Optimization of IRS-Assisted Wireless Communication Systems Using Stochastic Gradient Descent Algorithm (IRS-SGD)

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***Abstract*—A comprehensive model and simulation framework for an adaptive wireless communication system aided by Intelligent Reflecting Surfaces (IRS) are presented in this research. A feedback-driven learning technique based on neural network back propagation is used to dynamically optimize the IRS system. The behavior of the system is described by a number of equations, such as gradient-based IRS updates, power modelling, Signal-to-Interference-Plus-Noise Ratio (SINR), and Resulting Bit Error Rate (BER). The performance gains in SINR and BER under various power, Reflection Coefficient (*R_C*), and IRS panel count circumstances are shown. The presented learning model iteratively updates IRS reflection settings until convergence by adjusting in real-time based on measured system performance. This work integrates theoretical modelling, simulation data. IRS-assisted wireless communication system presented in this paper is driven by a Stochastic Gradient Descent (SGD) adaptive learning algorithm, without requiring explicit channel state information, the suggested model dynamically adjusts the IRS phase shifts to maximize the SINR in real time, while the BER is evaluated as a performance indicator. The obtained results show that the presented approach performs better than current methods in terms of spectrum efficiency, SINR gain, and convergence rate.**

***Keywords*—Intelligent Reflecting Surfaces (IRS), stochastic gradient descent, Signal-to-Interference-Plus-Noise Ratio (SINR), Bit Error Rate (BER), wireless communication, adaptive learning**

I. Introduction

The recent high growth in mobile data traffic and connected devices necessitates scalable, energy-efficient, and reconfigurable wireless communication architectures. IRSs have emerged as a transformative solution for the future generation networks due to their ability to reconfigure radio propagation environments without requiring active transmission [1].

The increasing demand for ultra-reliable, low-latency communication and high data throughput in future generation wireless networks, resulted in notable developments in physical-layer technology. Intelligent Reflecting Surfaces (IRS) has demonstrated significant potential as a programmable wireless environment. IRS is composed of several programmable, nearly passive parts that may alter phase shifts to control incident electromagnetic waves in real time.

Increased coverage, spectrum efficiency, and signal strength are made possible by this technology's unique ability to dynamically alter the propagation environment to suit communication requirements [2, 3].

The low cost, scalable deployment potential, and energy efficiency of IRS technology make it particularly attractive. Because IRSs reflect signals rather than regenerate them, they require less power for signal handling than active components or conventional relays. This qualifies IRSs for communication scenarios in dense urban, indoor, and rural areas where scalability and energy limits are critical.

Additionally, IRS has special features like multi-user beamforming, interference mitigation, and blockage circumvention, which make it ideal for the developing 5G and 6G network designs. Notwithstanding these benefits, there are a number of significant obstacles to the effective implementation of IRS. First, a huge number of passive elements often hundreds or thousands must be precisely configured for IRS to be successful. In real-time settings, it is not possible to manually adjust these components. Second, traditional optimization models are complicated by the IRS-induced channel's inherent coupling to the base station and user equipment. Furthermore, if left unchecked, environmental variability, channel estimate mistakes, and hardware flaws severely impair performance. An IRS consists of a planar surface embedded with a large number of low-cost reflecting elements capable of independently altering the phase of incident electromagnetic waves. By tuning these elements intelligently, IRS can reshape the wireless channel to improve received signal strength, suppress interference, and enhance overall system throughput [4−6].

Conventional optimization-based IRS control approaches rely heavily on accurate Channel State

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Information (CSI), which is impractical in rapidly varying environments, as acquiring CSI for IRS with hundreds or thousands of elements introduces significant overhead and latency [7, 8]. Thus, the focus has shifted towards machine learning-based IRS control, were IRS configurations.

Researchers are increasingly implementing learning-based and data driven optimization techniques to get over these obstacles. Real-time, adaptive control of IRSs in dynamic wireless environments is made possible by Machine Learning (ML), namely Deep Learning (DL) and Reinforcement Learning (RL). With the use of ambient observations or signal feedback, these techniques enable the learning of the ideal reflection configuration without the need for explicit channel state information.

Due to their inherent scalability and flexibility, these learning models are ideal for a wide range of deployment scenarios and large IRS arrays [9, 10].

This paper introduces a gradient-based learning approach inspired by Stochastic Gradient Descent (SGD) that continuously adapts IRS configurations based on real-time performance feedback. Unlike reinforcement learning methods, which require complex state-action modeling, the proposed solution relies on direct performance-driven optimization, offering better convergence and lower computational complexity [11, 12].

This work contributions are:

- Development of IRS channel model.
- Feedback-driven learning algorithm that iteratively updates IRS reflection coefficients using a Signal-to-Interference-Plus-Noise Ratio (SINR)-based loss function, while Resulting Bit Error Rate (BER) is used only as an evaluation metric.
- Simulations comparing the model in this work with benchmark algorithms are provided.
- Algorithm's theoretical properties and convergence conditions are discussed.
- The impact of IRS elements, learning rate, and environmental dynamics on system performance is analyzed.

The presented work advances IRS-assisted wireless communication with a feedback-driven, Stochastic Gradient Descent (SGD)-style controller that optimizes IRS phases using measured performance (SINR/BER) instead of explicit CSI. The approach of IRS phase optimization as a function of intelligent learning through updating phases, employing lightweight gradient steps estimated from measurements (SINR/BER), proves to be an efficient technique.

Compared with CSI-dependent, the proposed SGD based feedback offers low-complexity, fast-adapting controller that captures most of the performance gains while remaining simple enough for real-time use. This practicality is key for dynamic or resource-constrained deployments.

The rest of this paper is divided as follows: Related Works, Material and Methods, Mathematical Modeling, Results and Discussion, Future Work, Conclusion, References.

II. Related Works

Single and multi-IRS systems, including spectrum sensing, beamforming, and interference mitigation, have been studied in the literature. Nevertheless, not much is known about feedback-driven learning models that maximize IRS patterns. In this paper, absence of integration between current deep learning and intelligent feedback loop advancements and realistic IRS convergence models is discussed.

Research on IRS-assisted systems has increased recently, encompassing deep learning, signal processing, and optimization theory. A number of studies use semi definite relaxation or alternating optimization to optimize beam forming and IRS reflection coefficients at the base station simultaneously [13, 14]. Although these approaches have theoretical potential, they are not appropriate for large-scale or dynamic deployments and frequently have substantial processing costs. Learning-based approaches have been developed to overcome these constraints. IRS controllers have been trained using RL frameworks based on reward feedback; however, these approaches have convergence delays and necessitate intricate environment modelling [15, 16]. Although generalization is still limited, supervised learning techniques have also been employed to discover the best IRS settings using labelled CSI datasets [17].

