates the result of the theoretical finite blocklength error probability of the novel RSMA scheme in [96] with allocating optimal values for blocklength and power.

crucial to meet the demands for higher data rates, massive connectivity, and diverse quality of service (QoS) requirements. Rate-splitting multiple access (RSMA) emerges as a promising solution by enabling the transmission of both common and private messages to users, effectively managing interference and enhancing spectral efficiency. RSMA‘s flexibility allows it to adapt to various network conditions, making it suitable for scenarios involving imperfect channel state information and heterogeneous user requirements. By integrating RSMA with advanced technologies such as massive MIMO, RIS, and ISAC, 6G networks can achieve improved performance in terms of throughput, reliability, and latency. This integration facilitates efficient resource utilization and robust interference management, addressing the challenges posed by the diverse applications anticipated in 6G.

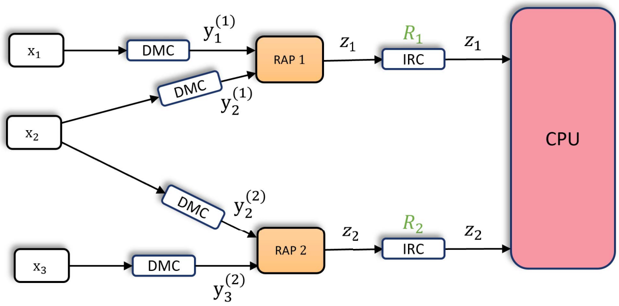
Furthermore, hybrid NOMA-time-division multiple access (TDMA) schemes have been investigated in the finite blocklength regime to support ultra-reliable and low-latency communication services while providing massive connectivity. These schemes combine the advantages of NOMA and TDMA, offering a design framework that jointly allocates blocklength and transmit power for each user. Such designs aim to optimize reliability and effective capacity, catering to latency-sensitive applications in future wireless communication networks. We proposed a framework in [96] for adapting the RSMA methodology, which lies in the hybrid NOMA-TDMA model. The main goal of this approach is to give the ability to select between different multiple access schemes to ensure the best quality of service and lowest error probability, which changes in different scenarios. The idea is that the message of each user is being divided into the private and common parts, where the common part is being transferred, like NOMA sharing the bandwidth with a series of private messages that are being transferred, like TDMA. Figure 5 depicts the min-max error probability between two users in a downlink transmission. The main motivation for proposing this generalized framework is to maintain the quality of service while reducing the successive interference cancelation (SIC) dependency.

B. CELLULAR TO CF-mMIMO

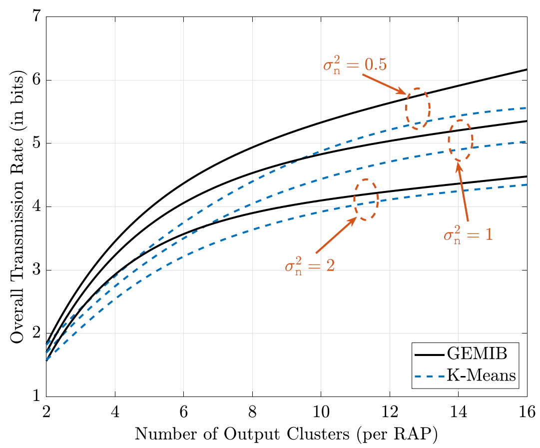
Traditionally, resource allocation in cellular systems has relied on algorithms solving optimization problems for every channel realization. However, in cell-less systems, where multiple access points cooperate as a single entity to establish connections with users, these traditional methods face challenges due to high signaling overhead and latency, rendering them unsuitable. Early developments in cell-free massive MIMO systems addressed this issue by performing all short-term processing locally. Recently, these ideas have evolved into architectures using two-time-scale operations. In this approach, long-term channel statistics are leveraged to solve an optimization problem with a solution that remains valid until the channel statistics change. More specifically, long-term optimization problems obtain the power profiles and the functions that access points should apply to the local short-term channel realizations to obtain the beamformers.

Despite these advancements, achieving optimal joint power allocation and beamforming remained challenging, leading researchers to propose heuristics that often fell short of optimal performance. Consequently, some studies suggested that cellular systems could outperform cell-free networks under certain conditions. However, developments in team decision theory [97] and fixed point theory within Hilbert-projective and Thompson metric spaces [98], [99], [100], [101] have provided the necessary mathematical tools that opened up the possibility for deriving provably optimal fixed point algorithms for distributed MIMO systems. These methods have demonstrated that earlier findings on operating schemes where cellular systems outperform cell-less and other distributed MIMO systems were, in fact, artifacts of suboptimal strategies. Furthermore, they also showed that, if the criterion for fairness to be used is the standard unweighted max-min fairness, then two-time scale approaches outperform more complex short-term approaches that solve an optimization problem for each channel realization.

The above-mentioned fixed-point algorithms can also be combined with machine learning tools to save energy in distributed MIMO systems [102]. In this technique, optimal power allocation and beamforming are used to enable the network to deactivate as many access points as possible while satisfying the traffic demand. In practical systems, transmit energy accounts for only a small fraction of the total energy consumed by hardware. Therefore, at the infrastructure side, these hybrid models and machine learning approaches reduce overall energy consumption despite any increase in transmit energy for establishing connections to network elements remaining active.



(a) An uplink transmission in a CF-mMIMO network where 3 users employing bipolar 8-ASK source signaling are served by 2 RAPs.



(b) A performance comparison between GEMIB [103] and K-Means [104] schemes to design the compressors at RAPs in terms of the overall transmission rate vs the number of output clusters (per RAP).

