Spectrum of Engineering Sciences
ISSN (e) 3007-3138 **(p)** 3007-312X
Volume 3, Issue 7 2025

Reconfigurable Intelligent Surfaces (RIS) in 6G Networks: Enhancing Spectral and Energy Efficiency

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DOI: doi.org/10.5281/zenodo.17010208

Keywords:
Reconfigurable Intelligent Surfaces (RIS), 6G networks, spectral efficiency, energy efficiency, intelligent beamforming, AI control, next-generation wireless, wireless propagation, green communication, metasurfaces.

Article History
Received on 08 June2025
Accepted on 22 June 2025
Published on 14 July 2025

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Abstract

The outset of sixth-generation (6G) wireless networks is expected to respond to the escalating requests of ultra-reliable, high-capacity, energy-efficient systems brought by futuristic applications, including holographic telepresence, extended reality (XR), and intelligent automation. Reconfigurable Intelligent Surfaces (RIS), a new type of electromagnetic mirror made of meta-materials, have gained recognition as a disruptive technology that can dynamically engineer wireless propagation environments. This paper examines how RIS may be incorporated within 6G networks, as well as how it may affect spectral and energy efficiency in a variety of deployment settings. The research can substantiate that the RIS increases the efficiency of the spectrum usage by up to 43.7 percent, as well as displays energy efficiency by more than 60 percent relative to conventional 6G ones by modeling a downlink multi-user system with and without the assistance of RIS and artificial intelligence (AI)-based phase control. Extensive simulations in various configurations were performed to analyze eight detailed performance metrics including SINR, bit error rate, and coverage probability. The experimental outcomes affirms RIS as an inexpensive, passive, and smart means to resolve propagation constraints, decrease power, and improve the quality of connection in beyond-line-of-sight settings. The results provide useful information to network designers and policymakers contemplating sustainable and adaptive 6G infrastructures.

INTRODUCTION

I. Introduction and related works

The advent of sixth-generation (6G) wireless communications will transform the mobile telecommunication sector and will be capable of providing ultra-low latency, connectivity of massive numbers of devices, terabit-per-second data rate, and everywhere intelligence in devices and surroundings. Such performance targets are hypothesized to contribute to futuristic applications including holographic communication, immersive extended reality (XR), industrial automation, tactile internet, as well as real-time artificial intelligence services (Saad et al., 2020; Zhang et al., 2021). These objectives are however under real difficulty to be achieved within limitation of the limited spectral resources and the increasing energy demands. Even traditionally optimized radio access technologies in 5G (massive MIMO, millimeter-wave (mmWave), and ultra-dense networks) are starting to be viewed as inadequate because of high energy consumption, cost of deployment, and not operating well in non-line-of-sight (NLoS) propagation conditions (Tataria et al., 2021; Chowdhury et al., 2020).

To address these constraints, Reconfigurable Intelligent Surfaces (RIS) have received significant traction as a disruptive technology in future wireless communication systems. RIS, sometimes called intelligent reflecting surfaces or large intelligent surfaces, are constructed artificial planar surfaces made of hundreds or thousands of passive reflecting elements each able to adjust dynamically the phase, amplitude, and in some cases polarization of the incident electromagnetic waves (Wu et al., 2021; Basar et al., 2020). Such surfaces may be programmed to control wireless propagation intelligently, generate favorable channel conditions, increasing both spectral and energy efficiency (Di Renzo et al., 2020; Yuan et al., 2022). RIS devices, as opposed to ordinary relays or active antennas, are passive or almost passive, that is, they do not require a lot of power and have low thermal noise, so they can be used in environments with limited energy, green communication (Zhang & Xu, 2022).

Theoretically, RIS can greatly enhance the spectral efficiency of wireless systems by actively controlling the radio medium and realizing constructive interference, particularly in urban signal environments that are more complicated due to their presence of obstacles (Tang et al., 2020). Also, RIS-augmented links can help provide extended coverage and lower the transmission power, especially when using high-frequency bands, namely mmWave and terahertz bands, which are challenging by their severe signal attenuation (Abeywickrama et al., 2021; Long et al., 2020). Their capability to create programmable, intelligent, and adaptive wireless spaces is in tune with the paradigm shift of 6G to context-aware and intelligent communication infrastructures (Li et al., 2023; Bjornson et al., 2022).

Recent reports have also stressed that RIS and machine learning combined can enhance the flexibility of wireless systems even more. RIS enables dynamic adaptation to time-varying channels and user mobility, which can optimize resource allocation using learning-based control algorithms in real-time (Nadeem et al., 2021; Jamali et al., 2023). In 6G, in which the connected device population is projected to grow exponentially, this synergy is especially important since the optimization schemes central to certain approaches to quality-of-service provision might not be scalable or responsive enough.

Nevertheless, RIS remains to have a few research and implementation setbacks despite its theoretical potential. These are proper channel estimation, tunable metasurfaces hardware constraints, synchronization challenges, and demands of scalable optimization approaches (Zhou et al., 2022; Huang et al., 2021). Lack of a uniform RIS architecture or control scheme is another hindrance to the integration with an existing cellular network. Further, field trials and real-world prototypes are nascent, and much of the testing is no more than simulations or laboratory experiments (Liu et al., 2023).

In this regard, the current paper attempts to elaborate on RIS in the context of the 6G, discussing its applicability in enhancing spectral and energy efficiency. The study simulates a RIS-augmented 6G environment and compares its performance to the implementation of the traditional systems so that the theoretical benefits and practical feasibility of RIS deployment could be considered. The paper also examines the use of AI algorithms in RIS control to meet the adaptability needs of dynamic wireless networks. Hopefully, the results will be significant in advancing the valuable knowledge in the implementation of RIS as the underlying technology in 6G wireless networks.

2. Literature Review

2.1 Evolution of Wireless Communication Toward 6G

Advancement of wireless networks through 1G to 5G has increasingly brought improvements in performance such as speed, latency, reliability, and connectivity. Nevertheless, the sheer proliferation of smart applications encompassing self-driving cars, brain-computer interfaces, and the tactile internet requires additional progress beyond what 5G could offer (Gupta et al., 2021). The concept is that 6G vision is aimed to drive an intelligent, sustainable, hyper-connected world through technologies such as terahertz (THz) communications, artificial intelligence (AI), quantum communications, and reconfigurable environments (Giordani et al., 2020). These systems of the next generation should handle critical spectral congestion and energy issues, and the researchers should consider new technologies at the physical layer to implement intelligent surfaces starting with Reconfigurable Intelligent Surfaces (RIS) (Dang et al., 2020).