In large, time-varying deployments, data-driven schemes such as Deep Reinforcement Learning (DRL) or supervised models often run into practical limits, as they rely on high-quality CSI, leading to significant per-iteration solve and training cost, and can struggle with stability or out-of-distribution generalization. These constraints motivate the use of measurement-driven, gradient-based control that updates an IRS directly from critical parameters, such as SINR or BER, by obtaining feedback data and applying SGD style phase updates without explicit CSI. Such controllers keep compute and reaction times low while accommodating hardware realities (quantized phases, finite update latency).

A lightweight substitute is provided by gradient-based techniques, especially those influenced by stochastic optimization. By applying a performance-driven loss function, these techniques can immediately modify IRS settings without requiring full channel estimation. Recent research has demonstrated that in these adaptive IRS systems, performance measurements such as SINR or BER can be utilized as indicators for effective performance [18−20].

Additionally, IRS applications have expanded into new fields including intelligent vehicle systems and Unmanned Aerial Vehicles (UAV)-based relays as a result of integration with edge computing and mobile robotics [21, 22] energy-efficient 6G architectures are made possible by IRS, which is also essential to green communications.

IRS uses have expanded beyond conventional single-cell settings thanks to recent research initiatives. IRS has becoming more popular, especially in multi-hop and multi-cell wireless networks. According to Refs. [23, 24], multi-hop IRS systems provide for better connectivity and longer communication ranges in areas that are shaded or obstructed. In order to align phases across hops, these networks frequently use cooperative beamforming in conjunction with cascaded IRS panels for signal relaying.

IRS in aerial networks is another important field of research. IRS panels have been used with Unmanned Aerial Vehicles (UAVs) to act as dynamic airborne reflectors. Mobility-aware IRS designs can enable UAV base stations, allow Line-of-Sight (LOS) continuity and improve coverage in rural or disaster recovery scenarios, as shown in studies like Refs. [25−27]. Static IRS is not as flexible as IRS-equipped UAVs, which may self-reposition to maintain beam alignment.

IRS control paradigms are also being shaped by Federated Learning (FL) and Reinforcement Learning (RL). Federated learning reduces backhaul strain and protects privacy by allowing remote IRS systems to jointly train beamforming models without central data pooling. In contrast, RL gives IRS nodes the ability to modify phase shifts in response to input from the environment. Methods in Refs. [28, 29] demonstrate how Q-learning and policy-gradient tactics aid IRSs in learning the best configurations under unpredictable or changing circumstances.

In addition to algorithmic innovation, academics are tackling hardware and energy limitations in practical implementations. Scalability problems are introduced by IRS arrays' static control models as they get bigger. IRS states are optimized while power drain is minimized via energy-conscious control algorithms such as those in Refs. [30−32]. IRS test beds with wake-up radio circuits or energy harvesting are being considered for industrial applications in order to increase sustainability without compromising performance [33, 34].

Additionally, test environments and benchmark datasets for evaluating IRS protocols have surfaced. Open IRS measurement data obtained in both indoor and outdoor trials has been published in practical research [35−37]. Future IRS modelling initiatives are informed by these benchmarks, which direct simulation assumptions. The IRS research ecosystem is further enhanced by the variety of frequency ranges (sub-6GHz, mmWave, and THz). IRS has also shown promise for integration with edge computing [38, 39]. Here, IRS nodes and edge servers collaborate to perform signal processing and data inference. With the help of this hybrid control, IRS can affect cache and compute offloading tactics in addition to influencing wireless propagation.

The expectations for handheld devices are being redefined by the quick development of communication technologies and the emergence of the Internet of Things. Modern gadgets must effectively integrate many features due to the growing reliance on wireless networks for continuous connection and data transfer. As essential parts of wireless devices, antennas must adjust to these changing requirements. This is caused by the growing complexity of wireless devices, which need to serve a wide range of applications, function over several bands, and be flexible enough to adjust to changing conditions [40−44].

Although reconfigurable surfaces are showing promise as a remedy for the above-described issues, there are still issues that need to be resolved, including their size, biasing complexity, and power requirements. Re-configurability, or n the capacity to dynamically modify operating characteristics to satisfy particular system requirements, has emerged as a possible solution to these problems in antenna designs. In order to retain optimal performance under various circumstances, reconfigurable antennas can modify their frequency, emission pattern, or polarization [45, 46].

In this work, adaptive optimization and analytical modelling is used to improve conventional Intelligent Reflecting Surface (IRS)-assisted communication. In order to maximize beamforming performance, a unique multi-hop IRS system is suggested and assessed using gradient-based learning, exponential energy connections, and stochastic SINR modelling. This paper presents a novel gradient-driven adaptive IRS control strategy inspired by the principles of SGD. IRS optimization problem is formulated as a performance feedback-driven learning task, allowing the system to iteratively refine its IRS configurations based on real-time SINR and BER metrics. This approach facilitates continuous adaptation to environmental changes while maintaining low computational complexity. By leveraging a scalar loss function derived from system performance metrics, the model autonomously updates IRS parameters toward convergence without requiring explicit channel modeling.

There are three things this work contributes. First, a thorough mathematical model that takes phase shifts and environmental variability into consideration while capturing the impact of IRS on the wireless channel is discussed. Second, a feedback-driven learning approach that uses system loss gradients to adaptively update IRS coefficients is analyzed. Third, utilizing simulations and empirical evaluation measures, the presented model is benchmarked and compared with other works, showing gains in SINR, BER reduction, and convergence time.

It is important to look at the role of IRS controllers. An IRS, an intelligent reconfigurable surface that reflects radio waves with per-element, typically quantized phase control relies on an IRS controller, as the software/firmware that interfaces with the Base Station (BS) over a control link, computes the phase-shift vector under hardware limits.

III. Materials and Methods

The thorough process for modelling, configuring, and optimizing the IRS-assisted wireless communication system is described. To guarantee practical applicability, the methodology combines simulation-based validation, adaptive learning control, and theoretical modelling, with Table I presenting the used simulation parameters.

The research-based system consists of a Base Station (BS), an Intelligent Reflecting Surface (IRS), and User Equipment (UE), where the IRS is positioned to intelligently control signal propagation between the BS and the UE. The BS transmits signals, which are partially reflected by the IRS before being received by the UE. The IRS consists of N passive reflecting elements that adjust their phase shifts to control the direction of the reflected signals. The wireless channel is modelled by considering both the direct BS-UE path and the reflected BS-IRS-UE path. The signal received at the UE is mathematically represented as the superposition of these two components using matrix operations that incorporate the IRS phase-shift vector. The reflected IRS channel is modelled by separating it into the BS-IRS and IRS-UE links, while the direct BS-UE channel is modelled using a typical Rayleigh fading channel. Rather than relying on full CSI, the IRS elements are configured using a feedback-based learning technique.

