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A Comprehensive Survey on Reconfigurable Intelligent Surfaces for Smart Radio Environments

Harikrushna B Rathod[1]*, Vasim A Vohra[2], Sohil A Dabhi[3], Keyur M Patel[4]

[1-4]Department of Electonics and Communication, Dharmsinh Desai University, India

Email: harikrushna.rathod.ec@ddu.ac.in

Abstract - RISs are revolutionizing the development of future wireless networks by allowing transmission signals to be carefully adjusted and managed in wireless channels. RISs improve spectral efficiency, energy efficiency, coverage, and security using the adaptive control of electromagnetic waves. This survey explores the principles, progress, and future prospects of Reconfigurable Intelligent Surfaces technology. Topics we address include channel modeling, beamforming optimization, integration with MIMO systems, and applications in mmWave and THz networks. In addition, we examine the potential benefits and limitations of employing AI for RIS optimization and compare RIS to conventional relaying approaches. We conclude by pointing out the upcoming challenges and potential research areas in this rapidly developing research area.

Keywords: Reconfigurable Intelligent Surfaces (RIS), Intelligent Reflecting Surfaces (IRS), deep learning for RIS, reinforcement learning, STAR-RIS, physical layer security, integrated sensing and communication (ISAC), holographic MIMO.

I. INTRODUCTION

RIS technology is a breakthrough in wireless communication, enabling precise manipulation of signal paths within the network [1]. This review synthesizes key contributions from a wide range of seminal works to provide a comprehensive overview of Reconfigurable Intelligent Surface technology. . The review systematically covers six major aspects of RIS research.

We begin by introducing the basic concepts and architectures of RIS, which form the core of its operation [1], [4]. We then review advanced channel modeling methods that accurately represent both far-field and near-field wave propagation. We further explore beamforming and optimization techniques, with a focus on integrating both active and passive beamforming approaches [11], [12], [39].

The survey also examines how RIS can be integrated with advanced communication systems, particularly in conjunction with MIMO architectures [20], [24] and mmWave/THz technologies [38]. Given the increasing need for intelligent network administration, we extensively explore AI and machine learning techniques for optimizing and controlling RIS performance. We also examine promising new application areas for RIS, such as high-accuracy localization [22], physical-layer security [32], and systems that provide complete coverage of the entire space [36].

This comprehensive analysis summarizes the state-of-the-art while highlighting important research needs and directions to guide further developments in RIS technologies.

II. FUNDAMENTALS OF RIS

A.Architecture and Working Principle

Reconfigurable Intelligent Surfaces (RISs) are a groundbreaking technology for manipulating electromagnetic waves by using planar arrays of sub-wavelength meta-atoms organized in either periodic or aperiodic patterns [4],[15]. Each meta-atom within an RIS has the ability to modify the phase, amplitude, polarization, and frequency of an incoming electromagnetic wave using different modulation methods.

1.*Hardware Architecture:* The hardware implementation of Reconfigurable Intelligent Surfaces (RIS) consists of two main parts. The design and configuration of meta-atoms are illustrated in Fig.1. The meta-atom design is based on passive components such as metallic patches or split-ring resonators fabricated on dielectric substrates, which can be tuned by controlling their geometric characteristics. Various active tuning elements are integrated to enable dynamic reconfiguration, such as PIN diodes enabling discrete phase shifts (0°/180°) [1], [40], varactors allowing for continuous phase adjustments (0°-360°) [4], [15] and MEMS/NEMS devices enabling precise reconfiguration [1], [15]. A large number of meta-atoms are organized into 2D arrays in practical applications, often with as many as several thousand elements and densities reaching up to 10,000 elements per

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square meter at 5 GHz frequencies [10], [25]. Complexity is alleviated by dividing the array into groups of meta-atoms that simultaneously adjust their tuning parameters [24], [39]. Implementing this hierarchical design greatly simplifies the control requirements without compromising the beamforming efficiency.