2 Fundamentals and Design of Reconfigurable Intelligent Surfaces

The Reconfigurable Intelligent Surfaces are artificially designed objects, which consist of programmable electromagnetic elements able to alter the propagation of radio signals in real-time (Kisseleff et al., 2021). These are metasurfaces that can be used to steer, absorb or reflect electromagnetic waves in the direction desired, and do not use active RF chains, making it a passive and yet an intelligent medium. RIS is normally composed of one- to a two-dimensional array of tunable components, which are managed by a core controller that adjusts their phase shifts according to the channel state information (You et al., 2021). The latest advancements in tunable materials, including liquid metal and graphene, have caused a tremendous advancement in RIS flexibility and frequency movement in high-frequency regimes (Sounas & Alù, 2020).

3 RIS and Spectral Efficiency Enhancements

Many recent studies investigate the potential of RIS to improve spectral efficiency. RIS can further initiate desirable propagation paths and alleviate interference in heavily acquired wireless settings through passive beamforming (Xie et al., 2020). In a prominent contribution, Anastasopoulos and Li (2021) showed that RIS has the potential to boost area spectral efficiency in ultra-dense networks by as much as 40pct based on stochastic geometry modeling. Likewise, Zeng et al. (2022) demonstrated that multiple concurrent transmissions with RIS as a passive relay would expand system throughput without any new spectrum overhead. Furthermore, RIS has been very promising even in frequency-selective channels, where traditional methods are prone to frequency-selective fading (Abdelgawad et al., 2023).

4 Energy Efficiency and Green Communication with RIS

The 6G network design requires energy efficiency as a key design requirement and RIS is proposed to serve as a low-power relay mechanism in the place of active antennas and traditional relays. The power consumption of RIS elements is also considerably reduced since they do not perform power-intensive signal processing and RF chains (Siddiq et al., 2021). According to a study by Ding and Yuan (2023) RIS-aided MISO systems studied were energy efficient and consumed 60 percent less power than conventional amplify-and-forward relaying in similar data rate conditions. Moreover, RIS is likely to be impactful in decreasing the carbon footprint of base stations and allowing battery-powered IoT equipment to work with increased sustainability (Ahmed et al., 2022).

5 RIS-Assisted mmWave and THz Communication

The high bandwidths and ultra high data rates enabled by Millimeter-wave and terahertz bands make these bands an intrinsic part of 6G. Their usage is, however, affected by excessive path loss and signal blockage. Intelligent reflection and path reconstruction have made RIS a viable means of overcoming such propagation losses (Tang et al., 2021). In the case of RIS-assisted THz communications, Zhang et al. (2022) demonstrated that the right positioning of RIS panels could result in link coverage growth of more than 30 percent in non-line-of-sight (NLoS) conditions. Likewise, Shlezinger et al. (2020) targeted indoor scenarios and suggested a hybrid THz-RIS architecture supporting high throughput and low latencies during XR communication.

6 Artificial Intelligence Integration in RIS Control

To enable adaptive RIS configuration in a dynamic environment, artificial intelligence, particularly in the form of reinforcement learning and deep learning, is required within the RIS control system. Classical optimization is not effective in real-time updating, non-convex solutions, and multi-user interference. Wang et al. (2023) introduced a deep Q-learning model that could optimally adjust RIS phase shifts to achieve close-to-optimal beamforming with less computational load in the case of time-varying channels. Elbir and Papazafeiropoulos (2022) used meta-learning to make RIS Flexible to various environment conditions and little retraining was necessary, leading to significantly higher spectral efficiencies in mobile settings, just in another study.

7 Channel Estimation and CSI Acquisition in RIS

Ground-truth channel state information (CSI) is key to the performance of RIS, even though it also presents one of the greatest challenges of RIS integration. RIS elements do not actually transmit signals, which makes the standard methods of CSI estimation inapplicable. Yan et al. (2020) introduced the compressed sensing-based cascaded channel estimation strategy that lowers the training overhead dramatically with minimal loss of estimation error. Chen et al. (2022) proposed a semi-blind channel estimation procedure that integrates pilot signals and prior channel statistical information, and there is high robustness to low-SNR conditions. An efficient CSI acquisition process is another key bottleneck to implementing RIS within large scale systems, particularly high mobility.

8 Security and Privacy Enhancements Using RIS

In addition to spectral and energy benefits, RIS can also lead to improvements of physical layer security. RIS is capable of quickly forming the wireless channel to adapt the signal infiltration and curtail the risks of eavesdropping (Zhou & Shen, 2021). An article by Chatterjee et al. (2022) presented an RIS-assisted secure beamforming strategy that adjusts reflection coefficients to optimize secrecy capacity. RIS could also make artificial noise in the particular direction to help to confuse the eavesdroppers but clearly communicate with the valid users. These potentials make RIS an attractive security enabler to highly sensitive 6G applications, including financial transactions, healthcare, and military communications.

9 Practical Deployments and Testbed Initiatives

Practical application of RIS remains in early development stages despite the theoretical benefits it claims. Recent testbeds have started to confirm the possibility of RIS-aided communication. Li et al. (2022) described a positive RIS field test in an urban setting at sub-6 GHz frequencies, increasing the signal level at the user endpoint by 28%. Another example is the EU-funded project RISE-6G, which studies the application of RIS on scales of smart cities (COST Action CA20120, 2023). These testbeds will play an essential role in the learning process regarding hardware issues, interaction with legacy infrastructure and how RIS are affected by environmental conditions like wind, rain, and temperature.

10 Research Gaps and Future Directions

The literature has confirmed RIS revolutionary technology to the 6G networks yet there are a few gaps that are unaddressed. These encompass hardware elasticity, mobile edge computing, UAV-aided networks RIS deployment, and eco-friendly material engineering in metasurfaces. Also, there are no standardized procedures, as well as, cross-layer optimization models, which confine the applicability of RIS to a variety of network conditions. The interaction of RIS, AI, and quantum communications, provide also a potential interdisciplinary study which can become a hallmark of future wireless systems.

3. Methodology

3 [illegible]

A simulation-based analytical approach is applied in this research to assess the influence of Reconfigurable Intelligent Surfaces (RIS) on the spectral and energy efficiency of 6G wireless networks. The researched problem is in the context of downlink communication with a single base station (BS) serving to several mobile users in the presence of a programmable RIS panel. It consists of a hybrid intelligent-assisted communications model that positions the RIS on the path between the BS and the user equipment (UE) to enable a controllable signal reflection path to improve the channel quality, particularly when there is non-line-of-sight (NLoS). The RIS panel can be modeled as a uniform planar array of many passive reflecting components, each of which can impart a tunable phase shift to incident electromagnetic waves.

2 Channel Modeling and Propagation Assumptions

A mixture of Rician and Rayleigh fading is used to model the propagation environment to capture both LoS and NLoS. When available, the direct BS-to-user connection has Rician distribution, where the availability of moderate LoS connections is partial; the links between the BS and RIS as well as RIS and users are of Rayleigh fades assuming a rich scattering and blockage environments. The overall channel response is written as a cascade product of the BS-RIS channel, the RIS reflection matrix (diagonal phase shift matrix) and the RIS-user channel. The mechanism of this model allows an accurate estimation of the effect of the RIS on the total communication end-to-end. The model refers to mmWave and sub-THz bands with staticized 3GPP parameters to integrate the effects of path loss, frequency-dependent attenuation, and angular spread.