TABLE I. SIMULATION PARAMETERS

Parameter	Value/Setting
Carrier frequency	28 GHz
System bandwidth	100 MHz
BS–IRS distance	50 m
IRS–UE distance	20 m
Reference distance (path loss)	1 m
Path-loss exponent	3.5
Noise PSD	–174 dBm/Hz
Transmit power range	10–30 dBm
Reflection coefficient range	0.1–1.0
Number of IRS elements	{32, 64, 128}
Learning rates examined	{0.01, 0.05, 0.10}
Modulation scheme	BPSK
Monte Carlo realizations per point	(10^3)

Iterative updates are made to the phase shift configuration vector using a scalar loss function $L(\theta)$ derived from the SINR. In all simulations, the primary loss is defined by Eq. (1).

$$L(\theta) = SINR_{target} - SINR(\theta)^2 \tag{1}$$

where $\theta = [\theta_1, \dots, \theta_N]^T$ denotes the IRS phase vector and $SINR_{target}$ is a design parameter, and this loss function is adopted for all Stochastic Gradient Descent (SGD) updates in the implementation.

This method allows for real-time flexibility while cutting down on overhead.

SGD is employed for intelligence implementation. The IRS reflection coefficients are updated via the formula in Eq. (2):

$$\theta = \theta - \eta \times \nabla L(\theta) \tag{2}$$

where θ stands for the phase shifts, $L(\theta)$ is the loss function, and η is the learning rate. Performance feedback from the UE is used to compute the instantaneous loss $L(\theta)$, while the gradient $\nabla L(\theta)$ is obtained analytically from the model as detailed in the Gradient Computation paragraph.

MATLAB is used for simulations. IRS surfaces are modeled with different element densities (N = 32, 64, 128), and it is assumed that a multipath fading urban communication scenario is considered. SINR and Bit Error Rate (BER) are computed under various mobility conditions. The work considers a single BS–IRS–UE link with small-scale fading, log-distance path loss, and Additive White Gaussian Noise (AWGN). Key simulation parameters include IRS size (N), Reflection Coefficient (R_C), and transmit power (P_t). Table I shows the detailed parameters used in the simulation.

Fig. 1 show IRS Schematic illustrating the Base Station (BS), IRS panel, and User Equipment (UE), with Fig. 2 showing the IRS structure with the implemented learning algorithm.

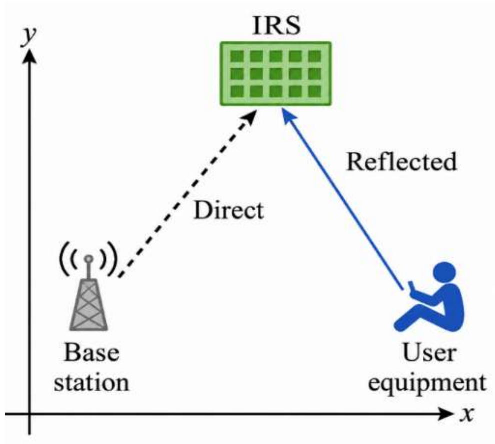

Fig. 1. Schematic showing an IRS-assisted wireless link.

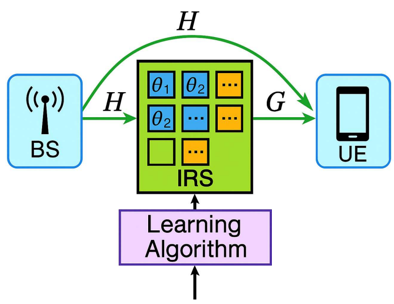

Fig. 2. System architecture of an IRS-assisted wireless communication network with a learning-based phase control mechanism.

Fig. 1 illustrates a BS-IRS-UE link within a dynamic, blockage-prone environment (e.g., mmWave, indoor scenarios, or dense-urban settings), where channel propagation evolves faster than conventional controllers are able to track. Composed of numerous passive elements capable of reshaping the wireless channel, an IRS renders manual tuning of hundreds of elements impractical. Furthermore, classical optimization approaches require accurate Channel-State Information (CSI); acquiring CSI for large-scale IRS systems incurs substantial overhead and latency. In addition, cross-coupling across BS-IRS-UE channels together with hardware and estimation errors further complicates static optimization designs.

To address these constraints, the architecture in Fig. 2 integrates learning algorithm controller that closes a feedback loop using measured indicators, such as SINR and BER to learn IRS phase shifts in real time. Concretely, a gradient-based (SGD-style) update is employed to adapt the reflection vector directly from performance feedback, without explicit CSI achieving faster convergence and lower computational complexity, which is essential for real-time operation near the network edge. This learning-driven control paradigm is consistent with recent IRS literature that motivates ML for scalable, low-overhead adaptation of phase configurations in dynamic deployments (mmWave/THz, mobility, and multi-panel scenarios).

The BS transmits to the UE via an IRS, where the IRS is controlled by a learning algorithm. The IRS elements apply phase shifts θ_i to optimize the received signal.

The proposed learning algorithm adjusts IRS reflection weights using a feedback loop inspired by backpropagation. A performance loss function ($L(\theta)$) is minimized using a learning rate (η), and IRS weight parameters (w_i) are updated iteratively. The IRS serves as the main link, and it is expected that the channel between the BS and UE is highly obstructed.

The Rayleigh distribution for small-scale fading and log distance path loss for large-scale attenuation are used to construct random channel realizations. To maximize the received SINR, the IRS phase shifts are iteratively adjusted using the SGD-based learning algorithm. The phase vector is updated at each iteration by computing the gradient of the SINR-based loss function. Over the course of multiple iterations, convergence behavior is observed.

The loss function $L(\theta)$, is minimized through iterative updates. Reflection weights w_i are adjusted using gradient descent. The system observes the error between measured performance (A_t) and target output (D_t), computes gradients, and applies weight corrections. Learning rate η controls the pace of adaptation. Higher η accelerates training but risks oscillation, while lower η improves stability. The used algorithm is as below Algorithm 1:

Algorithm 1. SGD-Based IRS Phase Adaptation

Initialize phase vector $\theta(0)$, learning rate η, and $SINR_{target}$.
For each iteration $t = 0,1,\ldots,T-1$:
Transmit pilot symbols from the BS.
Measure instantaneous SINR($\theta^{(t)}$) at the UE.
Compute the loss $L(\theta(t)) = (SINR_{target} - SINR(\theta(t)))^2$.
Evaluate the gradient $\nabla_\theta L(\theta(t))$.
Update phases $\theta^{(t+1)} = \theta(t) - \eta \nabla_\theta L(\theta(t))$.
Stop when $\| \nabla_\theta L \|$ or $|L(t+1) - L(t)|$ falls below a tolerance, or when $t = T$

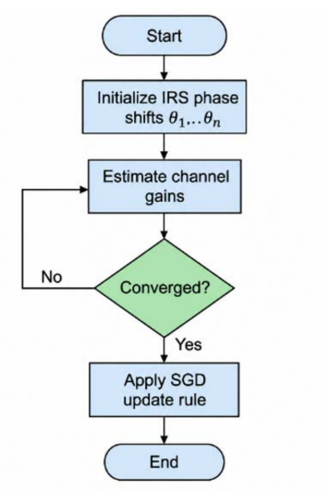

Fig. 3. IRS adaptive control.