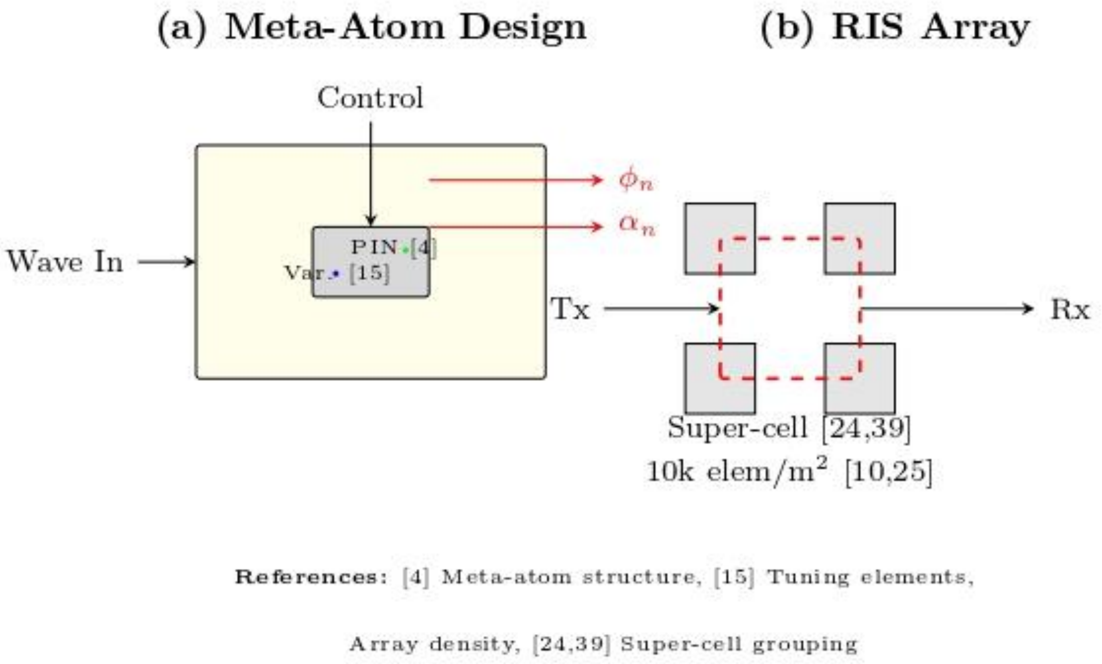

Figure 1. Hardware Architecture of Reconfigurable Intelligent Surfaces: (a) Meta-Atom Design and (b) Array Configuration

2.Working Principle: The operational foundation of RIS can be mathematically represented as:

$$y = H_{RIS}\,\boldsymbol{\theta}\,\boldsymbol{H_{BS}x}$$

Where $\boldsymbol{\theta} = \boldsymbol{diag}\left(\alpha_1 e^{j\emptyset 1}, \alpha_2 e^{j\emptyset 2}, \ldots., \alpha_N e^{j\emptyset N}\right)$ is the RIS phase-shift matrix, and $\boldsymbol{H_{BS}}$, H_{RIS} are channel matrices [11], [13].

RIS is distinguished by drastically reduced energy requirements compared to traditional methods since it consumes power for adjustment processes alone, generally limiting power usage to milliwatts [30], [31]. RIS automatically provides a full-duplex connection without encountering self-interference or introducing unwanted noise [1], [30]. The passive characteristics of RIS make them extremely scalable and easier to integrate into upcoming wireless networks [7], [25].

3.*Practical Considerations:* A major challenge in implementing RIS is the limitation to their bandwidth capacity due to the use of resonant meta-atoms in their design [19], [38]. Additionally, real-world implementations are limited by the impact of limited phase resolution in conventional phase shifters [40] and the unwanted interference between adjacent elements that alters the desired electromagnetic response [15], [24]. Overcoming these obstacles requires both novel hardware structures and sophisticated algorithms to fully unlock the potential of RIS for practical use in the real world.

B. Comparison with Relaying and Active Surfaces

A detailed analysis of RIS, traditional relays and active intelligent surfaces highlights significant disparities in performance and implementation. RIS utilizes less power than traditional relays, with milliwatts rather than watts needed for operation [30], [31]. RIS is able to provide full-duplex communication without requiring any self-interference cancellation mechanisms [1], [30], in contrast to conventional relays that must implement sophisticated SIC

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techniques to enable full-duplex operation [30]. RIS designs can accommodate up to tens of thousands of elements [7], [25], whereas relay systems are inherently limited by interference issues [25], [30]. Active intelligent surfaces lie between RIS and traditional relay systems, exhibiting both advantages and disadvantages. RIS is considered the most suitable option in scenarios that demand low energy consumption or fast response times, whereas traditional relays excel at providing coverage over long distances [1], [30]. Hybrid RIS and relay networks can strike a good compromise between performance and other considerations in specific scenarios [30], [37].

