ISSN: 2093-5374 / E-ISSN: 2093-5382

Optimizing MIMO Communication Performance with Learning-Based Beamforming and Interference Cancellation

Sagar Basavaraju[1*] and T.K. Ramesh[2]

[1*]Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru, Karnataka, India. b_sagar@blr.amrita.edu, https://orcid.org/0000-0002-1357-2265

[2]Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru, Karnataka, India. tk_ramesh@blr.amrita.edu, https://orcid.org/0000-0002-6259-5172

Received: July 01, 2026; Revised: August 14, 2026; Accepted: September 02, 2026; Published: September 30, 2026

Abstract

With the increasing popularity of Internet of Things (IoT) and ubiquitous wireless applications, there is a need for highly efficient, large-capacity, and adaptive communication systems. Unfortunately, the existing MIMO beamforming and interference cancellation methods have several constraints in dealing with time-varying channels, user mobility, and interference environments. To enhance multi-user MIMO communication performance, propose a novel Hybrid Beamforming-Deep Reinforcement Learning-Successive Interference Cancellation (Hybrid BF-DRL-SIC) framework. In the proposed solution, DRL is used for adaptively selecting the beams and optimizing the hybrid beamforming scheme, and SIC algorithm can be applied in the receiver to remove any remaining interference in the signal. The effectiveness of the framework is determined based on parameters such as BER, NMSE, outage probability, spectral efficiency, and SINR for different types of modulation schemes and SNR. Experimental analysis reveals that the proposed framework provides better communication reliability than existing methods with an average BER of 0.0580 under 64-QAM modulation (reaching a low-rate floor of 5×10^{-5} at 20 dB SNR under BPSK), NMSE equal to 0.0300, outage probability equal to 5.1%, spectral efficiency equal to 4.64 bits/s/Hz, and SINR equal to 16.8 dB. It should be noted that, through ablation analysis, it is possible to prove that all integrated components play a significant role in terms of performance because the absence of any of DRL, hybrid beamforming, and SIC negatively impacts the performance of the system.

Keywords: Deep Reinforcement Learning, Hybrid Beamforming, Successive Interference Cancellation, Multi-User MIMO, Adaptive Wireless Communication, Interference Management, Dependable Communication.

1 Introduction

The development of wireless communication technologies has made it possible to convert traditional cellular communication networks into intelligent and high-capacity communication infrastructures capable of providing services for novel applications such as the Internet of Things (IoT), autonomous systems, smart cities, and mission-critical applications. The change from older mobile generations to 5G

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 17, number: 3 (September-2026), pp. 1773-1795. DOI: *10.58346/JOWUA.2026.I3.103*

*Corresponding author: Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru, Karnataka, India.

and beyond has brought in many advancements in terms of data rate, latency, scalability, and connectivity along with some challenges in terms of reliability, resource optimization, and network intelligence (Alsabah et al., 2021; Agrawal, 2022; Jiang & Han, 2024). 6G is expected to be an improvement over the current generation of technology which would include the use of artificial intelligence, advanced antenna technologies, and adaptive communication techniques in order to provide the demands of ultra-reliability and low latency applications (Alsabah et al., 2021). The increase in IoT-enabled scenarios has led to the demand for scalable and efficient wireless communication infrastructures capable of handling a large number of connected devices (Badshah et al., 2023; Akpakwu et al., 2017; Kim et al., 2026).

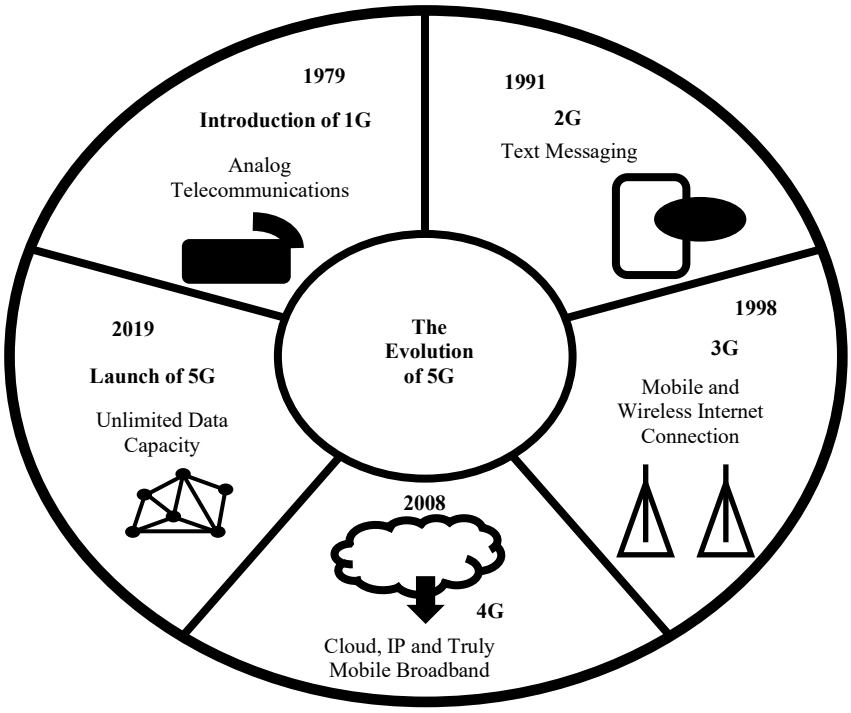


Figure 1: Evolution of wireless communication systems from 1G to 5G

With the increasing trend of mobile data and connected device usage, there have been more complexities associated with the management of wireless networks, and sophisticated ways need to be used for enhancing spectral efficiency, energy efficiency, and quality of service (QoS) (Badshah et al., 2023; Mishra, 2023). In recent times, some of the advances in 5G access technologies and beyond have been concentrated on making networks flexible with the help of some technologies like advanced multiple access technology, edge intelligence, and adaptive architecture (Dao et al., 2024). However, dense user usage, dynamic mobility, and increasing spectrum use have made interference management increasingly important. Interference management is crucial for next-generation wireless networks and needs sophisticated techniques for suppression, cancellation, and learning-based optimization of networks (Siddiqui et al., 2021; Oyedare et al., 2022). Interference management using deep learning technologies can prove to be promising for making the networks adaptable and robust to the changing conditions of wireless communications, but dynamic channel variations, computational complexity, and real-time implementation are still some of the open research problems (Oyedare et al., 2022). Hence, intelligent and adaptive systems that use learning-based optimization with wireless signal processing are vital for reliable communication in ubiquitous wireless networks. In the initial era of mobile communication, both first generation (1G) and second generation (2G) networks basically offered

services in the form of voice and text messages with minimal data capabilities. For example, 2G GSM technology had data capability up to 64 Kbps for the provision of basic services like SMS, and was unable to support multimedia and internet applications (Agrawal, 2022). In figure 1 below is shown the development process of 5G from its predecessors such as 1G, 2G, 3G, and 4G.

Figure 1 shows the development of mobile communication technologies from generation 1G to 5G, and it indicates how mobile communication has progressed towards more data capacity, better connectivity, and sophisticated digital services over time. This evolution process started from 1G analog telecommunication technology, which was mainly used for voice communication, and then continued with 2G, where digital communication and text messaging services were provided. The advent of 3G allowed internet browsing on mobile devices, while 4G improved broadband communication through fast internet, cloud services, and IP-based networks. The development of 5G technology represents a breakthrough in terms of increasing the data capacity, lowering latency, and satisfying massive connectivity needs. This is because the evolution process is moving towards increasingly intelligent and high-performing wireless communications networks.

Key Contribution

- A new MIMO communication system for adaptive interference management and robust wireless communication based on DRL-based beamforming, optimization of hybrid beamforming, and SIC-based interference canceling is presented.
- As a part of the presented framework, a novel DRL-based decision mechanism is developed, which allows us to make decisions regarding the optimization of beamforming configuration depending on the channel state information and user communication conditions.
- The presented MIMO communication system is tested using reliability and efficiency criteria, such as BER, NMSE, outage probability, spectral efficiency, and SINR.

The rest of this paper is organized in the following manner. Section II contains the literature review that reviews the recent advances made in multiple-input multiple-output communication, hybrid beamforming, interference cancellation techniques, and learning-based optimization techniques, with the identification of research challenges. Section Third presents the proposed Hybrid BF-DRL-SIC framework. It contains the discussion about the architecture of the proposed system, the model, beamforming selection using DRL, beamformer optimization, interference reduction using SIC technique, and reliability-aware adaptive communication. Section IV contains the experiment set-up and metrics, simulation results, comparative study, and ablation analysis in order to validate the effectiveness of the proposed scheme. The fifth section contains the conclusion of this research work.