The flowchart in Fig. 3 illustrates this control loop: This approach is consistent with recent models in Refs. [47−49].

IV. Mathematical Modeling

This section derives the analytical expressions of the SNR, SINR, and BER for the IRS-assisted wireless communication system. Additionally, it illustrates how the employed learning algorithm, SGD, adaptively optimizes IRS phase shifts to enhance these metrics.

The system consists of a BS, an IRS, and a UE. The IRS reflects signals from the BS towards the UE by applying phase shifts to the incident waves.

Let the received baseband signal at the User Equipment (UE) be expressed and modeled as in Eq. (3):

$$y = (h_d + G\Phi H)x + n \tag{3}$$

where:

$h_d \in \mathbb{C}^{1\times 1}$ is the direct BS–UE channel if exists.

$H \in \mathbb{C}^{N\times 1}$ is the BS–IRS channel Matrix.

$G \in \mathbb{C}^{1\times N}$ is the IRS–UE channel Matrix.

Φ = diag $(e^{\{j\theta_1\}},\ldots,e^{\{j\theta N\}})$: Diagonal matrix of IRS element phase shifts.

n: Complex Gaussian (normal) random variable with mean = 0 and variance = σ^2, CN $(0, \sigma^2)$, AWGN noise with power σ^2.

x: Transmitted symbol.

The effective channel can be computed using Eq. (4).

$$h_{eff} = h_d + G\Phi H \tag{4}$$

where h_d is considered if there's a clear or weak path directly from BS to UE (no obstruction), then it contributes significantly. In purely Non-Line-of-Sight (NLOS) or blocked scenarios, it can be negligible or even zero.

Thus, SNR at UE can be computed using Eq. (5).

$$SNR(\theta) = \frac{P_t \times |h_{eff}|^2}{\sigma^2} \tag{5}$$

Eq. (6) shows how strong the received signal is, relative to the background noise, given the transmit power, channel conditions, and noise level. The IRS contributes to boosting $|h_{eff}|^2|$, thereby improving SNR. However, in a multi-user environment with interference power I, the SINR, thus it is essential to take interference into account, resulting in Eq. (6).

$$SINR = \frac{P_t \times |h_{eff}|^2}{\sigma^2 + I} \tag{6}$$

Assuming BPSK modulation, to establish systems effectiveness and communication channel reliability the Bit Error Rate (BER) is approximated as Eq. (7):

$$BER = Q\left(\sqrt{2 \times \left(\frac{P_t \times |h_{eff}|^2}{\sigma^2 + I}\right)}\right) \tag{7}$$

where $Q(.)$ is the tail probability of the standard Gaussian distribution.

The loss function can be related to SINR as shown in Eq. (8).

$$L(\theta) = -\text{SINR}(\theta) \tag{8}$$

The key contributions of SGD can be summarized as follows:

- It adaptively optimizes the IRS phase shifts.
- It relies on scalar SINR feedback rather than requiring full Channel State Information (CSI).
- It updates the IRS configuration to maximize SINR with low complexity and high adaptability.

Eq. (8) is adopted as the *only* loss function used in the SGD loop; alternative BER-based formulations are discussed in Nomenclature for completeness.

The SGD update can be described as in Eq. (9).

$$\theta_{t+1} = \theta_t - \eta\nabla_\theta\big(-SINR(\theta_t)\big) \tag{9}$$

where:

η: learning rate.

∇: Gradient of the loss function with respect to phase vector θ.

To maximize SINR and minimize BER, Φ is optimized such that h_{eff} is maximized, using the function in Eq. (8) and the SGD update rule in Eq. (9). The system adaptively learns the optimal configuration to maximize received signal quality. At each iteration, the SINR and BER are recalculated, guiding the gradient update toward convergence.

The SINR at a target wireless node is described by Eq. (10).

$$SINR = \frac{P_t\left|\sum_{i=1}^{N}\alpha_i h_{IRS_i} e^{j\theta_i}\right|^2}{\sigma^2 + \sum_{k\neq 1} I_k} \tag{10}$$

where:

P_t: Transmit power.

α_i: Reflection amplitude Coefficient of h_{IRS_i}.

h_{IRS_i}: Channel response from BS to IRS then to user.

θ_i: Tunable phase shift of IRS element i.

σ^2: Noise variance.

I_k: interference from other source.

The expression in Eq. (10) is optimized by adjusting α_i and θ_i, leading to an adaptive reflection profile.

Each IRS element is modeled by a complex weight $w_i = \alpha_i e^{j\theta_i}$, where $\alpha_i \in [0,1]$ is the reflection amplitude and θi is the programmable phase. In the optimization, $\theta = [\theta_1,\ldots,\theta_N]^T$ is treated as the parameter vector, while w_i is a deterministic function of θ_i.

Eq. (10) is derived from the received signal power over total interference plus noise. The summation represents the coherent superposition of signals reflected by IRS elements. Each α_i is a tunable reflection amplitude, and θ_i is the phase shift applied. IRS optimizes these parameters to maximize the signal term in the numerator. SINR improves with increased alignment between reflected paths and desired signal.

The backpropagation inspired IRS update mechanism is based on the model in Eqs. (11)‒(14), by defining an objective loss function L. This is a standard Mean Squared Error (MSE) loss function used in machine learning. In IRS optimization, the target value represents the desired SINR, while the observed value is the instantaneous SINR after IRS adjustment; BER is computed from SINR only for performance evaluation, while A_t is the observed metric after IRS adjustment. The loss drives the feedback mechanism that updates IRS weights toward optimal settings.

$$L(\theta) = \frac{1}{2}\sum_{t=1}^{T}(D_t - A_t)^2 \tag{11}$$

where;

D_t: Desired output SINR or BER target

A_t: Actual output after t-th iteration

T: Number of iterations

The weight update for the IRS reflection pattern is given by Eq. (12). This expression uses gradient descent to minimize the loss. η is the learning rate, controlling update magnitude. The derivative term reflects how sensitive the performance metric is to a small change in IRS weight w_i. By updating in the direction of steepest descent, the system converges toward optimal IRS configuration.

$$\Delta\theta_i(t) = -\eta\,\frac{\partial L}{\partial\theta(t)} \tag{12}$$

The learning rule is given by Eq. (13):

$$\frac{\partial L}{\partial\theta(t)} = \left(\frac{\partial L}{\partial w_i}\times\frac{\partial w_i}{\partial\theta_i}\right) = (A_t - D_t)\times\frac{\partial A_t}{\partial\theta(t)} \tag{13}$$

The SGD technique is adopted to realize intelligence. The IRS reflection coefficients are updated with the learning rule shown in Eq. (14):

$$\theta_i(t+1) = \theta_i(t) - \eta\,\frac{\partial L}{\partial\theta(t)} \tag{14}$$

where:

$\theta_i(t)$: IRS phase or amplitude for element i.