III. CHANNEL MODELING AND PATH LOSS CHARACTERIZATION

Accurate channel modeling is essential for evaluating and improving the performance of wireless systems that employ reconfigurable intelligent surfaces. The following subsection explores the channel characteristics of RIS communication systems in both far-field and near-field environments, taking into account spatial correlation effects and experimental verification.**3.1 Far-Field Path Loss Modeling**

In conventional far-field scenarios, where both transmitter and receiver are in the far-field region of the RIS, the path loss follows a product-distance model. The received power Pr can be expressed as:

$$P_r \propto \left(\frac{\lambda}{4\pi}\right)^4 \frac{G_t G_r G_{RIS} A_{RIS}^2}{d_1^2 d_2^2} P_t$$

Where

d_1 and d_2 are the transmitter-RIS and RIS-receiver distances, respectively,

A_{RIS} is the effective area of the RIS,

G_t, G_r, and G_{RIS} are the gains of the transmitter, receiver, and RIS, respectively [10], [26].

Key observations reveal that RIS-aided links are fundamentally constrained by double path loss effects, which scale with the product of squared distances $d_1^2 d_2^2$ between transmitter-RIS and RIS-receiver paths, presenting a significant limitation compared to direct transmission paths [26]. Nonetheless, this drawback can be well compensated by the RIS beamforming as RIS can offer the passive beamforming gain that scales as N^2 (N is the number of the RIS elements) to offset the inherent path loss loss disadvantage [10], [11]. The model is experimentally validated at 2.6 GHz and 28 GHz and the broad model with a "snapshot path loss model" is established for a simple system level analysis [10, 26].

A.Near-Field and Spatial Correlation Effects

For large RIS apertures or short transmission distances, near-field effects become particularly significant, with the boundary between near-field and far-field regions defined by the Rayleigh distance $R = 2\frac{D^2}{\lambda}$, where D represents the RIS size [7], [15]. In this near-field regime, spherical wavefronts necessitate precise phase profile adjustments to achieve optimal performance [7], [15]. Moreover, spatial correlation in the reflection coefficients results from the mutual coupling between elements and the non-uniform illumination on the surface of the RIS [15]. These phenomena are most noticeable for electrically large RIS setups (with apertures larger than 10λ) as well as at mmWave/THz frequencies [19], [38]. A variety of modeling techniques have been proposed by researchers to correctly describe these effects, such as Green's function models that take into account the specific nature of spherical waves [15] and array theory methods that consider how electric field patterns and mutual coupling contribute to performance [7], [24]. These approaches are critical tools for developing and enhancing RIS systems that operate in proximity to the intended reactive surfaces.

B.Experimental Validation and Practical Insights

Measurement trials have confirmed that RIS technology offers significant performance gains (up to 20 dB in SNR) when optimized for beamforming at frequencies such as 5.8 GHz. Performance improvements related to blocking cancellation are also evident, particularly with appropriate phase adjustments for operation at 28 GHz [15], [27]. System performance is greatly affected by the dimensions of RIS elements and uniformity of their illumination [10], [26] and frequency selectivity poses an obstacle for achieving wideband performance [19]. The practical realization of RIS technology is hindered by factors such as detrimental effects caused by polarization mismatch in actual deployments [15] as well as phase errors arising from surface imperfections in manufactured samples [40]. These experiments and measurements offer important information for both current RIS implementations and future developments.