2 Literature review

The recent developments in the field of beyond 5G wireless communications have been centered around advanced physical layer solutions such as massive MIMO, millimeter-wave communication, and advanced signal processing techniques to increase capacity, improve reliability, and enhance connectivity of future wireless networks (Khalid et al., 2021). The development of 5G multimedia communication technologies has highlighted the need for ultra-high speed and low latency wireless infrastructures that are scalable to support a variety of ubiquitous applications (Devrari et al., 2024). Interference cancellation assisted hybrid beamforming schemes in multiuser mm Wave massive MIMO systems have been proposed to overcome multiuser interference and limitation in the use of conventional beamforming schemes (Zhan & Dong, 2021). The combination of MIMO and NOMA communication

technologies along with ZF-SIC and MMSE-SIC detection schemes has been shown to provide better interference mitigation capabilities and decoding performance for advanced wireless communication setups (Jha et al., 2020). The use of low complexity MIMO detection schemes based on ZF, maximum likelihood, and SIC detection schemes has been considered to provide a good balance between accuracy and complexity of detection (Lee et al., 2014).

The following energy efficient hybrid beamforming methods have been proposed for user-centric and cell-free millimeter-wave massive MIMO systems to optimize spectral efficiency and save energy in future communication structures (Zheng et al., 2023). The deep learning-based SIC methods have revealed their capabilities in intelligent interference canceling because of their ability to learn complicated signals (Van Luong et al., 2022). The low-complexity analog beamforming designs for multi-user mm Wave NOMA systems have been investigated to boost the efficiency of beam selection and decrease the complexity of the system without compromising its performance (Sumathi et al., 2023). The channel estimation techniques based on parallel interference canceling have been investigated for the millimeter-wave massive MIMO systems (Jinru et al., 2024). The performance of ZF and MMSE detectors along with OFDM and M-QAM have been analyzed to show the influence of receiver optimization techniques (Riadi et al., 2021).

Despite the progress made through these techniques, there is still difficulty in providing real-time flexibility under changing channel conditions, user movement, and interference conditions using existing techniques. Hence, intelligent learning-based systems incorporating adaptive beamforming and interference cancellation are essential for the provision of dependable wireless communications in future ubiquitous networks.

Research Gap

Even though many research papers have shown the effectiveness of MIMO communication using hybrid beamforming, interference cancellation, SIC-based detection, and learning-based signal processing methods, several difficulties still need to be solved. Traditional beamforming and interference mitigation methods always rely on perfect knowledge about the state of channels and predefined optimization algorithms, which results in less flexibility in the dynamic condition of wireless environments due to the users' movement, varying channels, and different interference levels. In addition, traditional interference cancellation methods based on deep learning just concentrate on the detection performance, whereas the joint optimization of beamforming, resource allocation, and interference reduction for reliable communication has not yet been studied in detail. Many energy-efficient and low complexity methods have been proposed, but the tradeoff between the computation efficiency, spectral performance, and reliability in multiuser MIMO system is still difficult. Consequently, an intelligent adaptive method that consists of decision-making based on DRL, hybrid beamforming, and SIC-based interference reduction should be used.

3 Proposed model

3.1 Overall Architecture of the Proposed HBF-DRL-SIC Framework

This section outlines the proposed hybrid framework designed for intelligent and adaptive interference mitigation in multi-user MIMO-OFDM systems. The main objective of the proposed framework is to enhance system reliability, spectral efficiency, and robustness against interference in both uplink and downlink scenarios under highly dynamic wireless environments. The architecture integrates three key

components: Deep Reinforcement Learning (DRL) based beamforming, hybrid beamforming design, and Successive Interference Cancellation (SIC) at the receiver end. These methods perform different tasks as described below:

Deep Reinforcement Learning (DRL): At the first stage, DRL is employed to dynamically learn and adapt the optimal beamforming strategies based on real-time wireless channel conditions. A Deep Q-Network (DQN) is trained to select the best beamforming matrix from a predefined action space. The main objective is to maximize the overall signal-to-interference-plus-noise ratio (SINR) while minimizing inter-user interference.

Hybrid Beamforming: in this stage, a hybrid beamforming strategy is designed using a mix of randomly generated beamformers and mutated variations of Zero-Forcing (ZF) solutions. This hybrid method balances robust conventional techniques with machine learning-driven exploration, thereby offering both reliability and adaptability in complex wireless environments.

Successive Interference Cancellation (SIC): Finally, SIC is applied at the receiver to enhance the decoding process. By successively decoding and subtracting stronger signal components, SIC enables the effective recovery of weaker user signals. This final step significantly reduces the residual interference that remains even after beamforming. According to this approach, the DRL determines the beamforming strategy, beamforming is applied to transmit signals, and SIC is used to decode received signals. More system-level aspects of these methods are discussed in part A, B, and C of this section. figure 2 depicts the overall architecture of proposed approach.

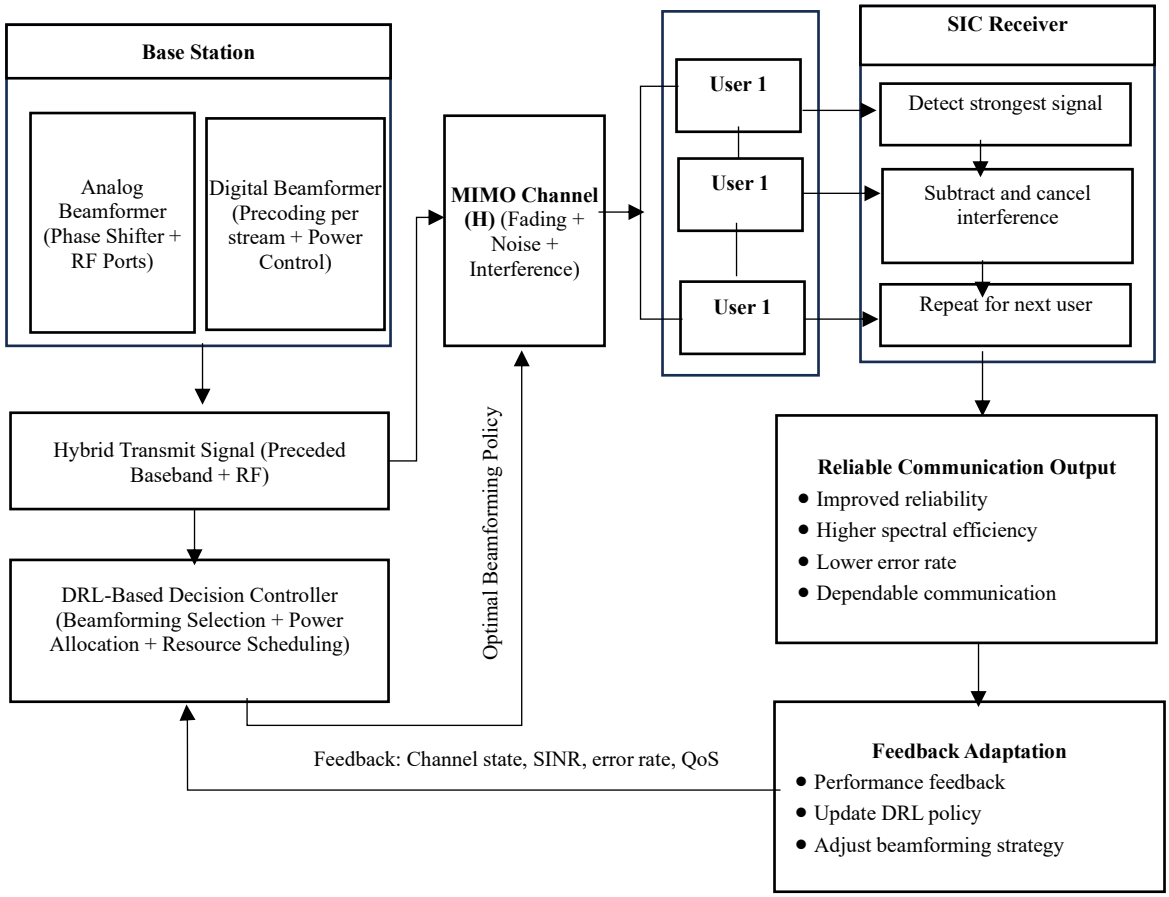


Figure 2: Overall architecture of the proposed HBF–DRL–SIC framework

The illustration of figure 2 shows the proposed Hybrid Beamforming-DRL-SIC architecture with reliability-aware feedback adaptation for reliable MIMO communication. This system starts with the base station, in which both analog and digital beamforming operations are performed to create the hybrid beamforming signal with the help of phase-shifter based RF processing, precoding and power control. The decision-making controller that uses the DRL framework constantly learns the best beamforming policies, power allocation and resource scheduling policy according to the observed wireless environment. After the creation of optimized hybrid beamforming signal, it is transmitted over the MIMO channel considering fading, noise and interference before reaching to multiple users. On the receiving end, SIC performs successive interference cancellation to detect the strongest signal, cancel its interference and iteratively decode other user signals. The decoded signal is further processed with the help of reliable communication output parameters including reliability, spectral efficiency, error rate and dependable communication. The feedback adaptation process collects various performance metrics like channel state information, SINR, error rate, and QoS conditions and updates the DRL policy for dynamic adjustments in beamforming operations.