FIGURE 6. **An example of data compression at RAPs in a CF-mMIMO network.**

C. FRONTHAUL RATE REDUCTION IN CF-mMIMO SYSTEMS

In spite of several benefits provided by CF-mMIMO, the architecture presents notable challenges, particularly in the uplink, where radio access points (RAPs) must transmit high-dimensional, noisy user signal observations to a central processing unit (CPU) over constrained fronthaul links [26]. To address these challenges, efficient data compression techniques are essential to minimize communication overhead and achieve EE.

In CF-mMIMO, vector quantization (VQ) is a powerful tool for compressing the extensive data generated at the RAPs. Each RAP collects high-dimensional user data and transmits it to the CPU via limited-capacity fronthaul links. By clustering observation vectors and encoding them as representative centroids, VQ significantly reduces the data rate required for transmission. This reduction not only alleviates fronthaul congestion but also enhances EE, which is a critical requirement for large-scale CF-mMIMO deployments.

The multi-source information bottleneck (IB) method introduced in [103] offers a novel distributed noisy source coding approach. This method allows terminals to compress noisy user signal observations using an IB-based vector quantization framework before transmitting them over rate-limited channels to a CPU. Unlike traditional VQ methods that focus solely on minimizing distortion, the IB-based approach prioritizes retaining information critical for reconstructing user signals. This selective information preservation is well-suited to the distributed architecture of CF-mMIMO, enabling RAPs to collaboratively compress their observations while ensuring efficient user signal recovery. The IB method strikes an optimized balance between compression and information retention [105], making it a scalable and energy-efficient solution for CF-mMIMO networks. Originally developed for clustering in unsupervised learning [106], [107], IB now serves as a task-oriented compression framework with applications extending to wireless communications.

In CF-mMIMO, the IB framework can be adapted using linear equalization at each RAP to mitigate spatial interference and separate user signals [108]. This adaptation reformulates the problem as a trade-off between two mutual information (MI) terms: (i) the relevant information, defined as the MI between the source signals and their corresponding received signals at the CPU, and (ii) the total compression rate, representing the MI between noisy observations (inputs) and the compressed outputs of the RAPs. The objective is to maximize relevant information while ensuring the total compression rate does not exceed the fronthaul capacity. This concept parallels data clustering, where the goal is to retain critical features while minimizing redundancy. The generalized multivariate information bottleneck (GEMIB) algorithm proposed in [103] solves this design problem for multi-source IB-based compression.

Consider a CF-mMIMO setup with three users served by two RAPs, where one user is served by both RAPs, as illustrated in Figure 6a. After applying linear equalization at the RAPs, RAP 1 observes $\mathsf{y}_1^{(1)}$ and $\mathsf{y}_2^{(1)}$, corresponding to source signals x_1 and x_2, respectively. RAP 2 observes $\mathsf{y}_2^{(2)}$ and $\mathsf{y}_3^{(2)}$, corresponding to x_2 and x_3. Assume a discrete memoryless channel that approximates a discrete-time, discrete-input, and continuous-output additive white Gaussian noise (AWGN) channel with identical noise variance, σ_n^2, for all access channels from the source signals to the corresponding outputs of equalizers at the RAPs. The RAPs compress their noisy observations into z_1 and z_2 before transmitting them over ideal rate-limited channels to the CPU. The compression schemes are evaluated using the relevant information metric, defined as the sum of MI terms $I(\mathsf{x}_1; \mathsf{z}_1) + I(\mathsf{x}_2; \mathsf{z}_1\mathsf{z}_2) + I(\mathsf{x}_3; \mathsf{z}_2)$.

Figure 6b compares the GEMIB and K-Means [104] methods for designing RAP compressors in terms of the overall transmission rate against the number of output clusters per RAP. GEMIB demonstrates superior performance in both information preservation and compression efficiency. For example, with noise variance $\sigma_n^2 = 1$, GEMIB achieves approximately 5 bits of relevant information with only 12 clusters, whereas K-Means requires 16 clusters for the same level of information. Alternatively, for a fixed 8-cluster configuration, GEMIB supports up to 4.5 bits of relevant information, outperforming K-Means, which supports only 4 bits.

VI. TRUSTWORTHINESS AND PHY SECURITY

To achieve trustworthy cellular communication, various security measures have been applied in 5G and the previous cellular network generations that focus on higher layers. However, the physical layer communication can be exploited for attacks, such as eavesdropping, spoofing, and jamming attacks [109]. Furthermore, attackers can also use measurements of signals they receive to obtain insights on their environment [110] or directly manipulate the physical hardware of base stations and other network equipment. To protect against such attacks, physical layer security can be employed, which has gained significant attention within the 6G research.

A. CONFIDENTIAL PHYSICAL LAYER COMMUNICATION

To protect the confidentiality of the data transfers against eavesdropping attacks on the physical layer, two approaches exist from information theory: First, confidentiality can be ensured based on a specific coding that employs a received signal strength difference of the legitimate receiver and the eavesdropper, which is referred to as the secrecy rate [111]. Alternatively, the randomness of the wireless medium can be utilized to generate a secret key, which is then utilized within cryptography methods [112], [113]. While the 5G standard already includes protection measures on higher layers, the introduction of physical layer security measures will introduce additional challenges for the eavesdropper and, thus, make it significantly harder to intercept messages.

The open systems interconnection (OSI) model [114] defines a separate physical layer on each link between neighboring network nodes. To achieve a positive secrecy rate, the provision of a difference in signal strength between legitimate and adversarial devices is crucial. For the cellular links, beamforming can be applied to focus the signal transmitted from the base station into the user direction, similar to the beamforming already employed in 4G and 5G. However, with the beamforming techniques applied in 4G and 5G, other devices located in a similar direction as the targeted receiver might still be able to decode the transmit signal. In the 6G downlink, narrower beamforming can be used to enhance confidentiality. To optimize the beamforming accordingly for the case that the eavesdropper location is unknown, the adversary channel needs to be modeled. Therefore, the eavesdropper channel can be assumed random, such as via the Rayleigh fading model, and the beamforming can be designed such that confidentiality is ensured with high probability. This way, the ε-outage secrecy rate, i.e., the secrecy rate that is fulfilled at a high probability, while tolerating a secrecy outage probability ε, can be maximized [115]. Alternatively, a wiretap region can be defined, i.e., a region in which the eavesdropper is allowed to roam freely without affecting the system's confidentiality [116]. Based on this, the system can be optimized under the assumption that the eavesdropper's location equals one of the worst of all locations in the wiretap area. The metric used in this case is the worst-case secrecy rate.