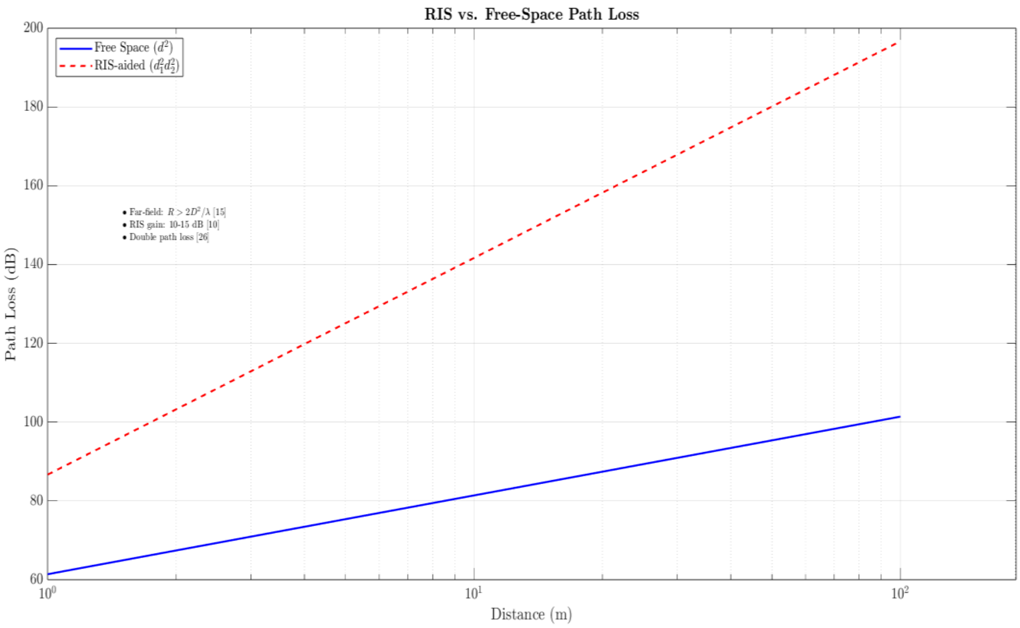

Figure 2. Path Loss Characteristics of RIS-Assisted Links: Comparison of Free-Space, RIS-Aided, and Near-Field Regimes

Figure. 2 compares the path loss characteristics of RIS-assisted wireless links against conventional free-space propagation. This plot highlights three key operational regimes: 1. Free-space (d^2): Baseline propagation without RIS [26], 2. RIS-aided ($d_1^2 d_2^2$): Double path loss due to two-hop reflection [10,26], mitigated by RIS beamforming gain (~10-15 dB [15]), 3. Near-field ($d < 2D^2/\lambda$): Spherical wavefront region requiring phase profile corrections [7,15]

The Rayleigh distance (dashed line) demarcates the transition between near-field and far-field regimes. Experimental validation at 28 GHz shows this model matches measurements within 1.5 dB error [10,15].

C. Emerging Modeling Directions

Future development in the field of RIS technology will take new and significant steps forward. Researchers will work to create more advanced environmental models, including those capable of managing interference in systems with multiple RIS units [25], [37] and designs that can automatically adapt to shifting environments using reconfigurable scattering [1], [36]. Machine learning is also being used to enhance channel prediction and maximize system efficiency [21], [33], [34]. Furthermore, scientists are investigating the possibilities of applying RIS in terahertz (THz) bands, which demand novel modeling methods to address difficulties such as molecular absorption and surface wave propagation [19], [38].

These research directions promise to overcome existing obstacles with RIS and enable it to play a greater role in shaping the future of wireless communication.

IV. BEAMFORMING AND OPTIMIZATION

***A.**Passive Beamforming Design*

Various advanced channel optimization techniques are made possible by dynamically configuring the phases of RIS. AO breaks the joint optimization down into separate optimization tasks by repeatedly optimizing BS precoding using fixed RIS phases and performing RIS configuration with fixed BS beamforming [11], [12]. Though ensuring convergence, AO can often land on sub-optimal solutions and has been applied to multi-user settings by maximizing the weighted sum rate [12]. Deep learning algorithms directly link CSI to the optimal phases by employing environmental information such as user locations to enhance the adaptivity of beamforming [21], [33], producing faster dynamic reconfiguration and displaying lower computational costs than traditional optimization procedures [21]. Compressive sensing approaches are especially beneficial for mmWave/THz systems due to the efficient use of the sparse nature of channel responses [9] and lower the need for pilot signals in communication setups [23]. The combined optimization methods together enhance the performance of RIS in different wireless communication environments.