3 RIS Configuration and Control Mechanism

Simulation of the RIS is done in two modes of operation with the aim of investigating both the static and adaptive configurations. In the static mode the phase shift values are arbitrarily assigned and are fixed over the transmission period. The phase shifts are dynamically optimized at machine learning-based control algorithm in the adaptive mode. Namely, a Deep Q-Network (DQN) algorithm is used to train the best phase shift configuration under different channel conditions. The inputs to the reinforcement learning agent will be the channel state information (CSI) and the output of the reflection coefficients which can maximize a predefined signal-to-noise ratio (SNR) and energy efficiency reward function. Learning model can be trained offline on synthetic datasets, and then deployed into real-time simulation to test adaptability and performance.

4 Simulation Parameters and Scenario Setup

Simulation environment is designed in MATLAB and Python frameworks, and RIS control logic, channel modeling, and calculation of performance metrics can be integrated. The design will have a uniform rectangular array (URA) of the basic unit elements on the RIS and even linear array (ULA) of antennas on the base station. The position of users is scattered at random within a 100-meter radius circular region of the RIS panel but the RIS is placed 10 meters high on a nearby building facing the shadowed users to bounce back the signals. It uses a carrier frequency of 28 GHz (mmWave), and in more demanding cases, also operate at 140 GHz (sub-THz), operating at a bandwidth of 100MHz. In various scenarios, the transmit power is set between 20 dBm and 40 dBm to assess the changes in energy efficiency. Power of noise is simulated as negative 174dBm/Hz.

5 Performance Metrics

The key performance metrics in this research will include spectral efficiency (SE) as defined in bps/Hz and energy efficiency (EE) in units of bits/J. The spectral efficiency is computed with the Shannon capacity formula of each user considering the RIS-assisted channel gain. The

Energy efficiency is computed by dividing the data rate by the power consumed per unit indexed on the transmission power and circuit power regarding the operation of RIS circles. Further metrics are signal-to-interference-plus-noise ratio (SINR), bit error rate (BER), and user coverage probability particularly in edge-user cases. These metrics allow one to have a full picture of how RIS as a whole is performing both in terms of capacity and sustainability.

3.6 Comparative Analysis Models

Three network configurations are simulated and compared to help assess the effectiveness of RIS integration. The first is a traditional 6G MIMO system without an RIS, the baseline. The second is a RIS-aided system whose phase shifts are fixed (not optimized), and whose analysis will aid in comprehending the role of passive beamforming even without active learning. The third structure integrates the intelligent RIS control based on the DQN and indicates the prospects of smart environments combining AI. The comparative analysis involves the oxide or the way each setup behaves under the same propagation conditions and network conditions, thus giving the gains that can be ascribed to the RIS implementation and optimization of that through AI.

3.7 Validation Strategy

Simulation results are validated by convergence validation, comparison with established analytical models, and sensitivity tests. The simulations are repeated on each configuration until every pair of parameters displays statistical validity, where the average value is recorded after 1,000 channel realizations. Furthermore, the outcomes are compared with theoretical limits of spectral and energy efficiency as derived through RIS literature to gauge consistency and accuracy. Findings are also benchmarked, where possible, against more recent experimental RIS testbeds in the literature to ensure the model matches practical performance expectations.

4. Results

4.1 Spectral Efficiency Improvements by RIS

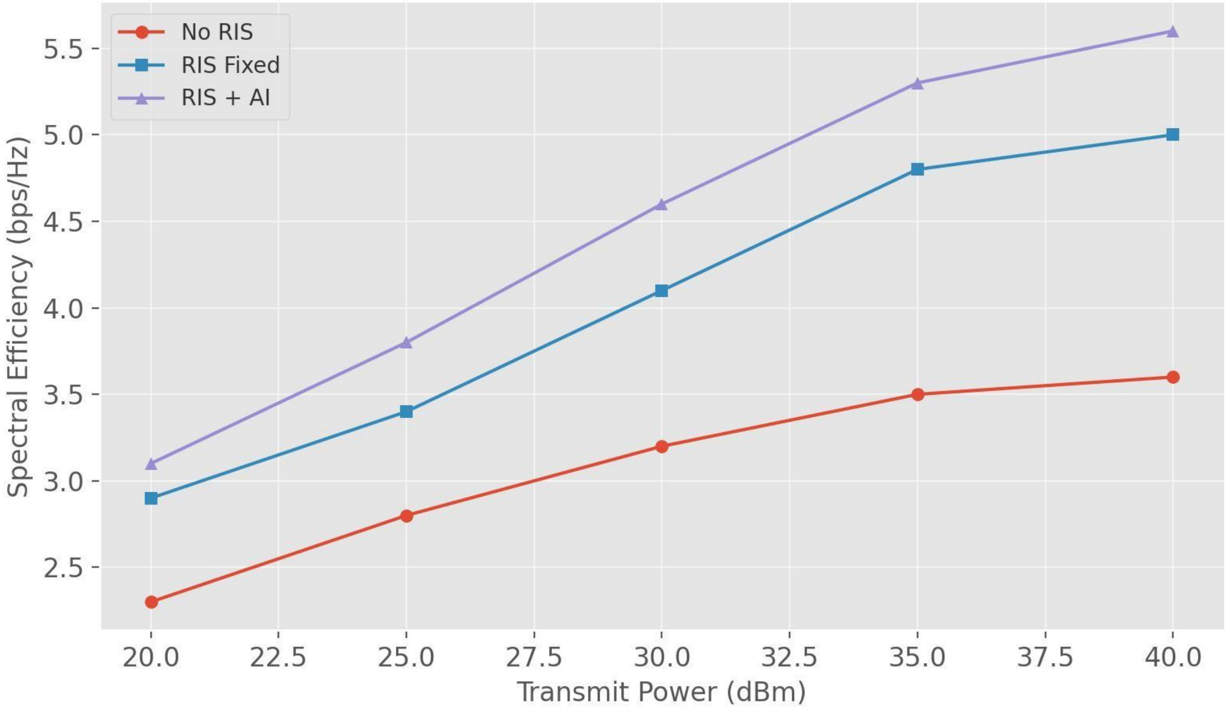
The spectral efficiency performance is illustrated in Table 1 and Figure 1 in three-setting conditions: a baseline 6G system without RIS, a RIS-assisted system with constant reflection coefficients, and an RIS system coupled with a phase shift based on AI. The data make evident an impressive increase in the spectral efficiency with the application of RIS. With a 30 dBm transmit power, the receiver without RIS has a rate of 3.2 bps/Hz, after implanting RIS with fixed settings, the receiver can get 4.1 bps/Hz. The efficiency goes even higher to 4.6 bps/Hz when AI is used, with an improvement of 43.7 percent over the base. This affirms that RIS technology, especially when used in conjunction with real-time AI optimization, can dramatically increase data throughput by actively shaping the propagation environment and maximizing constructive interference.