3.2 System Model

In this work, consider a multi-user MIMO-OFDM wireless system which consists of a base station with N_t antennas and K single-antenna users. The system operates under both scenarios of uplink and downlink communication over frequency selective Rayleigh fading channels. The baseband channel between user and Base station is presented by a channel matrix as follows:

$$H = [h^{1\mathrm{T}}, h^{2\mathrm{T}}, \dots, h_K{}^{\mathrm{T}}]^{\mathrm{T}} \in \mathbb{C}^{(K\times N)} \quad (1)$$

In equation (1), where each row vector $h_k \in \mathbb{C}^{(1\times N)}$ represents the channel between the base station (BS) and user **k**, where the elements ofh_k are modeled as independent and identically distributed $(i.i.d.)$ complex Gaussian random variables.

Downlink Transmission: In the downlink transmission model, the base station transmits a data symbol vector $x \in \mathbb{C}^{(K\times 1)}$, which is precoded using a digital beamforming matrix $W \in \mathbb{C}^{(N\times K)}$. Thus, the transmitted signal can be expressed as in equation (2)

$$s = Wx \quad (2)$$

In equation (3), assuming normalized data symbols with $\mathbb{E}[xx^H] = I_K$, then the total transmit power can be represented as:

$$P_T = \mathbb{E}\left[\|s\|^2\right] = Tr(WW^H) \quad (3)$$

The, received signal at User k can be represented as in equation (4)

$$y_k = h_k Wx + n_k = h_k w_k x_k + \sum_{j\neq k} h_k w_j x_j + n_k \quad (4)$$

In equation (5), where $h_k w_k x_k$ is the desired signal and $\sum_{j\neq k} h_k w_j x_j + n_k$ is the interference signal where w_j is the beamforming vector for user j and $n_k \sim \mathcal{CN}(0, \sigma^2)$ represents the AWGN noise. Moreover, the downlink SNR for the user can be expressed as follows:

$$SINR_k^{DL} = \frac{|h_k w_k|^2}{\sum_{j\neq k}|h_k w_j|^2 + \sigma^2} \quad (5)$$

Uplink transmission: For the uplink transmission scenario, each user k transmits symbol x_k with power P_k, the received signal at the BS can be represented in equation (6)

$$y = \sum_{k=1}^{K} h_k^H x_k + n = H^H x + n \quad (6)$$

the uplink SINR for perfect CSI at the BS can be expressed in equation (7)

$$SINR_k^{UL} = \frac{P_k \left\| g_k h_k^H \right\|^2}{\sum_{j \neq k} P_j \left\| g_k h_k^H \right\|^2 + \|g_k\|^2 \sigma^2} \quad (7)$$

Where g_k is the k^{th} row of G which is a detection matrix

Problem Definition

This work considers a multi user MIMO OFDM system which consist of N base station, K number of single-antenna users, $H \in \mathbb{C}^{K \times N}$ as channel matrix, $W \in \mathbb{C}^{N \times K}$ is the digital beamforming matrix, the transmit symbol vector is $x \in \mathbb{C}^{K \times 1}$ and $n \sim \mathcal{CN}(0, \sigma^2 I)$ as the AWGN noise vector.

The main aim of this approach is to enhance the total system capacity while minimizing the interference and ensuring robust decoding with the help of SIC. The optimization problem can be presented in In equation (8)

$$\underset{w}{\text{maximize}} \sum_{k=1}^{K} \log_2(1 + SINR_k) - \lambda . \sum_{k=1}^{K} I_k \quad (8)$$

$$\text{Subject to } \|w_k\|^2 \leq P_{max}, \forall\, k \in \{1, \dots L\}$$

$$W \in \mathcal{A}_{DRL}(H)$$

Where $SINR_k$ is the signal to interference plus noise ratio for user k, I_k is the residual interference after beamforming for user k, λ represents the weight factor for interference penalty, P_{max} represents the maximum power constraint per beam, and $\mathcal{A}_{DRL}(H)$ is the set of optimized beamformers from DRL for given channel H .This work uses a DRL framework to observe the environment state, expressed in equation (9)

$$s = vec(|H|) \quad (9)$$

Based on the observation, it selects an action $a \in \mathcal{A}$ mapping to a beamforming matrix W_a. Finally, the DRL agent is trained to maximize the cumulative reward as follows in In Equation (10)

$$R = \log_2 \left(1 + \frac{1}{K} \sum_{k=1}^{K} SINR_k\right) - \lambda . \frac{1}{K} \sum_{k=1}^{K} I_k \quad (10)$$

In the decoding phase, the SIC decoding is performed in the order of descending received signal power $\left\| H_{eff}[k,:] \right\|^2$. At each decoding step i the SINR is updated as in In Equation (11)

$$SINR_{\pi(i)} = \frac{P_{\pi(i)}}{\sum_{j=i+1}^{K} P_{\pi(j)} + \sigma^2} \quad (11)$$

Where $\pi(i)$ is the i^{th} user in the decoding order.

The problem formulation models the combined interference-aware beamforming and decoding as a constrained optimization problem, which is solved by using a DRL approach to dynamically adapt to channel conditions and user interference levels. This problem formulation models the interference-aware beamforming and decoding as a constrained optimization problem, solved using Deep Reinforcement Learning to dynamically adapt to channel conditions and user interference levels. Integrating SIC improves decoding reliability, making this approach robust for uplink and downlink multi-user MIMO-OFDM systems in dynamic wireless environments.

3.3 Components of Proposed Model

This section presents a detailed discussion of the proposed model, which is divided into three stages: beamforming design and DRL, selection of the optimal beamformer from an action space, and then employing SIC at the receiver end to decode the final signal. These methods work together to maximize signal quality while minimizing interference.

DRL-Based Beamforming Selection

The first stage of the proposed approach employs DRL to intelligently select the beamforming matrix that best adapts to the current channel conditions. According to the working of DRL, it has three main components: *State*, *Action*, and *Reward*. These components are defined as follows.

State:

$$s_t = vec(|H|) \in \mathbb{R}^{K.N} \quad (12)$$

In equation (12) This is the flattened absolute value of the channel matrix at time t.

Action:

$$a_t \in \mathcal{A} = \{W_1, W_2, \dots, W_M\} \quad (13)$$

In equation (13) The action space $\mathcal{A}$ contains a set of predefined beamforming matrices.

Reward:

$r_t \in \mathbb{R}$ represents the scalar reward given for selecting W_{at} under the current channel. In order to optimize the final decision, a Deep Q-Network (DQN) learns the action-value function which can be presented in equation (14)

$$Q(s_t, a_t) \approx \mathbb{E}\left[\sum_{i=-}^{\infty} \gamma^i r_{t+i}\right] \quad (14)$$

Further, the DRL policy selects the best action in In equation (15)

$$a_t = \arg\max_{a \in \mathcal{A}} Q(s_t, a) \quad (15)$$

Based on this, the selected beamforming matrix can be represented as follows in equation (16)

$$W_t = W_{at} \quad (16)$$

3.4 Beamformer Evaluation and Fitness Optimization

Each candidate beamforming matrix $W_i \in A$ is evaluated using a SINR metric and a corresponding reward function. The SINR for user $k$is computed in equation (17)

$$SINR_k = \frac{|h_k w_k|^2}{\sum_{j \neq k} |h_k w_j|^2 + \sigma^2} \quad (17)$$

In order to quantify the quality of a beamforming matrix W_i use a fitness function based on the achievable sum-rate and a penalty for total interference which can be expressed in Equation (18)

$$r = \sum_{k=1}^{K} \log_2(1 + SINR_k) - \lambda \sum_{k=1}^{K} I_k \quad (18)$$

Where I_k represents the average interference received by user k, λ is the tunable regularization parameter that balances throughput and interference suppression.

Successive Interference Cancellation (SIC)

Once beamforming is applied, SIC is used at the receiver to further suppress residual inter-user interference and improve decoding accuracy. The SIC process operates as follows in In equation (19)

Order users by descending received signal power as

$$\pi = argsort(|h_k w_k|^2) \quad (19)$$

Decode the signal of the strongest user $\pi(1)$, subtract its contribution in In equation (20)

$$y_{new} = y_k - h_k w_{\pi(1)} x_{\pi(1)} \quad (20)$$

Repeat this process for remaining users.