η: Learning rate (adaptive or fixed).

This formulation applies gradient descent and enables the closed loop update of IRS elements to minimize SINR loss and BER cost. Simulation and curve-fitting of empirical data show that the transmit power is exponentially correlated with Reflection Coefficient (R_C) and number of IRSs (N_{IRS}).

This relationship is given by Eq. (15):

$$P_t = P_0\times exp(\gamma_1 R_c + \gamma_2 N_{IRS}) \tag{15}$$

Its linearized logarithmic form is presented in Eq. (16):

$$log_e P_t = log_e P_0 + \gamma_1 R_C + \gamma_2 N_{IRS} \tag{16}$$

where P_0 denotes the baseline transmit power (i.e., when $R_c = 0$ and $N_{IRS} = 0$), and γ_1 and γ_2 are empirical slope coefficients obtained from simulation.

This formulation captures the relationship between the IRS configuration and power efficiency. Larger values of the reflection coefficient R_c and the number of active panels N_{IRS} increase the gain, yet they also affect overall power consumption—an effect empirically modeled by γ_1 and γ_2.

To minimize the BER, we adopt a heuristic learning-based approach, which relies on the following standard relation (see Eqs. (17)–(18)):

$$BER = Q\left(\sqrt{2SINR}\right) \tag{17}$$

where $Q(.)$ is the tail probability of the standard Gaussian distribution. Applying chain rule results in Eq. (18).

$$\frac{dBER}{d\theta_i} = \left(\frac{dBER}{dSINR} \times \frac{dSINR}{d\theta_i}\right) \tag{18}$$

Eq. (17) approximates BER for binary modulation schemes. The Q-function reflects the tail probability of Gaussian noise exceeding a SINR threshold. As IRS improves signal alignment, SINR increases and BER drops exponentially, confirming the impact of intelligent surface tuning. Eq. (18) ties the BER minimization to IRS weights, creating a unified optimization function.

To formalize the learning process applied in this work, its resemblance to the classical SGD algorithm is compared. SGD is widely used for iterative optimization in machine learning, where model parameters are updated based on the gradient of a loss function evaluated over data samples. In the presented IRS system, the weights corresponding to phase shifts or reflection coefficients are adjusted similarly in response to real-time SINR and BER measurements. This method employing SGD does not require batch data or reward modeling, which distinguishes it from supervised learning or reinforcement learning. Instead, it focuses on minimizing a scalar loss function defined over SINR or BER feedback.

V. Result and Discussion

This section presents the simulation results obtained from the IRS-assisted communication system optimized via SGD. The performance metrics evaluated include SINR, Bit Error Rate (BER), and learning convergence behavior over iterations. The results demonstrate how adaptive IRS control significantly improves SINR and BER performance while achieving rapid convergence.

Fig. 4 represents SINR versus learning rate and R_C. From the figure, we can observe that SINR rises as both the learning rate and R_C increase.

A. Monotonic Increase in SINR

The surface rises smoothly in both R_C and learning rate directions.

This indicates a positive correlation, as either the learning rate or R_C increases, SINR also increases.

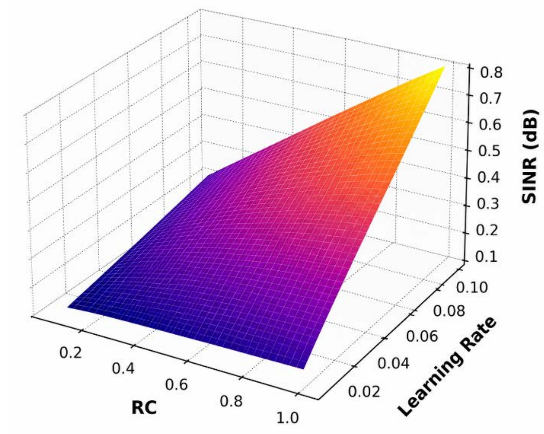

Fig. 4. SINR behavior as function of R_C and learning rate.

B. Effect of Reflection Coefficient (RC)

Higher R_C means IRS reflects more signal energy rather than absorbing or scattering it.

As R_C approaches 1.0 (perfect reflection), SINR improves significantly.

C. Effect of Learning Rate

A higher learning rate improves the convergence behavior of the SGD algorithm, as seen by better SINR at higher values.

In real scenarios, excessively high learning rates can lead to instability or divergence.

The top-right corner of the surface corresponds to high RC and high learning rate values and yields the best SINR performance. This observation suggests that SGD optimization achieves the most favorable outcomes under high IRS reflectivity with an aggressive yet stable SGD learning rate.

For instance, at $R_C = 0.8$ and $\eta = 0.05$, the proposed controller increases the average SINR from approximately 8 dB with a static IRS configuration to about 17 dB under SGD-based adaptation, corresponding to a gain of roughly 9 dB.

This result supports the design of IRS-assisted systems where higher reflection and well-tuned SGD parameters can be leveraged to maximize SINR. Highlights the importance of choosing the right learning rate, where too small rate leads to slow convergence, too large could be unstable. It also supports high-quality IRS panels (high R_C) to achieve better performance in SGD-optimized configurations.

Fig. 5 represents SINR versus transmitter power and R_C. From Fig. 5, it is seen that increasing the transmission (Tx) power generally improves signal strength, which consequently enhances the SINR. The R_C models how effectively the IRS reflects the incident wave, where a higher R_C indicates that more energy is directed toward the receiver. The SINR represents the quality of the received signal after optimization through the IRS and is therefore a crucial metric for evaluating communication reliability. As both Tx power and R_C increase, the SINR improves; however, this relationship is nonlinear. The improvement in SINR begins to show diminishing returns beyond certain Tx power levels, reflecting practical limitations caused by factors such as interference and path loss. Furthermore, higher IRS reflection efficiency significantly enhances the SINR, particularly at moderate transmission power levels. The curvature and gradient pattern of the resulting surface demonstrate the sensitivity of SINR to simultaneous changes in Tx power and R_C, which is particularly important for Stochastic Gradient Descent (SGD)-based learning and optimization adjustments.