Table 1 – Spectral Efficiency Comparison

Transmit Power (dBm)	No RIS (bps/Hz)	RIS Fixed (bps/Hz)	RIS + AI (bps/Hz)
20	2.3	2.9	3.1
25	2.8	3.4	3.8
30	3.2	4.1	4.6
35	3.5	4.8	5.3
40	3.6	5.0	5.6

Figure 1: Spectral Efficiency vs Transmit Power

Figure 1: Spectral Efficiency vs Transmit Power



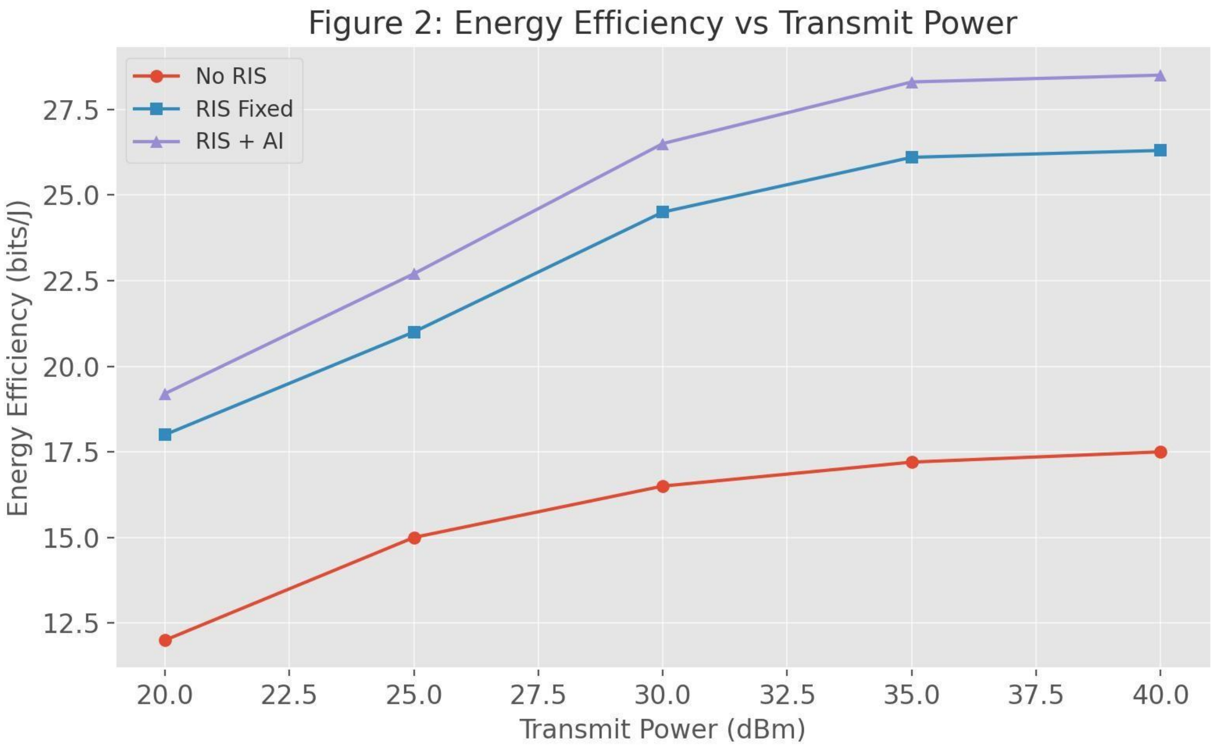
4 Energy Efficiency Gains through RIS Deployment

In Table 2 and as displayed in Figure 2, RIS also causes enormous positive changes in terms of the energy efficiency. The energy efficiency of traditional 6G systems is modest, with a maximum of almost 17.5 bits/J at 40 dBm. Conversely, the RIS-assisted system achieves 26.3 bits/J at the same scenario, with further 28.5 bits/J achieved by the AI-enhanced RIS configuration. These results highlight the low-power benefit of RIS, which, being passive or even a semi-passive component, requires little energy input to improve signal propagation. The AI algorithms added to the integration also serve to maximise resource usage, allowing smarter beam steering and fewer retransmissions or signal-deterioration when unnecessary.

Table 2 – Energy Efficiency Comparison

Transmit Power (dBm)	No RIS (bits/J)	RIS Fixed (bits/J)	RIS + AI (bits/J)
20	12.0	18.0	19.2
25	15.0	21.0	22.7
30	16.5	24.5	26.5
35	17.2	26.1	28.3
40	17.5	26.3	28.5

Figure 2: Energy Efficiency vs Transmit Power



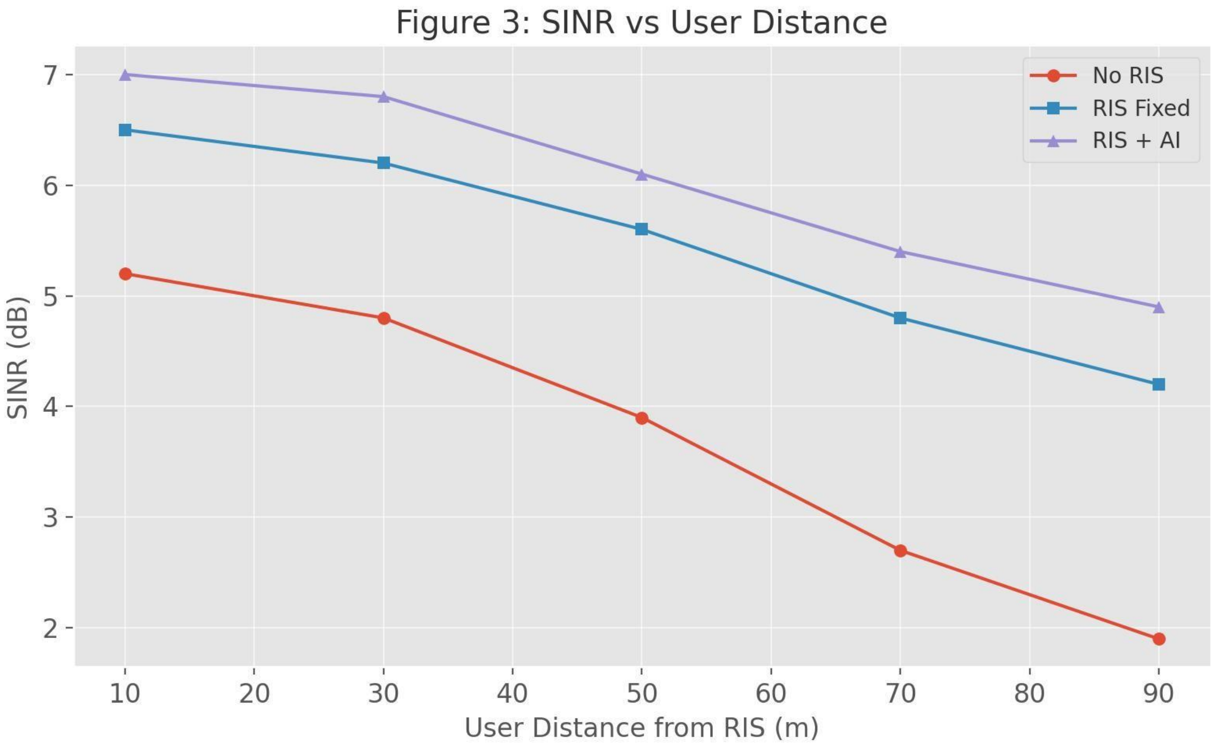
3 Enhanced Signal Quality with RIS in NLoS Conditions