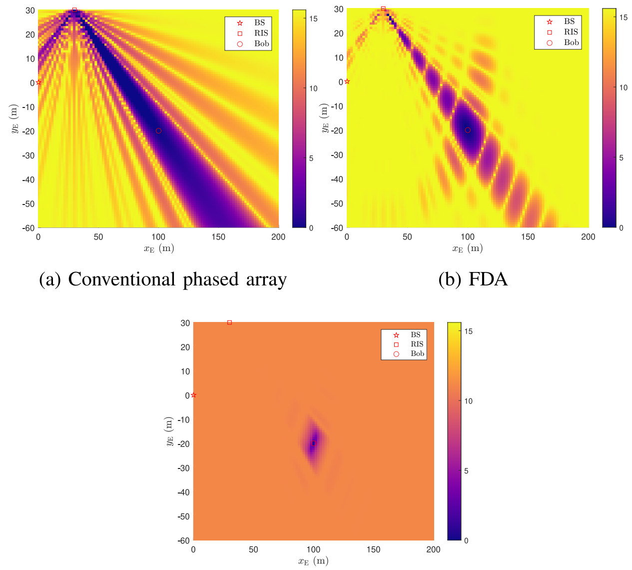
To protect the message transfer even in the case that the user and eavesdropper are in the same direction, the antenna array of the base station can be employed as a FDA [117]. Thereby, the same symbols are transmitted by different antennas, each of which employs a small frequency shift within the transmission. By then, engineering the phase of the transmit signal, the radio waves can jointly lead to a strengthened signal at the location of the legitimate user. For a receiver at other distances, the different phases will overlap destructively, leading to a reduced signal strength at an eavesdropper at these locations.

With the emergence of RIS, additional opportunities arise for secrecy rate maximization and secret key generation. For the secrecy rate, the high number of reflective elements of the RIS can be used to sharpen the beam of the signal towards the user. In an alternative approach, only parts of the RIS are chosen to strengthen the signal at the user, while another, random part of the RIS is inverted to randomize the received signal at an eavesdropper located in the side lopes [116]. Figure 7 shows that a joint application of FDA and such a partially random choice of the RIS elements allows the selection of a significantly larger wiretap region compared to only applying FDA. Furthermore, if the RIS is configured partially random and the configuration is changed frequently in time, the additional randomness can enhance secret key generation schemes. Thereby, potential leakages of parts of the RIS configuration and their possible effect on the confidentiality of the key need to be considered [118].

B. SENSING-AIDED SECURITY

Most software security concepts assume a certain, often high, level of hardware security. For instance, two parties wishing to communicate may set up a TLS session that involves server-side authentication using digital certificates, under the assumption that both the server and the devices constituting the public key infrastructure (PKI) are hardware-secure. Similarly, telecommunications infrastructure depends heavily on electronic hardware that provides essential functionality and supports operational availability. For example, a 5G RAN comprises UEs and the base station or gNodeB (gNB), which perform various tasks, including security functions such as authentication and data encryption.

The ENISA report titled "Security in 5G Specifications" highlights the importance of the assumption that "critical operations that use these (cryptographic) keys should, ideally, always be executed within a secure hardware environment" [119]. Further, the 3GPP security specification (TS



(a) Conventional phased array (b) FDA

(c) FDA and RIS

FIGURE 7. **Secrecy rate for various positions of Eve with different schemes [116].**

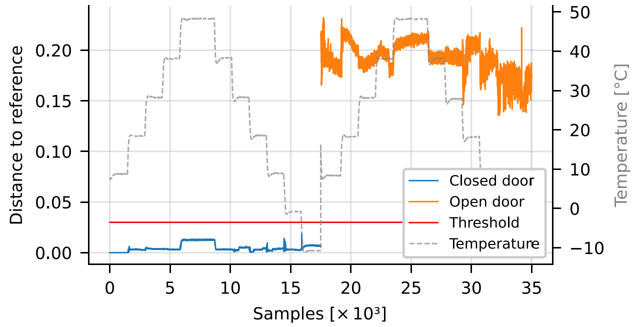


FIGURE 8. **Distances to a reference measurement with (orange) and without (blue) a physical tampering. A decision threshold (red) can be chosen to distinguish between the two states. However the controlled temperature changes (grey) make the score vary even without a tampering, which may cause problems when a more subtle tampering takes place.**

33.501) places requirements to secure the storage and processing of subscription credentials [120]. Specifically, it calls on stakeholders to ensure that secure, tamper-resistant hardware is used for storing and processing security-critical data (e.g., subscriber credentials and decryption keys).

There are several approaches to ensure hardware security, which can be broadly divided into two categories. On the one hand, there are prevention methods designed to mitigate attacks by physically or logically blocking unauthorized access (e.g., disabling ports). On the other hand, there are detection methods aimed at identifying an attack as it is happening and then triggering countermeasures. Common detection techniques include access control, intrusion detection systems, camera surveillance, and tamper-evident seals. However, these traditional methods are typically installed separately from the network and often require human supervision to maintain low error rates.