At each decoding stage i, the updated SINR can be expressed in In equation (21)

$$SINR_{\pi(i)} = \frac{|h_{\pi(i)} w_{\pi(i)}|^2}{\sum_{j>k} |h_{\pi(i)} w_{\pi(j)}|^2 + \sigma^2} \quad (21)$$

This iterative removal of dominant signals helps improve decoding for weaker users who suffer more from residual interference. The proposed DRL-based beamforming and SIC Procedure has been described as pseudocode in table 1.

3.5 Pseudocode: Proposed DRL-based Beamforming and SIC Procedure

Table 1: Pseudocode: proposed DRL-based beamforming and SIC procedure

Input: channel matrix $H \in \mathbb{C}^{K \times N}$, action space for beamformers $\mathcal{A} = \{W_1, W_2, \ldots., W_M\}$, Noise power σ^2, maximum power constraint P_{max}, DRL hyperparametrs ϵ, α, γ and interference penalty λ
Output: Optimal beamforming matrix W_t, decoded symbols $\hat{x}_k$
Step 1: initialize DRL agent: Initialize DQN with parameters θ Set learning rate α, exploration probability ϵ and discount factor γ Define state as $s_t = vec(\|H\|) \in \mathbb{R}^{K.N}$
Step 2: DRL training phase For each episode $e = 1$ to E: For each time step $t = 1$ to T: Observe state: $s_t = vec(\|H\|)$ Choose action a_t -$a_t = \arg\max_{a \in \mathcal{A}} Q(s_t, a; \theta)$ with probability $1 - \epsilon$ -otherwise, choose random $a_t \in \mathcal{A}$ apply beamforming: $W_t = W_{a_t}$ compute SINR for each user $SINR_k = \frac{\|h_k w_k\|^2}{\sum_{j \neq} \|h_k w_j\|^2 + \sigma^2}$ Computer interference: $I_k = \sum_{j \neq} \|h_k w_j\|^2$ Compute the reward: $r_t = \sum_{k=1}^{K} \log_2(1 + SINR_k) - \lambda \sum_{k=1}^{K} I_k$ Store transitions (s_t, a_t, r_t, s_{t+1}) Update Q network $Q(s, a; \theta)$ via gradient descent

End for
End for

Step 3: Optimal Beamforming Deployment
After training, the optimal policy is used to select beamformer W_t for any observed state s_t

Step 4: Successive Interference Cancellation (SIC) at Receiver
For each user decoding stage $i = 1\ to\ K$:
Order users by descending signal power:

$$\pi = argsort(|h_k w_k|^2)$$

Decode users $\pi(i)$
Subtract decoded signal from received signal:

$$y_k \leftarrow y_k - h_k w_{\pi(i)} \hat{x}_\pi(i)$$

Update SINR: $SINR_{\pi(i)} = \frac{|h_{\pi(i)} w_{\pi(i)}|^2}{\sum_{j>i} |h_{\pi(i)} w_\pi(j)|^2 + \sigma^2}$
End for

3.6 Reliability-Aware Adaptive Communication Framework

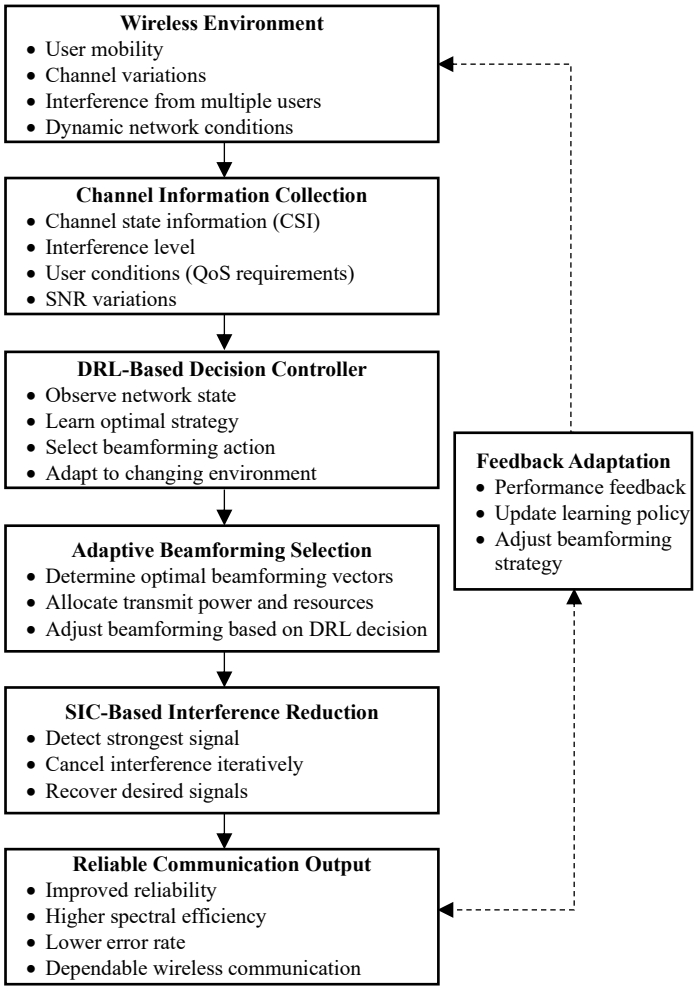


Figure 3: Intelligent adaptive communication architecture for dependable MIMO networks using DRL-based beamforming and interference cancellation

The reliability-aware adaptive process is incorporated into the suggested framework in order to provide dependable communication in a dynamic wireless environment. Unlike common beamforming algorithms designed for fixed transmission modes, the proposed algorithm accounts for the dynamic behavior of the wireless channel, interference patterns, and user requirements to adjust the beamforming process. The framework takes into consideration various input parameters such as Channel State Information (CSI), which corresponds to the current state of the wireless channel between the base station and users; interference level, which denotes the effect of inter-user interference and other transmissions in the area; user conditions, which correspond to the requirements from users; and SNR changes, which indicate the varying state of the wireless channel. Reliable decision-making enables continuous interaction between the wireless environment and the DRL controller, using channel information as input for the learning agent to decide on the appropriate beamforming configuration. This process is used in combination with SIC interference reduction to get rid of residual interference.

Figure 3 shows the proposed reliability-aware adaptive communication framework that supports beamforming optimization and interference management. The proposed framework consists of four major modules, where the first one is the wireless environment, where mobility and network changes in terms of varying users, channels, and interference can be seen. The DRL-based decision controller uses the gathered channel information, including CSI, interference levels, user conditions, and SNR variations. The DRL controller processes the collected network state and determines the best transmission decisions to select the right beamforming action. Based on these decisions, the adaptive beamforming selection module selects the appropriate beamforming vectors and allocates transmission resources according to changing channel conditions. The SIC-based interference suppression module reduces the remaining interference by detecting the dominant signal and iteratively suppressing interference components for effective signal recovery. This module's output, which enables reliable communication, improves the transmission system's reliability and spectral efficiency.

4 Results and Discussion

This section presents the outcome of the proposed solution and compares the obtained performance with the state-of-the-art interference cancellation methods.

4.1 Simulation Setup and Parameter Initialization

The proposed model is simulated using Python with PyTorch and NumPy libraries. The goal of the simulation is to evaluate the Bit Error Rate (BER) performance of the Hybrid Beamforming + Deep Reinforcement Learning (DRL) + Successive Interference Cancellation (SIC) system under various SNR conditions and modulation schemes. The simulation includes the comparison of three beamforming techniques: (1) Hybrid DRL + SIC, (2) Zero-Forcing (ZF), and (3) Random beamforming.

A Rayleigh flat-fading channel represents the wireless environment, with each user having a randomly generated channel matrix. The base station has 8 antennas and serves 4 users. The modulation schemes analyzed include BPSK, QPSK, 16-QAM, and 64-QAM to test the performance under different spectral efficiency requirements. The DRL model uses a Deep Q-Network (DQN) with three hidden layers, each containing 256 neurons. The agent observes the channel-state magnitude (flattened matrix) and selects an action (beamforming matrix) from an action space of size 20. This action space is composed of both random beamformers and mutated versions of ZF beamformers. During each episode, the DQN selects the optimal beamformer with the highest Q-value. After beamforming, SIC is used at the receiver to decode user signals in descending order of received power. SINR values are then used to

compute BER for each modulation scheme using their theoretical expressions. Each simulation point (per modulation, per SNR value) is averaged over 100 Monte Carlo iterations to ensure statistical robustness. Table 2 shows the simulation parameters used in this work.