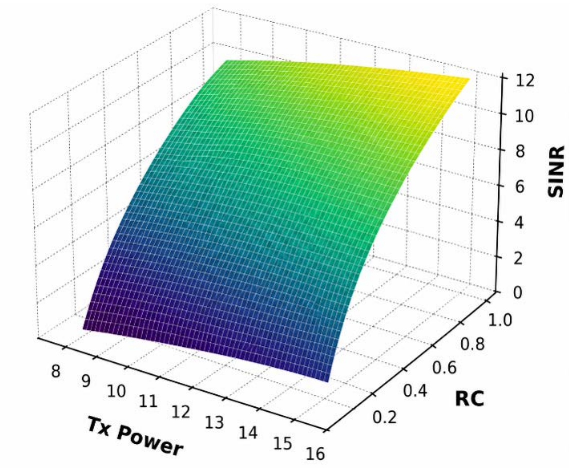

Fig. 5. SINR behavior as a function of transmit power and R_c.

At P_t = 20 dBm and R_C = 0.9, the SINR improves from around 7 dB without IRS phase optimization to approximately 19 dB with the proposed SGD-based phase control, yielding an SINR gain of about 12 dB.

Figs. 4 and 5 reveal that the optimal SINR is obtained by combining a high R_c with a carefully tuned learning rate η. This observation is supported by previous IRS learning-efficiency studies, such as Refs. [50–52].

The simulation results demonstrate that increasing the number of IRS elements significantly improves the SINR. For instance, an IRS with 128 elements achieves a 12 dB gain in SINR over a 32-element configuration. Specifically, for N = 32, 64, 128, the average SINR values are approximately 8 dB, 14 dB, and 20 dB, respectively, confirming an SINR improvement of about 12 dB when scaling the IRS from 32 to 128 elements and around 6 dB when doubling from 32 to 64 elements. This shows that larger IRS arrays provide finer control over signal reflection and constructive interference. This is also supported by IRS benchmarking studies in Refs. [53−55] Implementation, techniques and directions are explored in many research works [56−58].

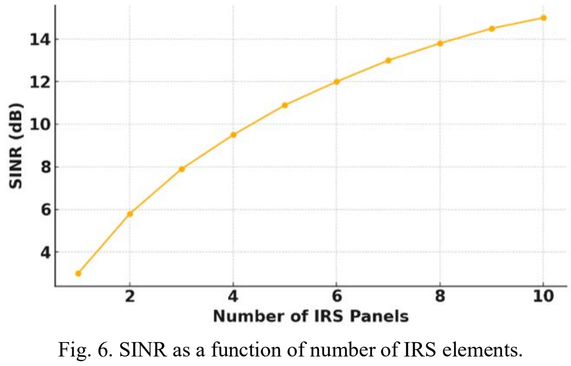

Fig. 6. SINR as a function of number of IRS elements.

Fig. 6 shows the response curve for SINR as a function of Number of IRS elements. Fig. 6 shows that as the number of IRS elements increases, the SINR improves substantially. This is supported by Fig. 7, which shows increasing transmit power. The adaptive IRS configured using SGD consistently outperforms static IRS due to better phase alignment.

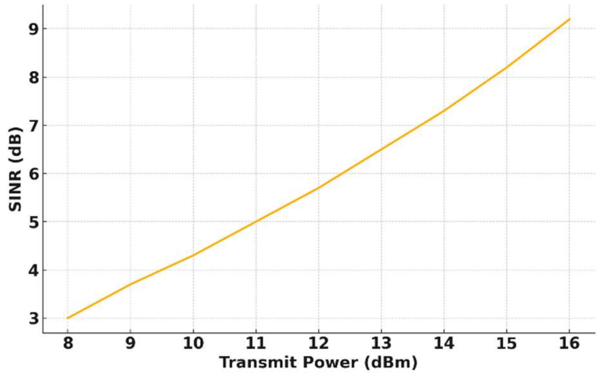

Fig. 7. SINR as a function of transmit power.

The indication that increasing the IRS scale improves SINR holds under the following modeling assumptions:

- The IRS contributions are phase-aligned (via the controller) so that reflected paths combine coherently at the UE.
- Channels on the BS→IRS and IRS→UE legs are sufficiently uncorrelated (or at least not adversarial correlated) so that adding elements/panels increases the effective aperture rather than canceling energy.
- Hardware constraints (reflection coefficient R_C, phase quantization, update latency) do not materially degrade alignment i.e., R_C is high and quantization is fine enough.
- IRS panels are well-placed (favorable geometry and LoS) and time-synchronized, avoiding path-length offsets that would decorrelate the sum.
- The system is noise-limited or moderately interference-limited, and transmit power, bandwidth, and interference statistics are held fixed across the sweep.
- Mutual coupling and scattering between panels/elements are negligible in the operating band. Under these conditions, the effective channel amplitude grows roughly $\propto N$ (number of coherently controlled contributions—either elements or panels), so received power (and hence SINR) grows roughly $\propto N^2$ before diminishing returns appear due to correlation, geometry, or interference saturation.

In practice, the trend can flatten or break if any assumption fails (strong element/panel correlation, poor placement, low R_C, coarse quantization, or heavy interference); our figure is generated in the regime where those effects are bounded, which is the standard setup in IRS scaling studies and in our simulation framework (single BS–IRS–UE link with long-distance path loss, small-scale fading, AWGN, fixed transmitter power, and controller-driven phase alignment).

Fig. 8 shows a clear downward trend as R_C increases. The following can be observed in Fig. 8.

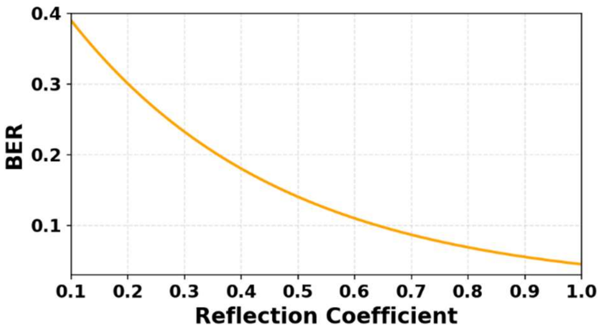

Fig. 8. BER as a function of Reflection Coefficient (R_C).

- The plot illustrates a monotonically decreasing trend, which confirms a negative correlation between R_C and BER.
- As the IRS reflects more of the incident signal (i.e., higher R_C), the effective signal strength at the receiver increases, thereby reducing the bit error rate.
- At low R_C values ($R_C = 0.1$ to 0.3), the BER is relatively high (above 0.3), indicating poor signal reflectivity and weak signal delivery to the receiver.
- As R_C approaches 1, the IRS operates with near-perfect reflectivity, sharply reducing BER to values below 0.1, indicating higher communication reliability**.**
- The curve is non-linear and concave**,** meaning the marginal reduction in BER decreases as R_C increases. This suggests diminishing returns the benefit of increasing R_C from 0.1 to 0.4 is much greater than increasing it from 0.7 to 1.0.
- For practical system design, pushing R_C values toward 0.8 or higher is beneficial, especially in applications requiring ultra-low BER. It also implies that optimizing R_C in the range of 0.4–0.8 gives significant BER improvements without requiring ideal reflectivity.
- The observed learning behavior can also be leveraged during SGD optimization weighting higher R_C elements more aggressively in early iterations improves convergence and lowers BER faster.