An alternative approach for direct integration into future 6G systems is based on wireless sensing. Wireless sensing refers to extracting information about the physical environment from the propagation of electromagnetic waves in the communication channel between two devices. The wireless channel is modeled using the complex-valued channel frequency response, which is typically estimated using CSI. In addition to practical applications for human-machine interaction like localization, human gesture recognition, or heart rate monitoring [121], this technique can also enhance physical security. The Anti-Tamper Radio technology (ATR), introduced by [122], leverages this technology to detect changes in the physical environment. It is shown that under optimal conditions, the technology is capable of detecting sub-mm changes in the physical environment.

To successfully deploy this system in real-world security contexts, several challenges must still be addressed:

- *Robustness* to environmental influences. Because the technology is highly sensitive to small environmental changes, legitimate modifications in the surroundings can inadvertently trigger false alarms.
- *Usability* is another problem to be solved. In the original paper, a 7 GHz bandwidth was used to detect such changes. This high precision introduces regulatory issues when applied in practical scenarios.

A solution to tackle these challenges by integrating an RIS into the system is proposed in [123]. By creating a controllable sensing environment, the effective bandwidth could be reduced drastically from 7 GHz to as low as 20 MHz without losing significant performance. Optimizing the RIS configurations, they were also able to exclude legitimate variations in the environment. In addition, they showed that the system is secure against attackers that actively manipulate the sensing antennas.

Despite significant progress, an open challenge remains: CSI exhibits temperature dependence. Because electromagnetic waves are affected by temperature, fluctuations can alter the measured signals. This issue is illustrated in Figure 8, where an enclosure is monitored with ATR technology. In this setup, CSI are used to sense the environment, and a set of initial reference measurements establishes a baseline for normal operation. A distance metric then compares each new measurement against this baseline, generating a score that quantifies any deviation. A decision threshold is finally applied to classify measurements as either tampering events or normal variations. The temperature inside the enclosure is systematically varied using a climate chamber, and after data is recorded at multiple temperature points, the enclosure is opened to simulate a tampering attack. Once opened, the measured score rises dramatically, demonstrating the effectiveness of ATR in detecting this tampering. Even though the score remains below 0.00019 during the first 1000 measurements when the temperature is stable, in the absence of any tampering, fluctuations in the score are still observed. Consequently, a threshold of around 0.03 is chosen. This elevated threshold may increase the likelihood of false negatives for more subtle tampering events. Hence, temperature dependence in CSI remains a concern that must be addressed in future investigations of ATR-based tamper detection.

For a solution like ATR to be effective in 6G, there must be a mechanism and a corresponding interface to extract CSI from the physical layer. Several configurations are conceivable. For example, the side channel between two UEs could be employed, or the reciprocal uplink and downlink channels between UE and gNB could be used (though this might mean weaker link quality and a less robust sensing setup). This requirement is met by other current-generation communication systems to a high degree. For instance, the IEEE802.11 Wi-Fi standard is already working on a framework for sensing using CSI. Similar updates are expected from Bluetooth and Ultra-wideband. However, when looking into integrated sensing for mobile communications, there are several challenges with respect to integration and interoperability. These include the availability of CSI from 5G/6G device manufacturers and standard interfaces to collect such CSI data. Aspects related to data flows, or the location of anomaly detection models (RAN, Core) are not yet clearly defined. Nevertheless, increasing interest in joint sensing and communication applications is likely to bolster the development of a unified sensing architecture in the coming years.

VII. AI INTEGRATION

Within this project, four representative use-cases that together span generative, supervised, hybrid, and reinforcement learning are investigated:

1) Generative channel modeling with diffusion models that yield differentiable, high-fidelity channel realizations for end-to-end transceiver optimization.
2) Interference prediction that combines temporal correlation and extreme-value statistics to support proactive scheduling.
3) Hybrid model or data-driven learning that embeds domain knowledge in the learning algorithm to cut data requirements and improve robustness.
4) RL-based online decision making for parameter tuning, exemplified by uplink power-control optimization in dense factory networks.

The remainder of this section summarizes the core ideas and key results for each topic.

A. DIFFUSION MODELS FOR CHANNEL ESTIMATION

Channel estimation is an integral part of communication methods, as information about the channel is essential to optimize and process signals, thereby achieving maximal reliability, safety, and data rates. Accurate channel estimates are crucial for the performance of advanced communication techniques such as NOMA MIMO systems.

Beyond traditional methods, channel estimation plays a pivotal role in advanced AI-driven techniques to enhance 6G-PHY layers. One significant application is in end-to-end channel coding, modulation, and coded modulation frameworks, where the encoder and decoder are jointly optimized. These frameworks have shown potential to match or even surpass the performance of classical methods [124]. Another critical application is in physical layer security-driven wiretap scenarios, which rely on new secure encoding strategies. In both these scenarios, end-to-end frameworks are necessary to ensure the required constraint, be it reliability, security, or rate, and they depend on accurate differentiable channel models to enable optimization through backpropagation.

Generative Adversarial Networks (GANs), originally from the field of computer vision, have been employed as state-of-the-art generative methods for channel estimation and generation [18], [125], [126]. While GANs have demonstrated high performance in generating wireless channels, their application is often limited by the phenomenon of mode collapse. Mode collapse results in a generated distribution that lacks uniform quality and emphasizes certain modes over others, which can be detrimental for more complex channel distributions. To address the limitations of GANs, we introduced diffusion models as an alternative for channel estimation and generation [127].

Diffusion models are emerging as a robust method that is not prone to mode collapse and is known for producing high-quality distributions, as demonstrated in computer vision tasks. For example, diffusion models can generate correlated fading channels, where GAN-based methods encounter difficulties due to mode collapse.