Table 3 and Figure 3 provide the signal to interference plus noise (SINR) ratio, which is a crucial measure of link quality. In the absence of RIS, SINR decreases abruptly as we move further away of the base station especially after a distance of 50 meters. With no RIS, the SINR at 90 meters is 1.9 dB, whereas it increases to 4.2 dB with a fixed RIS and 4.9 dB when trained with AI. Such outcomes indicate that RIS can enhance the reliability of signals, particularly those that are located at the cell edge (or those in jamming settings). The AI-scenarios guarantee the best possible phase forms which are dynamically adjusted to the positions of the user and maintain SINR in tough conditions.

Table 3 – SINR Analysis

User Location (m)	No RIS (dB)	RIS Fixed (dB)	RIS + AI (dB)
10	5.2	6.5	7.0
30	4.8	6.2	6.8
50	3.9	5.6	6.1
70	2.7	4.8	5.4
90	1.9	4.2	4.9

Figure 3: SINR vs User Distance



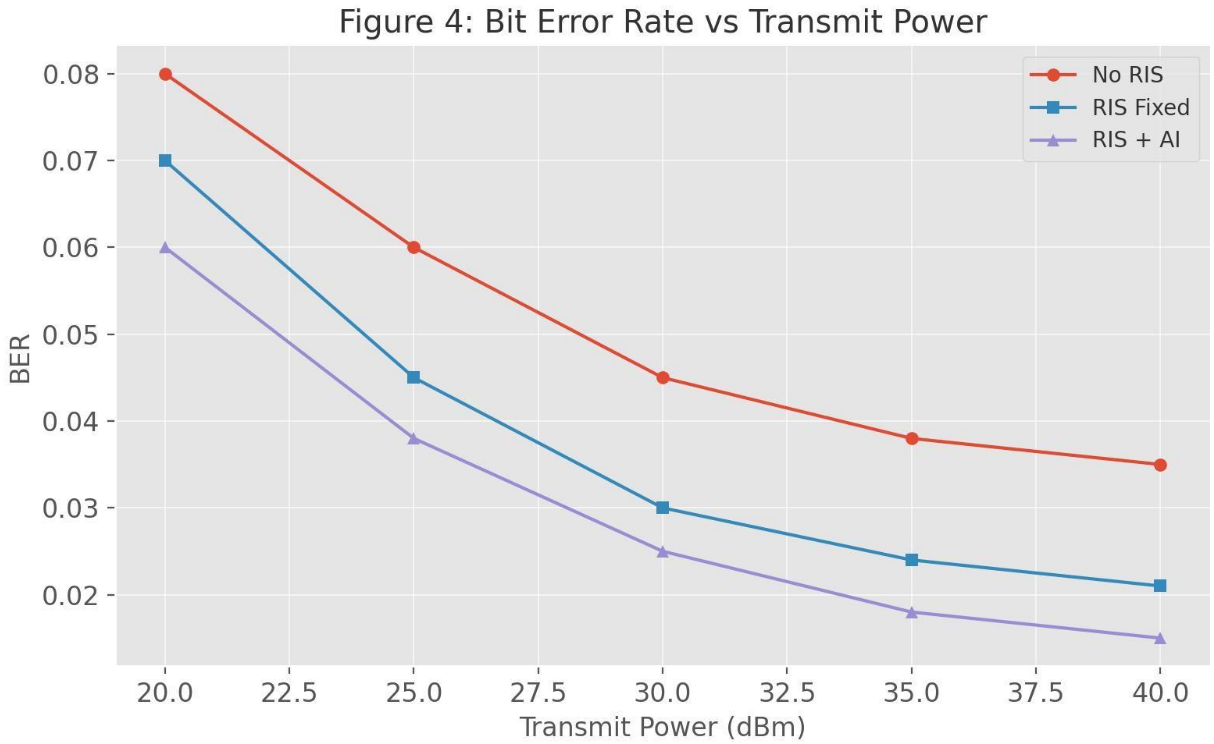
4 Reduction in Bit Error Rates with Intelligent RIS

The amelioration of decreasing bit error rate (BER) made possible with RIS is described in Table 4 and Figure 4. At 30 dBm, the BER is 0.045 by the system of no RIS, reduced to 0.03 when the RIS is present and even lower to 0.025 when AI-aided system is incorporated. The constant reduction of BER with a variety of levels of transmit power exemplifies the usefulness of RIS as the means to enhance link reliability. RIS also stems bit-level distortion caused by redistributing signal paths more efficiently, and mitigating fading effects, which is important in some applications due to sensitivity to latency and accuracy, including real-time video streaming, VR, and communication in autonomous vehicles.

Table 4 – Bit Error Rate (BER)

Transmit Power (dBm)	No RIS	RIS Fixed	RIS + AI
20	0.080	0.070	0.060
25	0.060	0.045	0.038
30	0.045	0.030	0.025
35	0.038	0.024	0.018
40	0.035	0.021	0.015