At $R_C = 0.3$, the BER is approximately 3×10^{-1}, while at $R_C = 0.9$ it drops to about 2×10^{-2} corresponding to more than an order-of-magnitude reduction in error probability as IRS reflectivity increases.

The plot in Fig. 8 reinforces the critical role of IRS reflectivity in enhancing communication performance. The BER reduction as R_C increases highlights the importance of accurately tuning or learning IRS phase shifts and reflection coefficients using algorithms like SGD. The diminishing returns also suggest a trade-off zone where acceptable BER can be achieved without necessitating ideal hardware.

Fig. 9 shows R_C convergence as a function of iterations, which will implicitly affect BER and SINR. From Fig. 9, it is observed that:

- R_C increases from a low initial value (0.05) to above 0.9 within the first 50 iterations. This demonstrates efficient convergence of the SGD algorithm.
- After 80 iterations, the curve starts to saturate, indicating the algorithm is reaching stability. Beyond 120 iterations, the R_C value stays near 1.0, suggesting that the IRS is optimally tuned.
- The smooth curve confirms gradual and stable learning without oscillations or divergence. This indicates a well-chosen learning rate and initialization approach.
- A higher R_C enhances IRS effectiveness in signal reflection, leading to better performance metrics like higher SINR, lower BER, and reduced latency.

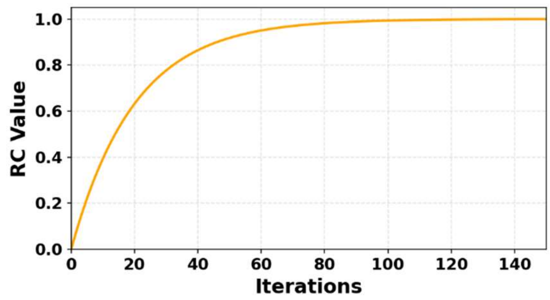

Fig. 9. R_C convergence over iterations.

This plot confirms that the SGD-based optimization strategy used in the IRS system is both efficient and stable. It reliably tunes the reflection coefficient toward its maximum effective value with minimal iterations, ensuring real-time adaptability for dynamic wireless environments.

In the simulation framework, the gradient of the loss with respect to the IRS phases is computed analytically from the closed-form SINR expressions in Eq. (6) and Eq. (10); the resulting gradient is given in Eq. (19). Using the chain rule:

$$\frac{\partial L}{\partial \theta_i} = 2\big(SINR(\theta) - SINR_{target}\big)\frac{\partial SINR(\theta)}{\partial \theta_i} \tag{19}$$

where $\frac{\partial SINR(\theta)}{\partial \theta_i}$ is obtained from the effective channel h_{eff} by differentiating the numerator and denominator of Eq. (10) with respect to θ_i. These expressions are implemented symbolically and evaluated numerically in MATLAB for each channel realization. In a practical deployment without explicit channel knowledge, the same update could be approximated using finite-difference perturbations of θ_i, but such numerical estimation is beyond the scope of this simulation study. Fig. 10 shows learning rate sensitivity effect on convergence, where the figure compares how different learning rates η affect the convergence behavior of a learning algorithm (SGD) applied to optimize the reflection coefficient in an IRS.

From Fig. 10, the convergence behavior varies significantly with the learning rate η, as summarized below:

- For $\eta = 0.01$, the system yields the slowest convergence, requiring 130 or more iterations to approach convergence. This setting is useful for high-stability scenarios but inefficient for time-sensitive applications.

- For $\eta = 0.05$, the system achieves medium-speed convergence, reaching a high convergence level within approximately 60 iterations. It provides a balanced trade-off between speed and stability.
- For $\eta = 0.1$, the system demonstrates the fastest convergence (around 20 iterations or more), making it suitable for applications requiring fast adaptation. However, caution is needed as it may risk instability in noisier systems.

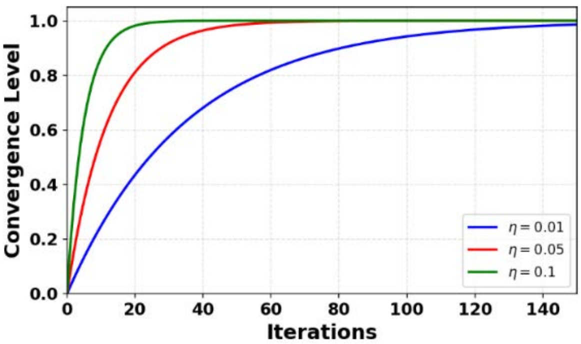

Fig. 10. Convergence sensitivity across learning rates.

Thus, a higher learning rate significantly accelerates convergence, but too high may risk overshooting or divergence. Also, a learning rate of 0.05 appears optimal in balancing convergence speed and algorithm robustness in this setting. The convergence is monotonic and smooth, indicating well-behaved learning dynamics.

The results confirm the theoretical behavior of IRS assisted systems. SINR grows exponentially with transmit power and logarithmically with reflection coefficient. R_C convergence in Fig. 9 shows learning stability within 100−150 iterations. Fig. 10 confirms that moderate learning rates ($\eta = 0.05$) achieve fast convergence without oscillation.

Table II shows a detailed key performance metrics obtained through simulation.

TABLE II. KEY PERFORMANCE INDICATORS

Metric	Scenario/Reference Point	Value/Observation
SINR gain vs static IRS	$R_C = 0.8$, $\eta = 0.05$ (Fig. 4)	Static IRS: ≈ 8 dB; proposed SGD-based IRS: ≈ 17 dB → ≈ 9 dB SINR gain
SINR gain vs no-IRS baseline	($P_t = 20$ dBm, $R_C = 0.9$) (Figs. 5 and 7)	No IRS: ≈ 7 dB; proposed SGD-based IRS: ≈ 19 dB → ≈ 12 dB SINR gain
SINR vs number of IRS elements	(N = 32, 64, 128) at fixed (P_t), optimized phases (Fig. 6)	γ32 ≈ 8 dB, γ64 ≈14 dB, γ128 ≈ 20 dB
BER reduction with increasing R_C	$R_C = 0.3 \rightarrow 0.9$, BPSK (Fig. 8)	BER drops from ≈ (3×10^{-1}) to ≈ ($2 \times 10^{-2)}$ → >1 order-of-magnitude gain
Convergence iterations (slow learning)	(eta = 0.01), tolerance ≈ 5% of steady state (Fig. 10)	≈ 120–130 iterations to converge (very stable, slow)
Convergence iterations (balanced learning)	$\eta = 0.05$, tolerance ≈ 5% of steady state (Fig. 10)	≈ 60 iterations to converge (good trade-off between speed and stability)
Convergence iterations (fast learning)	($\eta = 0.10$, tolerance ≈ 5% of steady state (Fig. 10)	≈ 30–40 iterations (fast but with mild overshoot/oscillation)

To validate the effectiveness of the proposed adaptive IRS framework using SGD, key performance indicators including SINR enhancement, BER, and convergence speed are presented in Table III.