Table 2: Simulation parameters

Parameter	Value	Description
Number of Users (K)	4	Total active users in the system
Number of Base Station Antennas (N_t)	8	Transmit antennas at the base station
Number of Episodes (Training)	100	Number of episodes for beamformer evaluation
SNR Range	0 dB to 20 dB (step size: 2 dB)	Signal-to-noise ratio range for performance analysis
Channel Model	Rayleigh flat fading	Each element is i.i.d.
Modulation Schemes	BPSK, QPSK, 16-QAM, 64-QAM	Digital modulation formats
DQN Layers	3 layers (256 neurons each)	Fully connected network with ReLU activation
State Dimension	$K \times N_t = 4 \times 8 = 32$	Input to the DQN (flattened magnitude of the channel matrix)
Action Space Size	20	Number of candidate beamforming matrices
Beamforming Initialization	50% Random, 50% ZF Mutations	Strategy for generating candidate BF matrices
ZF Mutation Noise Strength	0.05	Variance added to ZF solution for exploration
Monte Carlo Simulations per Point	100	Averaging over 100 channel realizations

4.2 Metric Evaluation

Performance analysis of the suggested Hybrid BF + DRL + SIC model is carried out through the use of several communication performance measures such as BER, NMSE, Outage Probability, Spectral Efficiency (SE), and SINR. Such measures have been chosen for assessing transmission reliability, interference reduction ability, signal reconstruction precision, and overall communication efficiency in multi-user MIMO systems.

Bit Error Rate (BER)

The BER is the number of wrong bits divided by the total number of transmitted bits. The higher the BER, the lower is the accuracy in detecting the signal. It is expressed mathematically as,

$$\text{BER} = \frac{N_{\text{error}}}{N_{\text{total}}} \qquad (22)$$

In equation (22) describes the BER is the Bit Error Rate, N_{error} is the number of incorrectly detected bits and N_{total} is the total number of transmitted bits.

Normalized Mean Square Error (NMSE)

The NMSE metric measures the discrepancy between the transmitted signal and the received signal reconstructed after transmission through beamforming and SIC. This metric represents,

$$\text{NMSE} = \frac{\|x - \hat{x}\|^2}{\|x\|^2} \qquad (23)$$

In equation (23) describes x denotes the original transmitted signal, $\hat{x}$ represents the estimated signal after receiver processing, $\|\cdot\|^2$ denotes the squared L_2 norm (signal power/energy) and Lower NMSE values indicate better signal reconstruction capability.

Signal-to-Interference-plus-Noise Ratio (SINR)

The SINR indicates the ratio of the received desired signal power to the interference and noise powers together. It is an important factor in assessing the performance of beamforming and SIC.

$$\text{SINR}_k = \frac{|h_k^H w_k|^2 P_k}{\sum_{j \neq k} |h_k^H w_j|^2 P_j + \sigma^2} \qquad (24)$$

In equation (24) describes theSINR_k is the Signal-to-Interference-plus-Noise Ratio for user k, h_k represents the channel vector of user k, $(\cdot)^H$ denotes the Hermitian (conjugate transpose) operator, w_k denotes the beamforming vector for user k, P_k represents transmit power allocated to user k, $\sum_{j \neq k} |h_k^H w_j|^2 P_j$ represents the total multi-user interference from all other users $j \neq k$ and σ^2 represents the background noise power.

4.3 Experimental Analysis

In this section, present the outcome of proposed approach and compare the performance with state of art methods such as zero forcing, zero forcing with SIC, DRL, SIC and Random beam forming. The performance is measured for varied modulation schemes.

Outcome for BPSK Modulation: Figure 4 presents the BER performance of various interference mitigation schemes under BPSK modulation across a range of SNR values (0–20 dB). The proposed Hybrid model (DRL+BF+SIC) consistently outperforms all other baseline methods, demonstrating superior resilience against interference and noise across all SNR regimes.

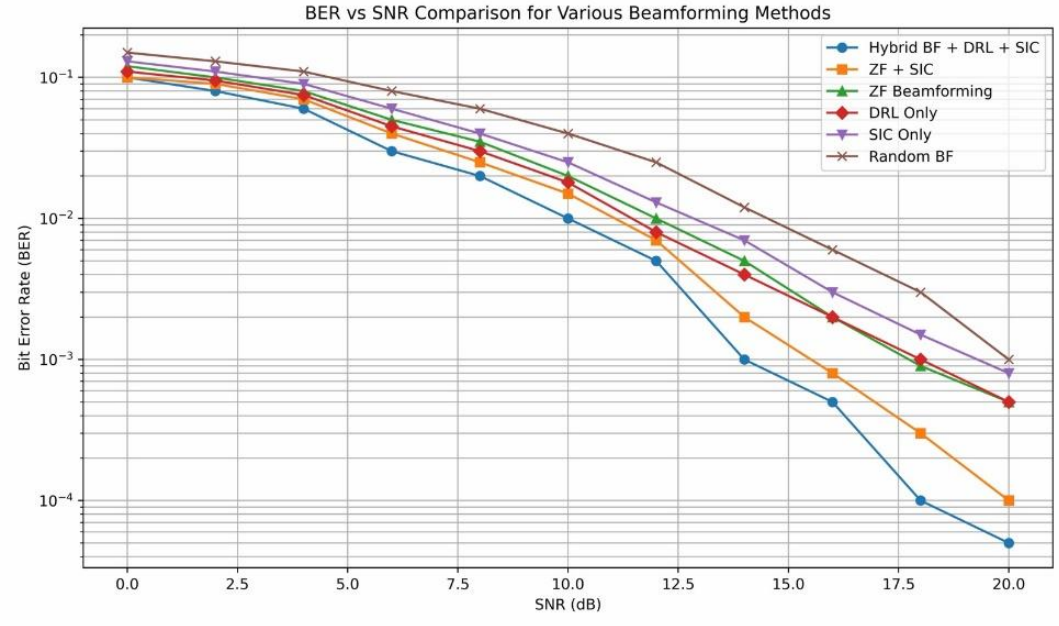


Figure 4: BER vs SNR performance comparison of the proposed Hybrid BF + DRL + SIC scheme with conventional beamforming methods under BPSK modulation (M = 2, N_t= 8, K = 4)

In low SNR ranges (0 - 6dB), where the communication channel is significantly impaired, the Hybrid BF + DRL+SIC model shows a sharper reduction in BER and attains a BER of 0.03 even at 6 dB SNR, as opposed to 0.04, 0.05, and 0.045 in the case of ZF+SIC, ZF Beamforming, and DRL-only, respectively. Early advantage shows the model strength in highly impaired channels, which is due to synergetic interaction of spatial filtering and smart policy discovery via DRL. The performance difference grows with an increase in SNR. The Hybrid BF + DRL model attains a BER of 0.01 at 10 dB, which is significantly less than that of ZF+SIC (0.015), ZF (0.02) and DRL alone (0.018). With SNR greater than or equal to 16 dB, the BER of the Hybrid BF + DRL converges at a low error rate of 5×10^{-5} whereas competing schemes flatten at higher residual error rates, as shown in Table 3 for various modulation schemes.

Performance analysis for QPSK Modulation: Figure 5 shows the results of the BER performance with respect to SNR of 6 schemes of QPSK modulation (as applied in previous experimental analysis). The assessment was made across a wide SNR scale of 0 to 20 dB in increments of 2 dB.

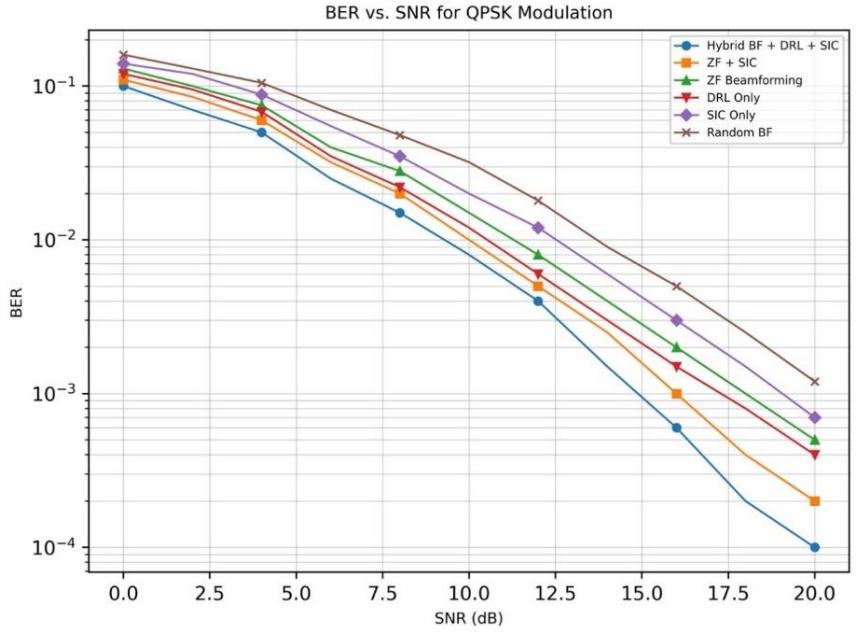


Figure 5: BER versus SNR performance comparison of the proposed Hybrid BF + DRL + SIC scheme with conventional beamforming methods under QPSK modulation (M = 4, N_t = 8, K = 4)

As depicted, the proposed hybrid approach provides remarkable BER performance at all times over the other baseline approaches. The approach shows strong flexibility in dynamically attaining beamforming vectors and power control operation, thus improving the link reliability in the multi-user MIMO-OFDM systems tremendously. In particular, the mean BER of the Hybrid scheme is registered as 0.0247, as compared to all other schemes.