However, a primary drawback of diffusion models is the slow sampling process, which involves traversing a lengthy Markov chain of small steps to convert Gaussian input noise into the desired distribution. This research focuses on overcoming this challenge by investigating and adapting state-of-the-art techniques to accelerate the sampling procedure. We proposed modifications and optimizations tailored to wireless channel generation to make the sampling process both fast and computationally efficient. Concretely, we adopt skipped sampling via DDIM: denoising along a shortened trajectory of length S. On an RTX 2060 for 2^{17} samples, DDPM takes 534 ms, whereas DDIM takes 26.9/246 ms for S = 5/50, respectively, while WGAN takes 1.40 ms.

Accurate and differentiable generative channel models not only improve the reliability of learning-based transceivers but also reduce the need for excessive pilot signaling, thereby contributing to EE. In this way, our diffusion-based estimation framework enables high-fidelity, low-overhead channel knowledge, supporting both spectral and energy-efficient operation in next-generation wireless systems.

In Figure 9 (reproduced from [128]), we consider a standard AWGN channel model. Our model is trained E2E for blocklength $n = 7$ and constellation size $M = 16$, using an SNR of 12 dB.

We implement a conditional DDPM whose model is conditioned on the channel input x', i.e., $p_\theta(x_{t-1} \mid x_t, x')$,

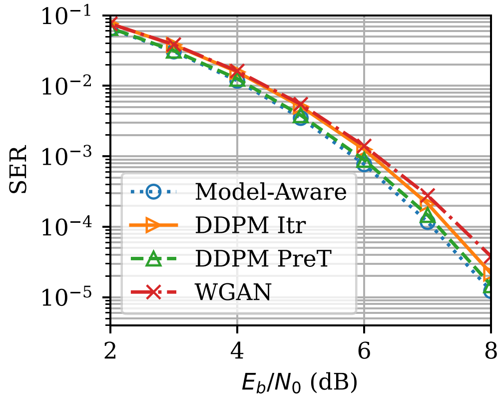


FIGURE 9. Achieved SER for the Diffusion model vs WGAN model.

where x_t is the diffusion state at step t. This makes the generated output differentiable w.r.t. x', enabling end-to-end training. For memoryless channels, we use a lightweight MLP with two hidden layers of size 128, with timestep embeddings multiplicatively injected into the hidden layers and $T = 100$ diffusion steps. For correlated fading, we use a 1D U-Net. We adopt a 0-SNR cosine noise schedule ($\bar{\alpha}_T = 0$), and therefore utilized v-prediction [129]. The corresponding Wasserstein GAN (WGAN) architecture for both generator and critic consists of two fully connected layers with ReLU activations and 256 hidden units per layer. To ensure model differentiability, the channel input is also fed into the input layers of both the generator and the critic. Training is performed using the PreT algorithm, which pre-trains the generative model extensively on random channel inputs before optimizing the autoencoder (AE), see [128]. This approach is compared to the iterative training algorithm (standard approach), in which the generative model and the AE are trained alternately. As shown in Figure 9, in terms of E2E performance in AWGN, all models closely track the model-aware case. Moreover, looking at Wasserstein distances (SWD at $p = 1$, 128 projections, 10^7 samples) of the generated distributions against the ground truth we see that DDPM with cosine scheduling attains the lowest distance, while DDIM (cosine) is most robust to step-skipping: AWGN SWD is 0.012 (DDPM) and 0.011 (DDIM-50) vs. 0.013 (WGAN); sigmoid/constant schedules are worse and less robust under skipping. Similar encouraging results were obtained for fading and non-linear channels, where DDPMs lead on WGAN was even more pronounced. Our findings, detailed in [128], demonstrate the feasibility and effectiveness of these enhanced diffusion models for practical 6G applications.

B. ML-BASED INTERFERENCE PREDICTION

Over the past decades, the vision of connecting "anything that can benefit from being connected" has driven an exponential increase in wirelessly connected devices, ranging from small sensors in homes and industries to vehicles

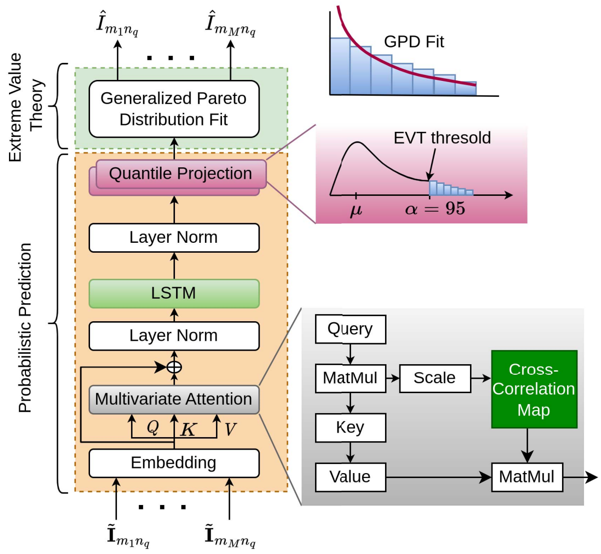


FIGURE 10. Interference predictor with EVT-based iQTransformer incorporating tail statistics [138].

and beyond. However, interference has remained challenging, significantly affecting wireless communication systems' capacity and performance. In ultra-dense environments, where numerous UEs share limited resources like sub-bands, high interference levels degrade the signal-to-interference-plus-noise ratio (SINR), impairing reliability and posing a critical barrier to efficient radio resource management. Consequently, effective interference estimation becomes an integral part of communication to ensure reliable resource allocation.