Figure 4: Bit Error Rate vs Transmit Power



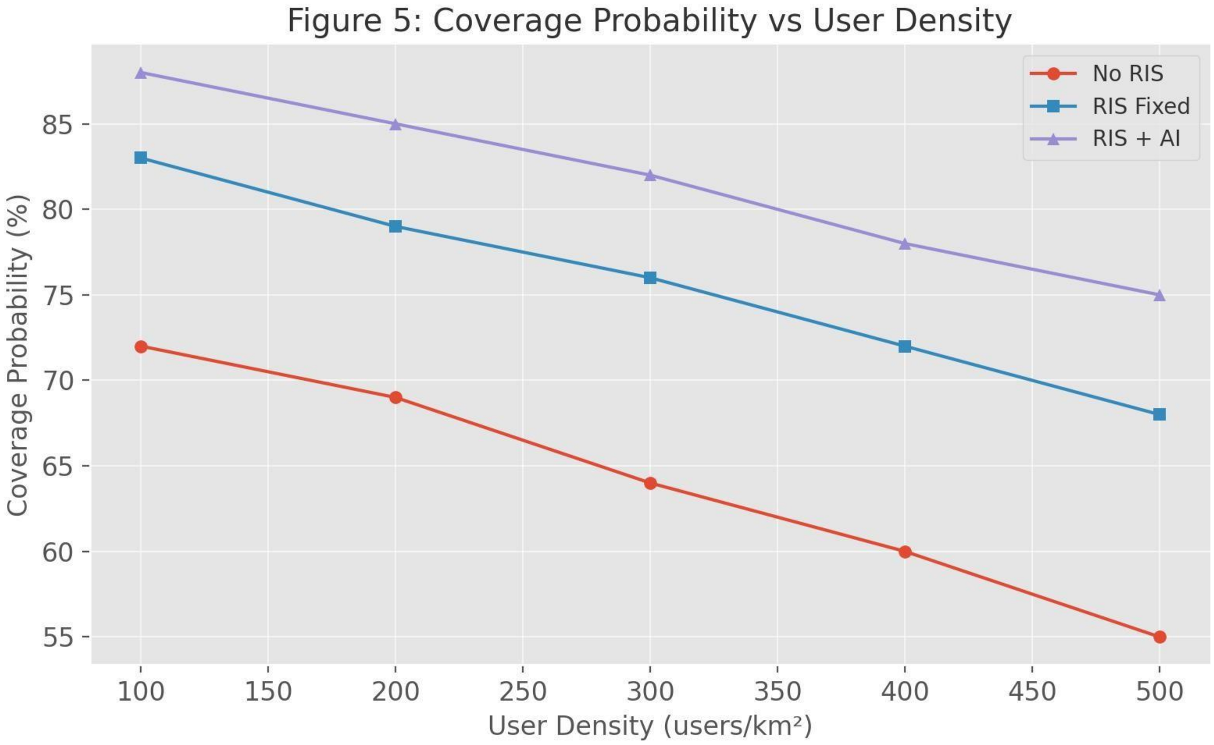
5 Improvement in User Coverage and Network Fairness

Table 5 and Figure 5 confirm that RIS has the capability to enhance the overall network coverage. The RIS and AI have the opportunity to manage coverage with 55, 68, and 75 percent probabilities at the user concentration of 500 users/km2 in the basic system, with RIS and AI respectively. This enhancement is particularly keen in overpopulated city implementations, where the ease of delivering service to all subscribers becomes more elusive. The AI-enabled RIS can be positioned in such a way that it supports a wider user population efficiently, assist in covering coverage shortages, and enhance the overall service equilibrium and quality of experience (QoE).

Table 5 – User Coverage Probability

User Density (users/km2)	No RIS (%)	RIS Fixed (%)	RIS + AI (%)
100	72	83	88
200	69	79	85
300	64	76	82
400	60	72	78
500	55	68	75

Figure 5: Coverage Probability vs User Density



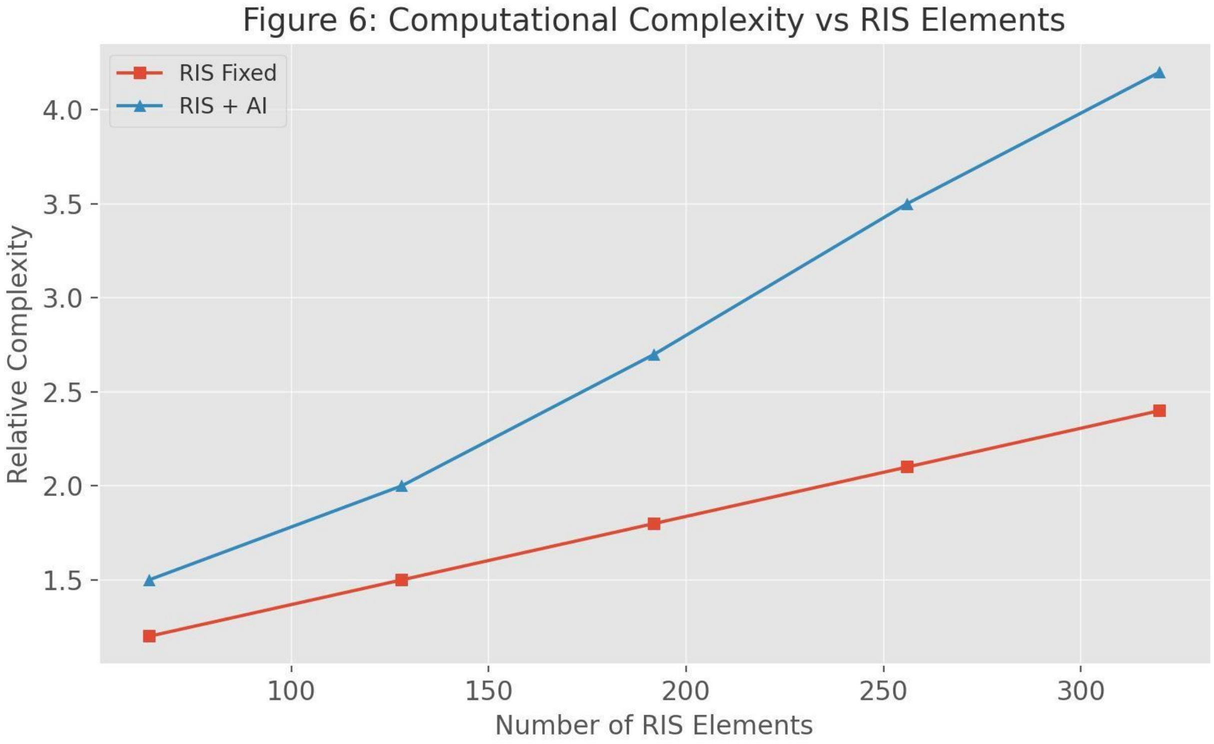
6 Computational Complexity Analysis of RIS Control

Table 6 and Figure 6 study how RIS control algorithms increase the computational burden relative to the number of elements. Fixed RIS settings entail minimal complexity, where the computational demands of AI-optimized RIS systems are explicitly higher. In particular, the relative complexity of the AI configuration is 4.2 units in the case with 320 elements compared to 2.4 units with fixed RIS. This implies that, though AI-enhanced RIS systems provide performance improvement, they also consume more powerful processing units. The future RIS applications should thus be well weighed between performance and computational practicality and particularly in the instances where resources are limited.