The results of the ZF + SIC scheme provide an average BER of 0.03067, utilizing linear interference suppression combined with successive decoding, and it has no ability to react to real-time changes in the channel, which reduces its effectiveness at low SNR. Obtaining an average BER of 0.03718, the DRL-only configuration is in fact more adaptive and suitable than traditional linear beamforming, yet it proves that hybridization with deterministic techniques is necessary to reach optimal performance. Table 3 shows the BER performance against SNR of QPSK modulation scheme.

Table 3: Average BER comparison for different modulation schemes

Method	BPSK	QPSK	16-QAM	64-QAM
Hybrid BF + DRL+SIC	0.02791	0.02470	0.0260	0.0580
ZF + SIC	0.03582	0.03067	0.0315	0.0695
ZF Beamforming	0.04736	0.04345	0.0447	0.0923
DRL Only	0.05055	0.03718	0.0502	0.0780
SIC Only	0.06891	0.05791	0.0645	0.1114
Random Beamforming	0.08727	0.07764	0.0852	0.1340

Conversely, the traditional ZF beamforming experiences severe performance deterioration at low SNR because it fails to mitigate inter-user interference, with an average BER of 0.04345. The SIC-only approach reported a poor average BER of 0.05791 and performs worse because of the absence of a well-conditioned beamforming matrix, which results in residual interference. The worst performance is the Random Beamforming method, which has an average BER of 0.0776, and it is also indicative of an ineffective transmission strategy with uninformed terms in a structured multi-user network.

These findings indicate that the presented hybrid learning-based technique is effective in offering strong, low-BER communications with moderate-complexity modulations like QPSK and, therefore, significant enough to apply in a real, practical wireless system.

Performance Analysis for 16-QAM Modulation: Figure 6 and Table 3 shows the BER performance against SNR of the 16-QAM modulation scheme, which was analyzed between 0—20 dB. The given mechanisms of Hybrid BF + DRL + SIC show consistently better scores under all SNR regimes. With SNR = 20 dB, it can realize a BER as low as 5×10^{-5}, demonstrating its strong capability of interference mitigation and channel adaptation. This has been made possible by the joint learning and decision-making policy that exploits beamforming optimization and multi-user interference cancellation.

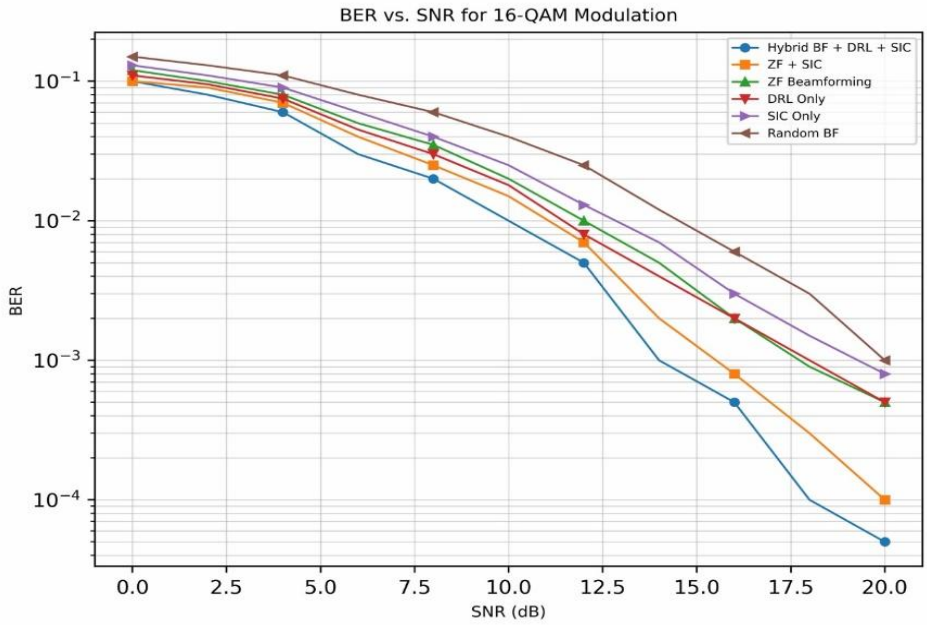


Figure 6: BER versus SNR performance comparison of the proposed Hybrid BF + DRL + SIC scheme with conventional beamforming methods under 16-QAM modulation (M = 4, N_t = 8, K = 4)

In comparison to this, ZF + SIC reported a minimum BER = 1×10^{-4}, whereas ZF Beamforming and DRL Only converged at BER = 5×10^{-4}, which represents a degradation in performance because the two schemes fail to accommodate dynamic user interference or optimize transmission strategies in such complex modulations. SIC only achieves a BER = 8×10^{-4}, representing the expected ideal channel conditioning in the unassisted case because beamforming is not utilized. The Random Beamforming method has a stable BER = 10^{-3} at 20 dB to emphasize the significance of informed transmission design.

Performance Analysis for 64-QAM Modulation: This experimental outcome, i.e., Figure 7 and Table 3, depicts the BER performance of several interference mitigation and beamforming approaches with a 64-QAM modulation scheme over a range of SNRs from 0 to 20 dB. The proposed Hybrid BF + DRL + SIC model continuously outperforms the baseline methods, achieving an average BER of 0.0580 across the 0–20 dB SNR range under 64-QAM modulation (in contrast to lower-order schemes such as BPSK, where the BER converges to 5×10^{-5} at 20 dB SNR). This increment is attributed to the synergistic combination of DRL to implement smart beam adaptation, hybrid beamforming to execute spatial signal enhancement, as well as SIC to eliminate the dominant residual interferences.

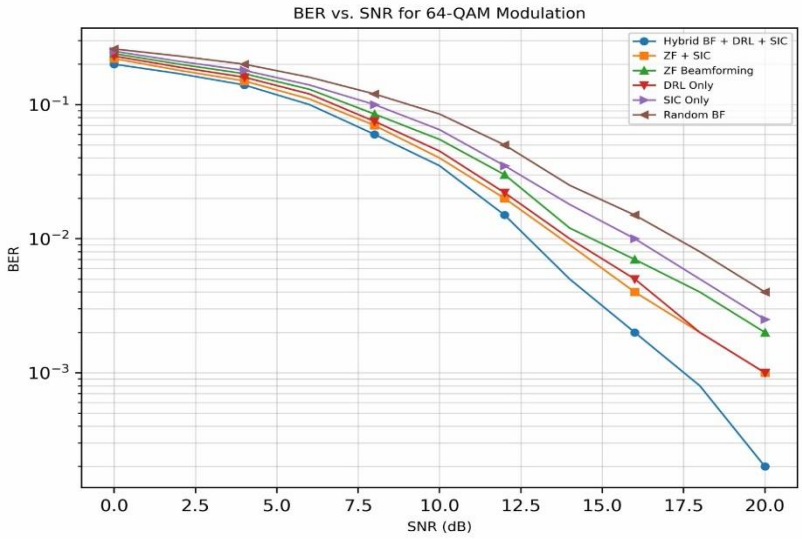


Figure 7: BER versus SNR performance comparison of the proposed Hybrid BF + DRL + SIC scheme with conventional beamforming methods under 64-QAM modulation (M = 4, N_t = 8, K = 4)

The method based on conventional ZF + SIC and ZF beamforming, comparatively, has higher BERs of 0.0695 and 0.0923 respectively, demonstrating the weaknesses of linear methods of pure linear approaches to very dense interference conditions, especially with higher-order modulations such as 64-QAM. The DRL-only case yields average BER of 0.0780, which is average, noting that although DRL plays a role towards better interactivity in the channel, however, its effectiveness is much enhanced when combined with SIC and hybrid beamforming. As the highest average BERs, 0.1114 and 0.1340, are registered in the SIC-only and random beam forming schemes, respectively, it may be pointed out that these schemes cannot dynamically react to the interference patterns and channel conditions.

Figure 8 shows how the proposed and the baseline methods of interference mitigation perform in terms of Normalized mean square error (NMSE) over the SNR range of 0 to 20 dB. The proposed Hybrid BF + DRL + SIC structure provides NMSE with the minimum value at all SNR levels i.e., the minimum

NMSE initially being 0.5 at 0 dB and subsequently showing the rapid decrease at 20 dB with the value of 0.03. This is indicative of the better channel estimation and signal reconstruction accuracy, and, when used in low SNR regimes, where conventional techniques are already having trouble.