Proactive Interference estimation, i.e., interference prediction, has been explored in many existing literature with model-based approaches utilizing tail statistics, such as [130], [131]. Moreover, exploiting temporal dynamics of interference within successive interference power values, utilized to predict interference by utilizing ML-based methods [132], [132], [133], [134], [135]. Interference prediction that accounts for uncertainties, particularly by incorporating tail statistics, holds great significance due to the inherent impact of random traffic, deep fading, and noisy observations resulting from measurement errors. The importance of moving beyond central-limit theorems with the inclusion of extreme and rare events has been highlighted for URLLC in [136]. The probabilistic interference prediction with a Gaussian process and attention-based-quantile BiLSTM has been proposed in [137]. Such methods can track the local variability as well as quantify associated uncertainties in predictions. Some hybrid approaches are extreme value theory-based inverted quantile transformers for interference prediction, a hybrid probabilistic model that accounts for stochastic statistics related to extreme and rare events caused by traffic, noise, or heavy-tail distributions of interference [138]. Such methods are useful to estimate tail statistics for designing a reliable resource allocation.

Figure 10 shows the hybrid interference prediction technique proposed for a subnetwork with multiple sensor-actuator pairs, exploiting temporal correlation over successive TTIs and cross-correlation between the interference of multiple sensor-actuator pairs. It combines a transformer-based architecture with extreme value theory (EVT) to predict interference, incorporating extreme interference events. Moreover, a long short-term memory (LSTM) network within the Transformer framework, where the LSTM employs a gated mechanism, input, forget, and output gates to store and retrieve relevant temporal information. This capability allows the model to retain long-term interference patterns and adapt to dynamic variations, improving predictive accuracy. The iQTransformer predicts dynamic probabilistic thresholds, which, combined with EVT's Peak-over-Threshold method, enable robust and proactive resource allocation, outperforming baseline methods in both accuracy and reliability. For this, the model first predicts a threshold at the 95th quantile (or any other chosen tail quantile) and uses EVT to characterize the statistical distribution of interference beyond this threshold, capturing extreme events to ensure reliable communication. Further details about the algorithm can be found in [138].

Figure 11 presents the achieved block error rate (BLER) under isochronous and Bernoulli random traffic for various interference prediction methods based on predicted interference. The training and testing were conducted offline using interference data generated from the 3GPP-compliant Indoor Factory with Dense clutter and Low base station height (InF-DL) model based on [139]. We consider 20 subnetworks (SNs) deployed in an industrial factory environment, where each SN operates within a (25×25 m^2) area and each SN moves at a constant velocity of (2 m/s) in random directions, representing collaborative mobile robots. Among these SNs, we consider five SNs that utilize the same sub-band, resulting in co-subband interference. Baseline approaches, such as Moving Average and Wiener predictors, are unable to maintain low BLER, particularly under random traffic, due to their limited ability to capture interference dynamics and associated uncertainties. Here, the moving average method is used as a simple predictor that relies on previously estimated interference values through a first-order infinite impulse response (IIR) filter to smooth short-term variations [130], while the Wiener filter captures second-order statistics by exploiting prior correlation information for prediction [135]. The iQTransformer, a quantile-inverted Transformer-based ML technique, captures specified quantiles such as the 95th percentile while exploiting both temporal and spatial correlations among interference signals, enabling quantile-aware prediction. In contrast, the EVT-based iQTransformer accurately predicts interference and enables proactive resource allocation that meets target reliability constraints. By effectively modeling extreme interference events, this hybrid approach ensures near-optimal BLER performance while using only slightly more resources than the ideal Genie-aided solution. Further details about the implementation and resource allocation can be found in [138]. Overall, the predicted interference, obtained by effectively utilizing advanced ML models such as the iQTransformer combined with EVT, supports the design of predictive and proactive interference management schemes, enabling highly reliable communication in industrial scenarios with the strictest reliability requirements.

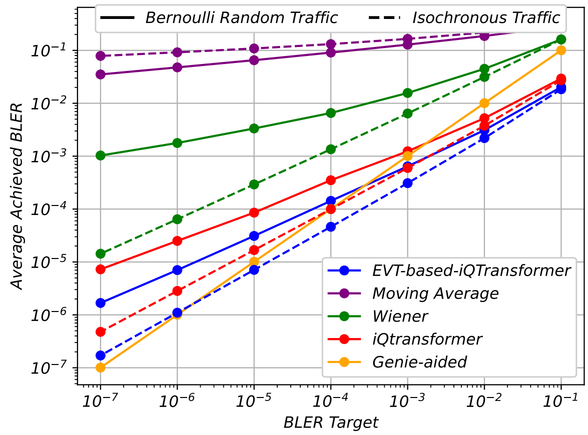


FIGURE 11. Achieved BLER with different traffic model.

C. HYBRID ML

In applications of machine learning, such as computer vision and speech recognition, neural networks have far surpassed the performance obtained with classic learning tools based on, for example, kernel methods and hidden Markov models. Consequently, the wireless community has been investing considerable effort to integrate neural networks into the physical layer of wireless systems. However, this integration is challenging because of the unique characteristics of the wireless propagation channel, which differ considerably from those in traditional machine learning applications. In particular, the signal statistics in the physical layer can change drastically over short periods because of, for example, the ever-changing interference patterns. This high variability causes serious problems in obtaining large, stable training datasets, which has been a key requirement for the high performance typically associated with neural networks. In scenarios with small training sets, the classic learning tools may be able to provide better performance than neural networks. However, the amount of data required for training can still be large, considering the time scales involved for training and data transmission in the physical layer.

In modern wireless systems, pure data-driven methods are often bypassed in favor of models leveraging the sophisticated theoretical frameworks developed by the wireless and information theory communities. However, as systems grow more complex, the mathematical models quickly become intractable, requiring numerous simplifications that are potentially unrealistic in practice. These include assumptions related to the linearity of amplifiers and the accuracy of knowledge about the array responses, channel covariance matrices, and noise distributions, to name a few. As a result, in practical systems, the performance achieved with pure model-based methods can significantly deviate from theoretical predictions.