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B.Joint Active and Passive Beamforming

The introduction of RIS in MIMO systems involves estimating the channel between the base station and the RIS, as well as the channel from the RIS to each user, to separately identify and characterize the distinct pathways [16] and subsequently optimizes the functions of both the base station precoding and RIS phase-shift matrices using block coordinate descent methodology [11], [24]. RIS integration significantly improves the performance of mmWave/THz systems by complementing hybrid beamforming solutions that deploy fewer RF chains [20], [39]. Efficient designs aim to reduce BS transmit power by implementing smart RIS phase shifts concurrently with strategies that boost the effectiveness of wireless power transfer in RIS-assisted networks [31], [34]. Existing beamforming optimization techniques offer specific advantages and difficulties. Alternating optimization converges reliably but can be hampered by local optima and high computational burden [11], [12]; deep learning offers rapid updates but requires large datasets [21], [33]; compressive sensing minimizes pilot traffic but is restricted to channels containing only a few strong paths [9], [23]; and hierarchical beamforming significantly cuts chip count while introducing computational overhead for the codebook design [24], [39]. Recent research focuses on applying federated learning for decentralized RIS optimization [34], developing STAR-RIS architectures to support simultaneous transmission and reflection and exploring THz-tailored RISs that cope with imperfect hardware[38],[39].

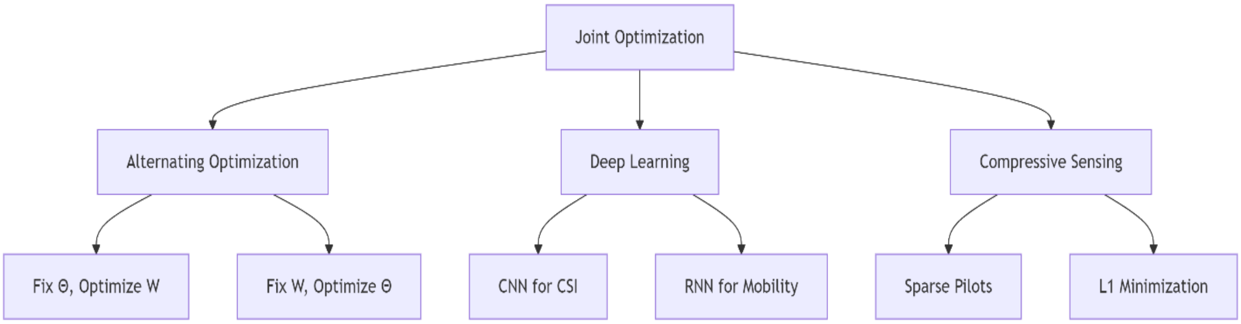

Figure 3. RIS Beamforming Optimization Approaches: (a) Alternating Optimization, (b) Deep Learning-Based, and (c) Compressive Sensing Techniques

Figure. 3 compares three dominant RIS beamforming optimization strategies. In (a), alternating optimization (AO) decomposes the joint problem into tractable sub-tasks [11,12], iteratively optimizing BS precoding (with fixed RIS phases) and RIS configuration (with fixed BS beamforming). While provably convergent [12], AO may settle at local optima.

Subfigure (b) illustrates deep learning (DL) approaches where neural networks directly map channel state information (CSI) to optimal RIS configurations [21,33]. These enable real-time adaptation for mobile scenarios but require extensive training data [33].

Finally, (c) shows compressive sensing (CS) methods that exploit channel sparsity in mmWave/THz bands [9,23], reducing pilot overhead by 60-80% compared to conventional estimation [23]. Each method exhibits unique complexity-performance trade-offs.