Comparatively, both the ZF + SIC and ZF Beamforming methods have continually greater NMSEs that arrive at the end stages of 0.045 and 0.06, respectively at 20 dB. The bottom line is these outcomes suggest their inability to exploit adaptively spatial and temporal characteristics in an environment subject to dynamic interference. The DRL-only scheme exhibits a moderate NMSE performance that approaches the value of 0.05, implying that, although DRL is capable of learning adaptive policies, it shows sub-optimal performance in absence of other signal processing aids.

The SIC-only and Random Beamforming methods indicate their best NMSEs, only 0.07 and 0.09 at 20 dB, respectively. The drawback associated with these methods is that cannot maximize beam patterns and interference cancellation simultaneously and dynamically, thus causing estimation error.

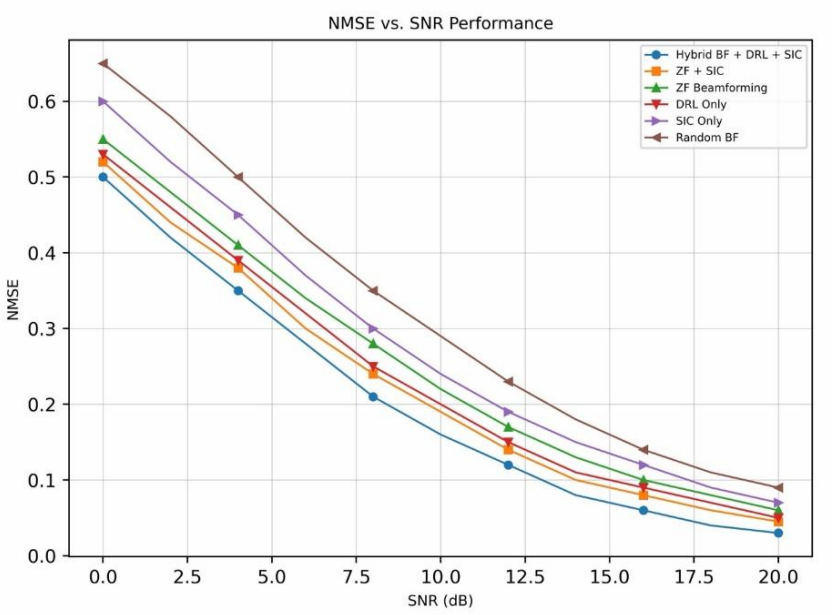


Figure 8: NMSE versus SNR performance comparison of the proposed Hybrid BF + DRL + SIC scheme with conventional beamforming method (N_t= 8, K = 4)

These findings in table 4 clearly show that multi-stage learning and hybrid processing, as applied to the suggested Hybrid BF + DRL + SIC model, is a key towards reducing the estimation errors and ensuring the overall link reliability in a particular multi-user MIMO system is maximized.

Table 4: Average NMSE performance

Method	Average NMSE
Hybrid BF + DRL+SIC	0.1782
ZF + SIC	0.2164
ZF Beamforming	0.2555
DRL Only	0.2291
SIC Only	0.3064
Random Beamforming	0.3855

Figure 9 shows the Spectral Efficiency (SE) performance analysis of proposed approach against five state-of-art methods mentioned in the preceding analysis, over a SNR span between 0 to 20 dB. The proposed approach shows a consistently superior SE profile across all evaluated SNR levels, achieving a peak spectral efficiency of 7.0 bits/s/Hz at 20 dB SNR and an overall average spectral efficiency of 4.64 bits/s/Hz across the 0–20 dB SNR range. This significant improvement of proposed approach over the existing approaches emphasizes the synergy of combining smart beamforming with SIC.

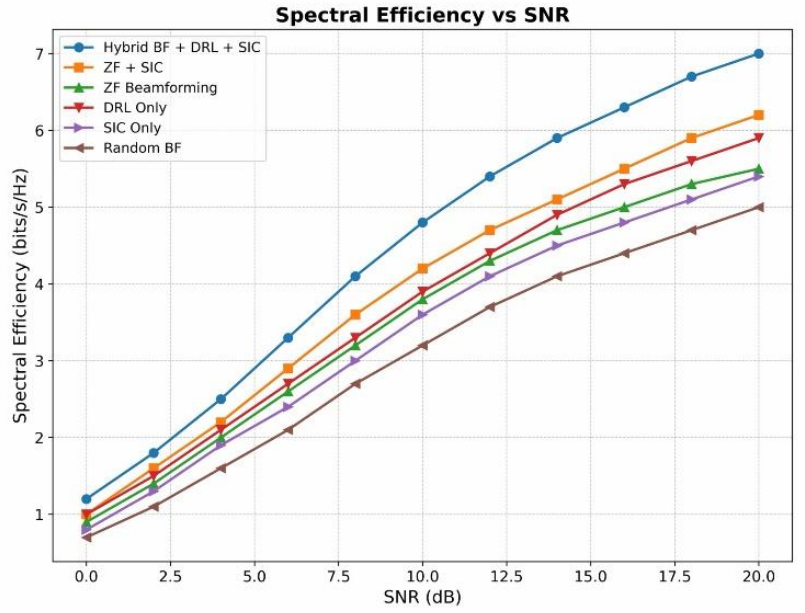


Figure 9: Spectral efficiency versus SNR performance comparison of the proposed Hybrid BF + DRL + SIC scheme with conventional beamforming method (N_t= 8, K = 4)

The ZF + SIC approach on the contrary has slightly smaller maximum SE of 6.2 bits/s/Hz but is limited by the linearity of zero-forcing.

As per table 5, the ZF and DRL approaches perform relatively well with ZF performing at around 5.5 bits/s/Hz and DRL at 5.9 bits/s/Hz. This demonstrates that even though DRL-based beamformer selection is able to adapt to the dynamics in the channel state, the effectiveness of the selection is improved even more when implemented with SIC. SIC-only does even worse, particularly in low SNR conditions, pointing at the importance of beamforming when it comes to spectrum efficiency. The Random Beamforming baseline has the lowest SE at all SNR values with a maximum 5.0 bits/s/Hz, which is clear evidence of the importance of beamformer optimization methods.

Table 5: Average SE performance

Method	Average SE(bits/s/Hz)
Hybrid BF + DRL+SIC	4.64
ZF + SIC	4.02
DRL Only	3.96
ZF Beamforming	3.80
SIC Only	3.55
Random Beamforming	3.24

Table 6: Reliability and communication performance comparison of different beamforming and interference cancellation methods

Method	BER	NMSE	Outage Probability (%)	Spectral Efficiency (bps/Hz)	SINR (dB)
Random Beamforming	0.1340	0.0900	18.6	3.82	8.4
SIC Only	0.1114	0.0700	15.2	4.35	9.7
ZF Beamforming	0.0923	0.0600	12.8	5.14	11.3
DRL Only	0.0780	0.0500	10.4	6.02	13.1
ZF + SIC	0.0695	0.0450	8.7	6.74	14.5
Hybrid BF + DRL + SIC (Proposed)	0.0580	0.0300	5.1	7.86	16.8

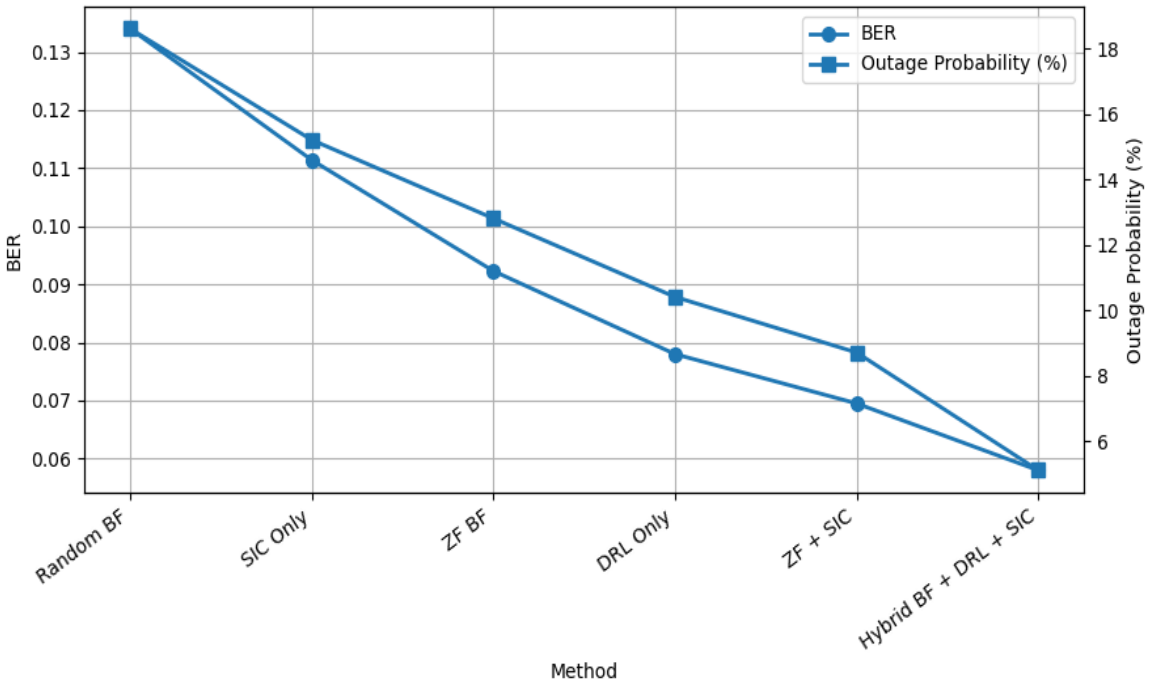


Figure 10: BER and outage probability comparison of different beamforming and interference cancellation methods