Against this background, a new trend has been emerging in recent years: the integration of traditional models with data-driven learning tools. This hybrid approach can take many forms, and it is not limited to any specific learning tool, such as neural networks. The goal is to incorporate model knowledge into learning algorithms to address model imperfections and gaps in information. From the perspective of the learning algorithms, training can be performed more efficiently compared to purely data-driven approaches because the search space is significantly constrained to scenarios that are plausible from an engineering perspective.

In one particular hybrid model and data-driven framework, we use theoretical models to obtain high-level properties expected from the system, and learning tools are constrained to adhere to these high-level properties. For instance, if the objective is to estimate load in wireless networks, standard arguments in the literature show that cell load at every base station is a monotonic function of rates, a manifestation of the fact that increasing rates come at the expense of increased interference in the network. Furthermore, theoretical models show that the function mapping rates to load is Lipschitz continuous. These two properties can be incorporated into robust learning techniques to learn, with very few samples, functions mapping rates to load in a network [140]. Similarly, [141], [142] shows that an optimal symbol estimator in the UL of a network is nonlinear in general, and it can be represented by a point in a reproducing kernel Hilbert space. Nevertheless, if the number of antennas is sufficiently large relative to the number of scheduled users, the performance of a linear estimator can be adequate. Therefore, we can construct a reproducing Hilbert space containing both the linear and nonlinear estimators mentioned above, and use kernel methods to produce online methods that automatically decide whether the function for symbol detection should be linear or nonlinear, without explicit knowledge of the number of interfering users.

There are several existing works in the literature that use the models more directly, e.g., [143] has the objective of reconstructing angular power spectra from channel covariance matrices, assuming that the array response is known. This problem is inherently ill-posed because the same covariance matrix can be produced by different functions describing the angular power spectrum [143], [144]. To address this ambiguity, [143] leverages a training set to reconstruct a spectrum that is not only plausible for the given array configuration but that is also similar, in a well-defined sense, to the distribution of the training set. In another line of work that leans towards model-based methods, we first develop numerical schemes offering many parameters to be tuned (e.g., step sizes). Typically, there may be no mature theory to guide parameter design for ensuring, for example, fast convergence. In this scenario, we can use learning tools solely to tune these parameters, thereby retaining the convergence properties of the original model-based methods. For a concrete example of such approaches, we refer the readers to [145].

D. RL-AIDED DECISION MAKING

In order to cope with the complex optimization problems involving large matrix inversion and NP-hard problems, ML is considered as one of the 6G key technologies to optimize radio system configurations via observations and active interactions with the environment. In the following, we outline how ML can be used for automated UL open-loop power control parameters (OLPC) parameter optimization as an exemplary use case.

Proper selection of UL OLPC is known to be very important to limit the interference towards neighbor cell users and thus maintain a high overall system performance. The most relevant parameters are the nominal transmit power spectral density P_0 and the fractional pathloss compensation factor α. The total power used by a UE to transmit M_{RB} allocated physical resource blocks over the physical UL shared channel with subcarrier scaling factor μ and UE estimated DL pathloss PL from DL reference signal is given by the expression $P = \min\{P_{\max}, P_0 + \alpha \cdot PL + 10\log_{10}(2^{\mu} M_{\mathrm{RB}})\}$[dBm]. It is well known that the selection of optimum OLPC configuration is a non-trivial task because it depends on various aspects like network deployment, data traffic characteristics, quality-of-service requirements, duplexing scheme, and system bandwidth etc. Today, network planning tools and human domain expertise are frequently used to identify settings that show good performance with respect to median and cell-edge users throughout figures. The main disadvantage of these solutions is the static parameters configuration, i.e., the inability to follow power control configuration relevant dynamic changes within cell coverage. In the context of 6G, proper UL OLPC configuration will be even more challenging due to an expected increase in heterogeneity of network deployments, new device classes, and use cases with more stringent or novel minimum requirements on reliability and spectral efficiency.

Recently, different flavors of ML or alternative optimization techniques have been utilized to optimize UL power allocation. The most popular branch of ML to obtain the best PC configuration is reinforcement learning (RL). In this approach, an agent interacts, via so-called actions, with the environment by planned or random alteration of the parameters to be optimized. From subsequent observation of the environment's status and measuring the overall quantitative system-performance response in the form of so-called rewards, the agent learns over time the best configuration by maximizing rewards. Various strategies had been investigated in the past: Centralized versus distributed learning agents [146], learning with and without [147] cooperation, or whether the ML algorithm tries to optimize

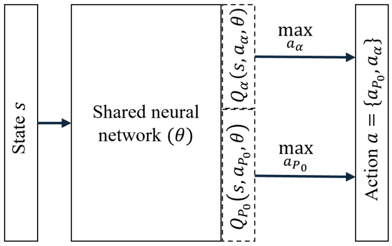


FIGURE 12. **Selected deep Q-learning architecture for OLPC optimization.**

the total transmit power directly [148] or OLPC parameters [149], where the latter approach has better alignment to current 3GPP standards. RL strategies either employ iterative learning with Q-tables or integrate neural networks (NN) to get the optimum functional approximation of the Q-function. The Q-table approach may be the best choice in case the total number of possible states and actions is relatively small, but a typical radio system may require many states and parameters to achieve a specific optimization objective. Therefore, the deep-reinforcement learning (DRL) strategy employing a deep neural network (DNN) to approximate the optimum policy has attracted significant attention [146].

From a conceptual perspective one may follow a Q-learning framework featuring an action branching architecture approach first proposed by Tavakoli et al. [150]. Key idea of this approach is to utilize the dueling double DQN (DDDQN) [151] principle featuring a shared decision module followed by several action advantage branches, one for each action dimension, and one common value branch. This strategy leads to very efficient Q-learning implementations because of a substantial reduction in the number of state-action Q-value outputs in systems with high-dimensional action spaces and a high degree of freedom per dimension. Figure 12) shows the selected architecture to learn optimum OLPC parametrization. A comprehensive description is provided in [149]. The main difference of our approach to the general architecture [150] is that the output branches are represented by the single output layer of a shared dense neural network, and a scalar state-value function is omitted.