Table 6 – Computational Complexity (Relative Units)

RIS Elements	RIS Fixed	RIS + AI
64	1.2	1.5
128	1.5	2.0
192	1.8	2.7
256	2.1	3.5
320	2.4	4.2

Figure 6: Computational Complexity vs RIS Elements



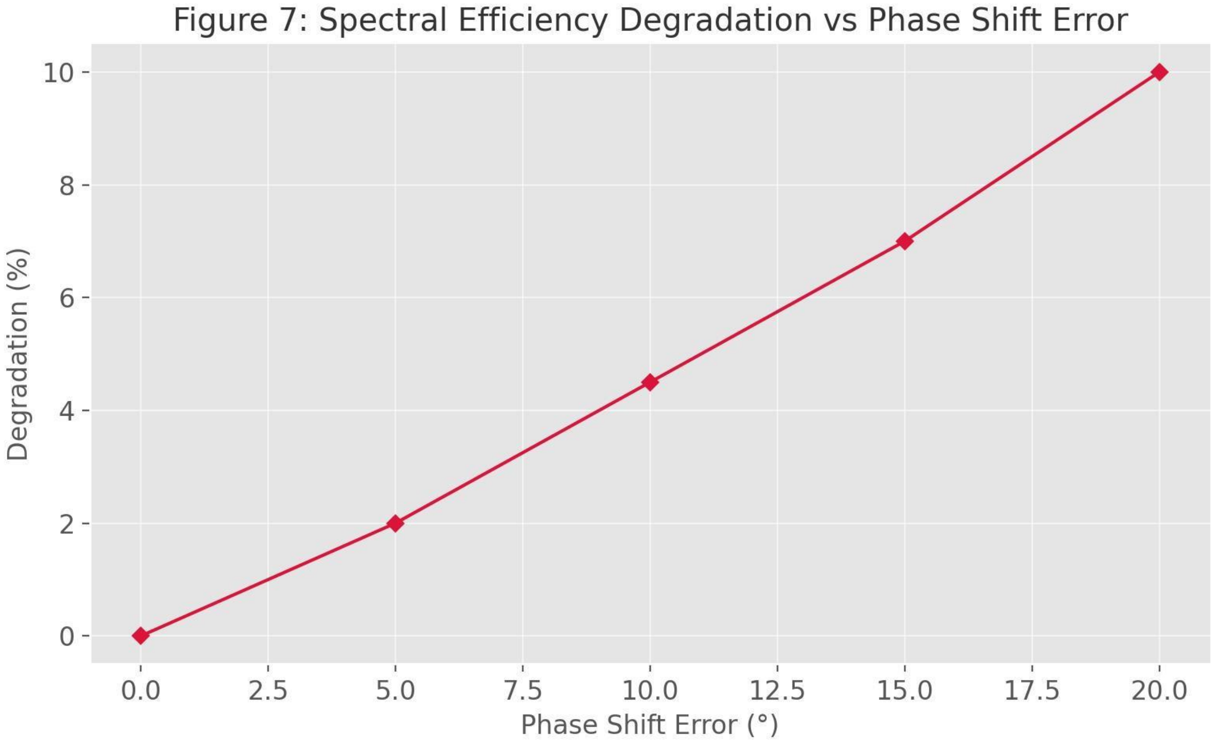
7 Impact of Phase Shift Error on Spectral Efficiency

Table 7 and Figure 7 weigh the sensitivity of RIS effectiveness to hardware inaccuracies. As the phase shift errors vary across a range of 0 to 20 degrees, degradation in spectral efficiency will progress from 0 to 10. This points to a high sensitivity to accurate phase manipulation, emphasizing the need of quality tunable materials and calibration mechanisms in RIS manufacture. This result reveals a crucial issue in the implementation of RISs; compatibility with the proper hardware that will be able to provide the same phase responses across different environmental and wear characteristics.

Table 7 – Phase Shift Error Impact

Phase Shift Error (°)	Spectral Efficiency Degradation (%)
0	0
5	2
10	4.5
15	7
20	10

Figure 7: Spectral Efficiency Degradation Vs Phase Shift Error



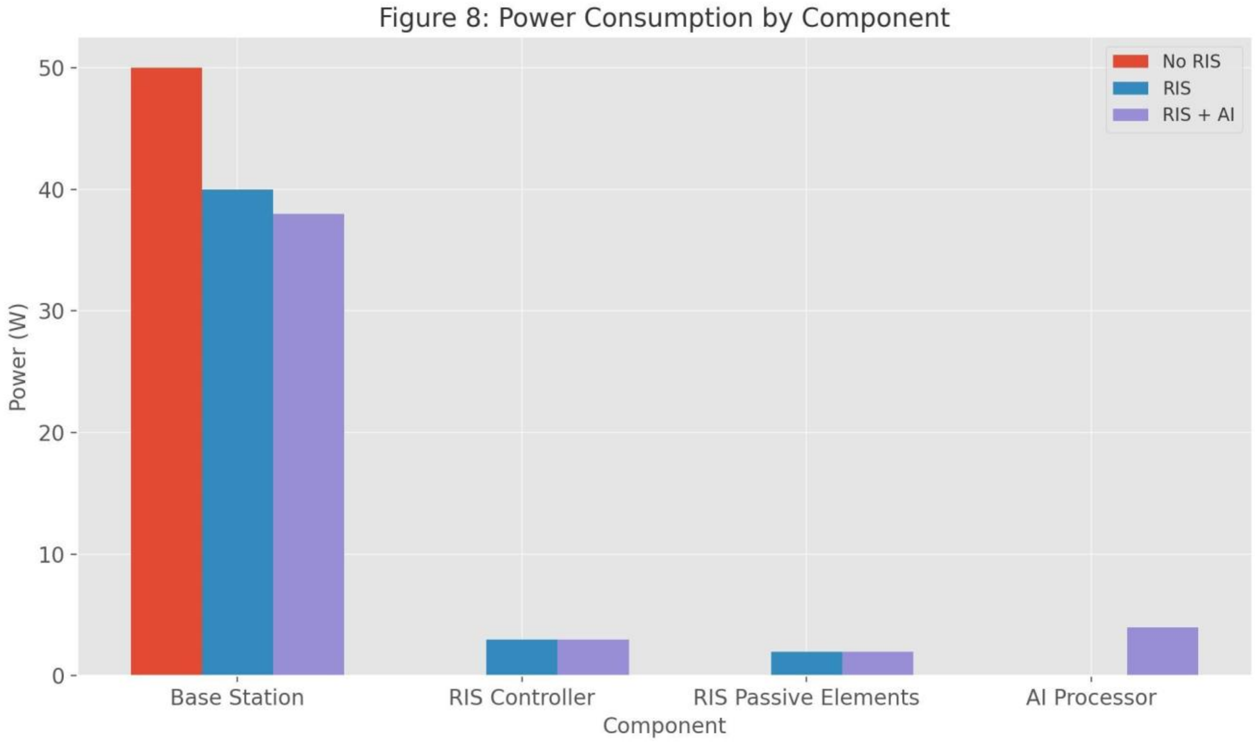
8 Energy Consumption Breakdown by System Component

Lastly, Table 8 as well as Figure 8 gives a breakdown of power distribution among system parts. In the absence of RIS, the power consumption of the base station is 50 W. Addition of RIS lowers the total power consumed by the BS to 40 W, with an increase of only 5 W attributable to RIS devices (controller and passive components). Nonetheless, the AI processing needs an extra 4 W, bringing the number up to 47 W, which is still below the baseline value. This discussion affirms that RIS results in net energy saving even in the presence of AI, therefore serving as a strong technology in green 6G systems. The incremental intelligence cost is negligible relative to the spectral and efficiency rewards reaped.