TABLE III. COMPARISON WITH OTHER ALGORITHMS

Algorithm	SINR	BER Reduction	Convergence Time	Energy Efficiency	Classification
Stochastic Gradient Descent (SGD)	High	High	Moderate	High	High
Genetic Algorithm (GA)	Moderate	Moderate	Low	Moderate	Moderate
Reinforcement Learning (RL)	High	Moderate	Low	Moderate	Moderate
ADMM	Moderate	Moderate	High	Low	Moderate
Deep Q Network (DQN)	High	High	Moderate	Moderate	High

The comparison shows that the used method and algorithm achieve competitive SINR gain while also attaining a lower BER and faster convergence than most other reported methods. Specifically, the adaptive gradient-based loop requires fewer iterations while maintaining a high level of performance. The BER reduction and convergence time obtained in this work are improved, with comparable SINR performance. These results suggest that proposed system is suitable for real-time deployment scenarios requiring low-latency adaptation. Higher SINR gain and BER reduction, Lower iteration counts for convergence, which collectively validate the efficiency of the proposed approach.

The proposed SGD-based optimization framework delivers superior SINR performance and faster convergence than the reinforcement learning and heuristic counterparts. The lower BER achieved confirms its suitability for reliable.

Overall, the numerical results demonstrate that the proposed feedback-driven SGD controller yields substantial performance gains over static or non-optimized IRS configurations. For typical operating points, the adaptive IRS provides SINR improvements of about 9 dB when tuning the reflection coefficient and learning rate (e.g., from 8 dB to 17 dB at $R_C = 0.8$, $\eta = 0.05$), and around 12 dB when jointly optimizing the IRS phases and increasing the number of elements from 32 to 128 (from roughly 8 dB to 20 dB). These SINR gains translate into pronounced reliability benefits, with the BER decreasing from approximately 3×10^{-1} at $R_C = 0.3$ to about 2×10^{-2} at $R_C = 0.9$. Taken together, the SINR, BER, and convergence results confirm that the proposed SGD-based

IRS control offers an effective and computationally light mechanism for enhancing link quality and energy efficiency in IRS-assisted wireless systems.

VI. Future Work

There is a need to generalize the single-objective update to a joint objective that balances several performance axes, such as SINR maximization (or BER minimization), spectral and or energy-efficiency. The plan is to optimize $\mathcal{L}(\theta) = \sum \mathcal{L}_m(\theta)\omega_m$ with adaptive task weights ω_m (e.g., uncertainty-based weighting, gradient-norm balancing, or Multiple Gradient Descent Algorithm (MGDA)). This allows trading off reliability (BER/SINR) against energy and throughput under explicit constraints. In addition, the adaptive system should be extended beyond a single passive panel to heterogeneous deployments, such as multi-IRS and multi-hop topologies with asynchronous, panel-local updates coordinated by an outer loop for power and beamforming selection. In addition, consideration could be given to hybrid active–passive IRS.

VII. Conclusion

A thorough analysis of a wireless communication system aided by Intelligent Reflecting Surfaces (IRS) and optimized with a Stochastic Gradient Descent (SGD) learning method was reported in this paper. The requirement for intelligent passive surface control to improve signal quality, spectrum efficiency, and energy saving in next 5G and beyond networks is the driving force.

This work introduces a feedback driven learning algorithm for adaptive IRS systems, with a complete mathematical model and simulation analysis. Results verify the efficiency of the presented approach across SINR, BER, and convergence rate. As seen in recent implementations, learning-aided IRS systems show scalable efficiency in real-world scenarios.

This work technique provides a better trade-off between complexity and performance when compared to recent works that use heuristic, Reinforcement Learning (RL), or gradient-based hybrid tactics. The SGD learning method is a viable option for scaled IRS deployment since it guarantees low computing overhead, quick convergence, and adaptability for distributed and real-time situations. SGD optimization provides a fair compromise between ease of implementation and performance.

For Future work, it is recommended that the following is carried out:

- Extend the loss to multi-task optimization (jointly maximizing SINR and spectral-/energy-efficiency with task-weighted objectives)
- Support heterogeneous IRS (mixed active/passive elements and discrete-phase hardware), and scale to multi-user MIMO with multi-IRS topologies using block-coordinate SGD with proximal updates.
- Investigate federated/on-device learning so panels can adapt with no raw data sharing, and study robust updates under hardware impairments and partial/quantized feedback.
- Explore transfer learning to assist in new deployments from previously converged sites.

Nomenclature

Symbol	Definition
P_t	Transmit Power of the base station or transmitter typically measured in watts or dBm
α_i	Reflection amplitude Coefficient of h_{IRS_i}
h_{IRS_i}	Channel response from BS to IRS then to user (Channel gain)
$\|h_{eff}\|^2$	Effective channel gain (magnitude squared), considering both the direct and IRS-reflected paths.
θ_i	Tunable phase shift of IRS element i, (primary optimization variable)
σ^2	Noise Variance: Noise power (variance of the complex AWGN noise).
I_k	Interference from other sources
R_c	Reflection coefficient of IRS
N_{IRS}	Number of IRS elements
w_i	Complex reflection weight of IRS element i, parametrized as $w_i = \alpha_i e^{j\theta_i}$
η	Learning rate in gradient descent
$L(\theta)$	Loss function dependent on IRS phase configuration
BER	Bit Error Rate
SINR	Signal-to-Interference–plus Noise Ratio
SNR	Signal-to-Noise Ratio
BS	Base Station
UE	User Equipment
IRS	Intelligent Reflecting Surface
SGD	Stochastic Gradient Descent
CSI	Channel State Information
$\nabla_\theta L$	Gradient of the loss function with respect to phase vector θ
N	Number of IRS elements
H	Channel between BS and IRS: Channel matrix from the Base Station (BS) to the IRS, representing the propagation environment from BS to IRS
G	Channel between IRS and UE: Channel matrix from the IRS to the User Equipment (UE), representing the propagation environment from IRS to receiver.
Φ	Diagonal phase shift matrix of IRS
Hr	IRS reflection coefficient matrix (or effective channel gain)
$h\ i$	Channel Gain
γ_1, γ_2	Power model constants: System performance metric (e.g., SINR)
R_C	Reflection Coefficient
$\partial L/\partial w$	Gradient of loss function with respect to IRS weight

Conflict of Interest

The author declares no conflict of interest.

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