In extensive system-level simulation evaluation campaigns, we investigated the proposed deep Q-learning approach for a short range, high cell- and UE-density 6G in-Factory sub-network [152] with beyond current 5G NR capabilities to support URLLC for machine-like data traffic. The key performance indicator is the end-to-end delay. The delay is considered as an L3-delay that includes all relevant delay components originating, e.g., frame structure, packet buffering, HARQ retransmissions, or UE half-duplex operation. Our target is to receive periodic data packets of 32 Bytes/ms per UE and DL/UL direction within $\approx 100\mu sec$ time limit, and the measured complementary cumulative distribution function (CCDF) is used to determine the likelihood of failures. The online Q-learning process had been started without any knowledge of the optimum OLPC parameter configuration. Figure 13 shows the final UL delay

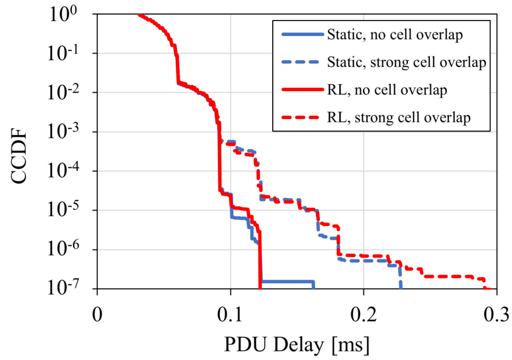


FIGURE 13. **Obtained UL latency performance for OLPC configuration obtained via extensive search (static) or online learning (RL) and for low (no cell overlap) and high (strong cell overlap) UL inter-cell interference situations.**

CCDF after conducting a sufficient number learning-iteration steps. The results show that UL OLPC parametrization from RL achieved the same delay performance compared to a static parameter configuration obtained via extensive search.

VIII. FUTURE RESEARCH DIRECTIONS

Looking ahead, the evolution of 6G physical layer design needs to evolve by tightly coupling energy efficiency, capacity and coverage, trustworthiness, and AI-driven adaptation within a single, coherent framework. Rather than optimizing each of them in isolation, future work should pursue methods that treat the different aspects of sustainability, performance, and security as equal design objectives. Therefore, we believe that new and integrated metrics can be beneficial such as energy per delivered bit at target reliability and latency. Moreover, this calls for hardware-software co-design at the transceiver, where waveforms, coding, beamforming, and front-end architectures are selected and configured dynamically in response to traffic demand, channel conditions, and device constraints, with end-to-end models that capture the joint impact of amplifiers, converters, oscillators, and signal processing on spectral and energy efficiency.

On the capacity and coverage front, future research should emphasize scalable distributed architectures that remain robust under dense deployments and mobility. This includes multiple-access schemes that flexibly share resources under diverse quality-of-service targets, integrated with distributed antenna paradigms that leverage statistical channel insights for efficient resource orchestration, as well as compression-aware backhaul designs to alleviate infrastructural bottlenecks.

Trustworthiness must be advanced by design at the physical layer and harmonized with higher-layer protections. Future systems might combine directional signaling and channel-aware techniques to reduce exposure to eavesdropping and jamming, while leveraging integrated sensing to monitor the radio environment for anomalies. Progress here depends on robust models of uncertainty (e.g., location and channel variability), standardized interfaces for extracting and protecting measurement data, and systematic evaluation of security-efficiency trade-offs so that added protections do not impact energy efficiency significantly.

AI will play a central role across all these directions, but its deployment must be rigorous. A key challenge is to guarantee minimum performance under user mobility and hardware constraints. Therefore, to make AI-enabled PHY dependable, future research should embed domain constraints and priors, quantify uncertainty, and satisfy real-time computation and peak memory limits in specific scenarios. Another challenge is to set operational boundaries for robustness and to achieve decision-process transparency through explainability for algorithmic trustworthiness. Equally important are open datasets, reproducible hardware-in-the-loop testbeds, and standardized benchmark suites that can assess algorithms on a joint performance-energy-security metric rather than isolated single-metric measures.

IX. CONCLUSION

This paper has presented a comprehensive set of physical-layer insights generated within the German 6G-ANNA research initiative. By analyzing the fundamental trade-offs that will shape 6G, from spectrum scarcity versus data-rate demand, through SE/EE duality, to densification versus cost, the work establishes a coherent systems perspective that can guide a smooth evolution from 5G to standalone 6G deployments.

On that foundation, several innovation tracks were investigated. First, notable energy-centric advances were reported, including low-PAPR PMCW/CO-PMCW waveforms, adaptive Gearbox-PHY modulation with hardware-aware optimization, and end-to-end transceiver models that quantify the EE–SE trade-offs. Second, capacity and coverage were addressed via rate-splitting multiple access, hybrid NOMA-TDMA schemes, cell-free massive-MIMO architectures, and fronthaul compression techniques. Third, methods to strengthen trustworthiness through frequency-diverse arrays and reconfigurable intelligent surfaces were discussed that can enlarge the wiretap-free region, complemented by wireless-sensing–based tamper detection that integrates seamlessly with future ISAC frameworks. Finally, the study positioned 6G as the first AI-native generation, demonstrating diffusion-based channel estimation, hybrid model-driven learning, and deep-RL uplink power control that achieve near-optimal latency in factory networks.

Taken together, these results give a clear perspective towards a 6G PHY that reconciles sustainability, capacity, resilience, and security. By continuing this cross-disciplinary effort, 6G can deliver ubiquitous gigabit-per-second rates, sub-millisecond latency, and carbon-aware operation while maintaining the security and inclusivity at the core of its objectives.

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