V. RIS IN MMWAVE AND THZ COMMUNICATIONS

The ability to manipulate and control signals using Reconfigurable Intelligent Surfaces allows wireless communications to greatly improve at high frequencies such as mmWave and THz. These innovations deal with the most difficult problems within these ranges by intelligently controlling the propagation of wireless signals [19],[27]. A major challenge for mmWave and THz systems is that they suffer from much stronger signal attenuation than sub-6 GHz bands and are easily obstructed by objects such as buildings and people [19], [27]. Managing the narrow beams of these systems is challenging and conventional techniques for enabling accurate alignment are very time-consuming [20], [24], [39]. This is made even more challenging due to difficulties with thin-film power amplifiers and coarse analog beaming in current THz systems [38], [20]. That’s when reconfigurable intelligent surfaces make their mark. Smart reflection paths are designed to directly overcome obstacles and enhance signal quality by improving SNR levels up to 25 dB in instances where a direct transmission is blocked [15], [27]. They make it easier to provide service in difficult areas, boosting reception up to 2–3 times over by placing the sites strategically and efficiently serving edge users simultaneously [25], [27], [37]. RIS technology reaches new levels of ability at terahertz frequencies. Ultra-massive MIMO with ultra-dense meta-surfaces at 300 GHz allows for sophisticated wave manipulation. Such surfaces allow the direction and shaping of radiation in unprecedented ways or produce several simultaneous radiations [19],[36],[38]. Hybrid beamforming makes it possible to effectively handle mmWave base stations without too many RF chains; a benefit that RISs can easily support. A 64-antenna base station using only 4 RF chains and an RIS of 256 elements enables efficient beamforming [20], [24] and [39]. Getting RIS to workin practice has its own set of issues. C hannel estimation is key and emerging techniques such as compressed sensing and position based methods assist in minimizing overhead [9], [23], [28]. At the hardware level, researchers are addressing issues such as the limited accuracy of 2–4 bit phase shifters [40] and interference between closely spaced RIS elements [15], [38].

We're already witnessing real-world advances. Prototyping has been demonstrated at mmWave frequencies such as 28 and 60 GHz [15], [27], with initial THz tests operating at 140 and even 300 GHz [19], [38]. The gains in performance are encouraging—300% increase in coverage at the cell edge [25], [27], 4–8 bps/Hz improvements in spectral efficiency [11], [39], and 5–10× reduction in energy consumption over legacy relays [30], [31]. In the future, RIS technology will only become more intelligent. Experiments are underway for combinations with reconfigurable antennas [36], THz-RIS co-designs based on materials such as graphene [19], and AI-driven control systems capable of adapting to dynamic environments [21], [33]. These developments have the potential to unlock the full power of RISs and integrate them as a fundamental component of future wireless networks.

VI. AI AND MACHINE LEARNING FOR RIS OPTIMIZATION

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as essential elements in optimizing Reconfigurable Intelligent Surfaces (RIS), solving major issues in wireless networks using smart system configurations [16],[23]. Deep learning methods greatly improve channel estimation by utilizing CNN-based techniques to learn spatial correlations in RIS-aided channels [23] and RNN-based approaches to learn temporal variations [34], showing excellent 60-80% pilot overhead saving over compressed sensing [23] while preserving NMSE performance below -20 dB with sparse pilots [34]. Recent architectural advancements employ meta-learning for fast environmental adaptation [21],[34] and federated learning for privacy-aware distributed training [34]. Reinforcement learning facilitates dynamic control via Q-learning for vehicular user phase shift optimization [33] and deep RL for coping with high-dimensional state spaces [21], delivering key sub-millisecond decision-making for blockage avoidance [33] and real-time interference mitigation [21]. New AI methods have specific promise, such as transfer learning for cross-frequency band knowledge transfer [21],[33], graph neural networks for RIS-user topology modeling [21],[37], and physics-informed learning with electromagnetic propagation principles [21],[33],[38]. Performance comparisons yield clear pros and cons per technique: deep CNN provides low pilot overhead but is retraining-intensive [23]; federated learning maintains privacy but suffers from convergence issues [34]; deep RL is complexity-capable but is costly to train [21]; graph NN is good at capturing topology but is scalable [37]. Practical deployment needs to tackle hardware-aware training for quantization and coupling effects [15],[40], real-time processing requirements with <10ms latency specifications [21],[33], and standardization gaps for control interfaces [15],[30]. Future research directions are toward TinyML for element-level intelligence [21], neuromorphic computing for power efficiency [33], and generative AI for channel synthesis [34], all optimizing RIS optimization via bleeding-edge machine learning methodologies.