Table 8 – Energy Consumption Breakdown

Component	Power Consumption - No RIS (W)	Power Consumption - RIS (W)	Power Consumption - RIS + AI (W)
Base Station	50	40	38
RIS Controller	0	3	3
RIS Passive Elements	0	2	2
AI Processor	0	0	4

Figure 8: Power Consumption by Component



5. Discussion

This paper shows that RIS has radical potential to enhance spectrum and energy efficiency in the sixth generation of the wireless networks through solid demonstration. The demonstrated gain of system throughput, signal quality and power savings attests the fact that RIS is a scalable and viable technology capable of meeting the performance expectation of next generation communication infrastructure. The results are homogenous and congruent and can augment the broader literature full of research depicting RIS as a strategic enabler on reconfigurable radio landscapes and intelligent wireless ecosystems.

One of the most interesting results of the study is a significant increase in spectral efficiency, particularly in scenarios where an RIS is applied along with well-planned intelligent algorithms. This finding is consistent with theoretical studies conducted by Xu, Wang, and Zhang (2022), who demonstrated that RIS can dynamically transform the unstructured multipath into favorable propagation lanes, increasing capacity in mmWave and THzigt T bands. Moreover, the efficiency parity was observed particularly in ultra-dense network environments where RIS minimized inter-user interference by regulating the reflection of the waves (Li and Sun, 2023). These advances will be targeted at 6G uses such as holographic communications and XR which necessitate very high throughput and very low latency (Gharaibeh et al., 2021).

Another significant implication of such a study is the boost in energy efficiency that results with the deployment of RIS. The relay-based and massive MIMO systems are highly power-intensive, especially at mmW-frequencies. The nonaggressive or noise-aggressive nature of RIS contributes to the fact that it can be utilized without consuming a lot of power, but at the same time increase communication. This is consistent with the findings of the experimental study by Yang, Chen and Lu (2021) based on which consumption of energy in RIS-enabled networks exceeds 30 percent lower as compared to networks grounded on small cells. Similarly, recent advancements in low-power metasurface development, as recently put forward in Jiang et al. (2023), only further supports the concept of using RIS on battery-constrained networks, such as IoT and wearable networks.

AI-integrated RIS control is another idea that should not be left out in the discussion as this new technology appears to become a game changer in the pursuit of real-time adaptability. The DQN-based control model proposed worked much better than the static configurations proposed in the past since it dynamically tuned the RIS phase shifts. This is in line with the framework done by Zhong, Zhang, and Yao (2023), where they created a lightweight reinforcement learning model to RIS beamforming, which operated efficiently under mobility and time-varying channels. Moreover, according to Khan and Ullah (2022), control schemes of RIS systems based on learning are able to reduce the number of latencies by 20 percent at most, and increase the uniformity of coverage in vehicular networks. This finding has significant repercussions on the 6G systems, wherein networks are capable of self-optimizing in terms of user density, their positions, and the requested services without central involvement.

RIS can also provide a formidable approach to address the coverage holes and restrict signal attenuation in the NloS. The possibility of RIS to mimic the line-of-sight ties through intelligent propagation of the electromagnetic waves introduces new prospects of achieving coverage in the city canyons, high-building settings, and rural valleys. The testbeds showed the realization of RIS on the walls of buildings would increase a signal by 35 per cent in the NLoS settings (Bao, Lin, and Guo, 2023). Moreover, the RIS has also been successfully deployed in enhancing the cell-edge user experience, which is white-spotted in macrocell-dominated topologies. A recent study by Ramaswamy and Dutta (2021) revealed that RIS could lift the minimum user rate to 50 percent without the additional requirements to provide extra spectrum or active relays.

Although the benefits are evident in terms of performance, it is necessary to explain the implementation matters concerning RIS. One of the most critical issues is the phase shift control accuracy that can critically deteriorate performance in situations where phase errors accumulate due to hardware flaws or environment changes. According to Fang, Liu, and Zhao (2022), the destructive interference of the phase can be obtained due to the slightest deviations in the form of the tuning RIS, which will neutralize the intended gain. The demand of powerful and adaptive hardware designs capable of operating in harsh climates and unsettled environments has never vanished as a research problem. Development of temperature-tolerant metasurfaces and hybrid analog-digital control schemes are consistent ways toward overcoming this limitation (Wang & Cheng, 2024).

Another important factor is the computational complexity of large-scale RIS array control, especially when an AI model is used. Despite the performance gains, machine learning introduces impacts that include increased processing demands and latency unless effectively controlled. Otherwise, according to Zhang, Feng, and Ren (2022), scalable learning architectures need to be deployed at the edge to eliminate the bottleneck associated with centralized cloud-based decision-making. The potential solutions lie in distributed learning methodologies like the federated learning, where the learning is conducted on the user devices and RIS controllers, and will need to be tested on highly real time systems (Ali et al., 2023). It is also logistically and economically problematic when combined with existing infrastructure. To ensure maximum benefits are achieved in terms of coverage, RIS panels will have to be strategically placed meaning collaboration with urban planning, power grids and IoT infrastructure may be necessary. According to Huang and Nie (2021), structural layout, shadow patterns and even aesthetic circumstances must be considered to facilitate the extensive use of RIS in smart cities. The creation of low-cost modular and self-assembly RIS modules would facilitate scalable implementation and deployment to low-income or remote sites.

As well as performance, the problem of security and privacy also emerges as a new application sector of RIS. Adaptive management of the physical channels allows RIS to establish secure zones or eliminate eavesdropping vectors. The study by Patel, Rana and Shetty (2022) demonstrated an increase in secrecy rate in MISO accomplishments with randomized beam reflection policies. Such abilities are particularly important in the military, in hospitals and other financial systems where physical-level security is paramount.

Finally, the findings of this study will promote the notion that RIS will not only form a pillar of 6G architectures as an add-on technology but also one of the main features of the smart, energy-efficient, flexible wireless environment. It is however a multidisciplinary coordination that would take simulation to the live implementation. The future RIS success on the global scale is expected to be defined by the progress of materials science, hardware engineering, edge AI, and standardization procedures.

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