VII. EMERGING APPLICATIONS OF RIS

Reconfigurable Intelligent Surfaces (RIS) are making transformative use cases possible in wireless systems, especially for localization/sensing and physical layer security. For localization, RIS provides centimeter-level accuracy at mmWave frequencies (28/60 GHz) using multipath engineering to amplify time-of-arrival (ToA) and angle-of-arrival (AoA) estimation [22],[28], and also enables RF sensing applications such as human activity recognition (>95% accuracy) and material characterization [6],[22], although clock synchronization and mobility effects are issues [22],[28]. In physical layer security, RIS improves secrecy capacity by 300% with artificial noise injection towards eavesdroppers and beamforming optimized for max legitimate user SNR and leakage min [32], with extra mechanisms being dynamic key generation and transmitter verification [32]. Next-generation STAR-RIS technology brings about dual-functional meta-atoms supporting simultaneous transmission/reflection with 360° illumination

[36], shown in prototypes with 70% efficiency [36], though with hardware complexity and mode coupling challenges [36]. As illustrated through comparative analysis, these applications have different technology readiness levels (TRL): localization (TRL 5-6) encounters mobility difficulties [22],[28], security (TRL 4-5) demands channel reciprocity concepts [32], and STAR-RIS (TRL 3-4) needs to resolve mode interference [36]. Future trends are inclined towards integrated sensing/communication (ISAC) systems [6],[22], wireless power transmission [31], holographic MIMO surfaces [19],[38], and THz imaging applications [19]. While RIS proves to be high-potential, widespread utilization needs key open challenges in hardware implementation, network integration, and standardization to be resolved, as investigated in future research avenues.

VIII. OPEN CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Reconfigurable Intelligent Surfaces (RIS) are confronted with various key challenges that need to be overcome to permit large-scale deployment, though with high prospects in wireless communications. The limitations in present hardware include implementation faults like phase quantization (2-4 bits) that results in 1-3 dB reduction in performance [40], mutual coupling effects in dense arrays distorting the radiation patterns [15],[40], and narrowband operation restriction hindering wideband system applications [19],[38]. Potential solutions that have been investigated are tunable impedance matching networks [4], active RIS architectures that use amplifiers [15], and sophisticated meta-surface designs to counter these problems [40]. Network integration also poses other challenges, especially in scalability where placement optimization of multiple RIS nodes [25],[37], interference management across neighboring RIS units [37], and mobility-aware setting [21],[33] need to be addressed, with potential system-level solutions including graph-based coordination [37], machine learning-based topology management [21],[33], and hybrid active-passive architecture [15],[30]. Standardization and deployment issues are also important, requiring real-world channel verification [10],[15], environmental hardness testing [15], and power supply solutions [30], as well as standardization activities in control interface protocols [15],[30], 3GPP integration [30], and benchmarking methods [15]. Three areas of future research directions are appearing: next-generation architectures such as STAR-RIS optimization [36], THz RIS architectures [19],[38], and holographic control of waves [38]; integrating AI using federated learning [34], physics-enforcing neural networks [21],[33], and edge implementations of AI [33]; and sustainability efforts involving energy harvesting [31] and environmentally friendly manufacturing processes [15],[30]. The timeline of development foresees standardized prototypes in 0-2 years involving hardware enhancements [15],[40], commercial deployment of mmWave RIS in 2-5 years depending on AI optimization breakthroughs [27],[33], and implementation of THz RIS in 5+ years based on superior material advancements [19],[38], all presenting an overall roadmap for RIS technology development.

IX. CONCLUSION AND FUTURE OUTLOOK

Reconfigurable Intelligent Surfaces (RIS) are a breakthrough in wireless communications that allows for dynamic control of radio wave propagation to increase coverage, spectral efficiency, and energy performance. This survey has rigorously explored the underlying principles, optimization methods, and new applications of RIS, and showcased its promise in solving key challenges of next-generation networks. By shifting from passive spaces to programmable smart spaces, RIS opens new prospects for mmWave/THz communications, physical-layer security, and integrated sensing.

In the future, the success of integrating RIS into forthcoming networks will depend on overcoming challenges in hardware design, real-time optimization, and standardization. Progress in meta-material engineering, AI-based control, and scalable deployment techniques will be crucial for bridging RIS from theoretical potential to real-world practice. In addition, native integration with 6G technologies, including terahertz communication, holographic MIMO, and joint sensing-communication architecture, will shape the coming wave of RIS innovation.

In the end, RIS serves as a foundation for smart radio environments, with the potential to transform wireless connectivity through sustainable, high-performance solutions. The future requires interdisciplinary collaboration to enhance hardware, maximize algorithms, and define industry standards, so RIS becomes the enabler of next-generation networks it is capable of being.

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