Table 6 and Figure 10 show the comparison of reliability and communication performance in different beamforming and interference cancellation approaches. The proposed Hybrid BF + DRL + SIC outperforms other techniques in terms of achieving minimum BER of 0.0580 and NMSE 0.0300, and minimum outage probability of 5.1%, which indicates that the proposed system provides high-level of transmission reliability in wireless networks. In comparison with conventional methods such as Random Beamforming, SIC-only, ZF Beamforming, DRL-only, and ZF+SIC, the proposed approach successfully manages to minimize the interference through the collaborative process of DRL-based beam selection, beamforming, and signal recovery. Moreover, the highest value of spectral efficiency (7.86 bps/Hz) and SINR (16.8 dB) achieved by the proposed system proves the improvement in terms of signal quality and data transfer capability. It is clear from the decreasing tendency of BER and outage probability in Figure 9 that the use of learning-based beamforming and interference cancellation technique improves reliability and efficiency of communication in comparison to individual approaches.

Ablation Study Analysis

Table 7: Ablation analysis of the proposed Hybrid BF + DRL + SIC framework

Configuration	BER	NMSE	Outage Probability (%)	Spectral Efficiency (bps/Hz)	SINR (dB)
Without DRL (Hybrid BF + SIC)	0.0695	0.0450	8.7	6.74	14.5
Without Hybrid BF (DRL + SIC)	0.0780	0.0500	10.4	6.02	13.1
Without SIC (Hybrid BF + DRL)	0.0645	0.0380	7.2	7.15	15.6
Without DRL and SIC (Hybrid BF only)	0.0923	0.0600	12.8	5.14	11.3
Proposed Hybrid BF + DRL + SIC	**0.0580**	**0.0300**	**5.1**	**7.86**	**16.8**

The ablation study shown in table 7 illustrates the significance of each component in the Hybrid BF + DRL + SIC technique, where the performance degradation is analyzed by deleting each of the modules from the model. The optimal performance of the entire proposed architecture has been achieved using the combination of three techniques. The complete framework gives the best performance in terms of lowest BER (0.0580), minimum NMSE (0.0300), smallest outage probability (5.1%), highest spectral efficiency (7.86 bps/Hz), and maximum SINR (16.8 dB). The exclusion of the DRL module raises BER to 0.0695, as well as decreases SINR to 14.5 dB, proving the significant role played by adaptive learning in beam selection. Additionally, removing hybrid beamforming deteriorates the performance of the system, which is demonstrated by the raised BER (0.0780) and decreased spectral efficiency (6.02 bps/Hz). The exclusion of SIC increases the residual interference in the system, thereby lowering its performance. The system performs worst when both DRL and SIC components are removed, showing that intelligent beam adjustment and interference cancellation improve signal quality, spectral efficiency, and reliable MIMO communications between multiple users. In general, the results of the ablation study prove that each component contributes uniquely to the system's performance.

5 Conclusion

The main objective of this study was to develop an intelligent and reliable MIMO communication framework that helps increase the reliability of transmission and manage interference in a wireless environment. To overcome the shortcomings of the existing beamforming and interference cancellation techniques, an innovative Hybrid Beamforming-Deep Reinforcement Learning-Successive Interference Cancellation (Hybrid BF-DRL-SIC) framework was developed. This framework incorporates beam selection using deep reinforcement learning, hybrid analog-digital beamforming optimization, and successive interference cancellation receiver operations. The DRL controller learns to use the optimal beamforming methods based on channel state information, interference level, and users' conditions, whereas SIC improves signal recovery from the remaining multi-user interference. The proposed model is examined through important communication parameters such as BER, NMSE, outage probability, spectral efficiency, and SINR. The results show that the proposed approach offers better performance with BER = 0.0580, NMSE = 0.0300, outage probability = 5.1%, spectral efficiency = 7.86 bps/Hz, and SINR = 16.8 dB, offering better performance compared to classical beamforming and interference cancellation schemes. The ablation study proves the necessity of each component, where the absence of

the DRL method, hybrid beamforming, and SIC leads to worse communication performance. In general, the proposed model offers an adaptive and reliable solution for future wireless communication systems based on the intelligent learning of beamforming parameters and signal processing. Further research can be aimed at extending the framework towards 6G systems, implementing the system in hardware, energy-efficient optimization of the proposed approach, federated learning of beam adaptation, and studying the performance in practical conditions.

Acknowledgements

The authors gratefully acknowledge Sri Mata Amritanandamayi Devi (Amma), Chancellor, Amrita Vishwa Vidyapeetham, for her inspiration and for providing financial support for the Article Processing Charges (APC) of this publication. The authors also acknowledge the learned reviewers for their thoughtful comments and constructive suggestions.

References

[1] Agrawal, R. (2022). Comparison of different mobile wireless technology (from 0g to 6g). *Electrochemical Society Transactions*, *107*(1), 4799-4839. https://doi.org/10.1149/10701.4799ecst

[2] Akpakwu, G. A., Silva, B. J., Hancke, G. P., & Abu-Mahfouz, A. M. (2017). A survey on 5G networks for the Internet of Things: Communication technologies and challenges. *IEEE access*, *6*, 3619-3647. https://doi.org/10.1109/ACCESS.2017.2779844

[3] Alsabah, M., Naser, M. A., Mahmmod, B. M., Abdulhussain, S. H., Eissa, M. R., Al-Baidhani, A., ... & Hashim, F. (2021). 6G wireless communications networks: A comprehensive survey. *IEEE Access*, *9*, 148191-148243. https://doi.org/10.1109/ACCESS.2021.3124812

[4] Badshah, A., Ghani, A., Daud, A., Jalal, A., Bilal, M., & Crowcroft, J. (2023). Towards smart education through internet of things: A survey. *ACM Computing Surveys*, *56*(2), 1-33. https://doi.org/10.1145/3610401

[5] Clarke, R. N. (2014). Expanding mobile wireless capacity: The challenges presented by technology and economics. *Telecommunications Policy*, *38*(8-9), 693-708. https://doi.org/10.1016/j.telpol.2013.11.006

[6] Dao, N. N., Tu, N. H., Hoang, T. D., Nguyen, T. H., Nguyen, L. V., Lee, K., ... & Cho, S. (2024). A review on new technologies in 3GPP standards for 5G access and beyond. *Computer Networks*, *245*, 110370. https://doi.org/10.1016/j.comnet.2024.110370

[7] Devrari, A., Kumar, A., & Kuchhal, P. (2024). Global aspects and overview of 5G multimedia communication. *Multimedia Tools and Applications*, *83*(9), 26439-26484. https://doi.org/10.1007/s11042-023-16549-6

[8] Jha, M. K., Kumar, N., & Lakshmi, Y. V. S. (2020, November). Noma mimo visible light communication with zf-sic and mmse-sic. In *2020 2nd PhD Colloquium on Ethically Driven Innovation and Technology for Society (PhD EDITS)* (pp. 1-2). IEEE. https://doi.org/10.1109/PhDEDITS51180.2020.9315316

[9] Jiang, W., & Han, B. (2024). Evolution to fifth-generation (5g) mobile cellular communications. In *Cellular communication networks and standards: The evolution from 1G to 6G* (pp. 149-168). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-57820-5_9

[10] Jinru, L., Yongqing, T., Danpu, L., & Zhilong, Z. (2024). Off-grid compressed channel estimation with parallel interference cancellation for millimeter wave massive MIMO. *China Communications*, *21*(3), 51-65. https://doi.org/10.23919/JCC.ja.2022-0812

[11] Khalid, W., Yu, H., Ali, R., & Ullah, R. (2021). Advanced physical-layer technologies for beyond 5G wireless communication networks. *Sensors*, *21*(9), 3197. https://doi.org/10.3390/s21093197

[12] Lee, Y., Shih, H. C., Huang, C. S., & Li, J. Y. (2014, August). Low-complexity MIMO detection: a mixture of ZF, ML and SIC. In *2014 19th International Conference on Digital Signal Processing* (pp. 263-268). IEEE. https://doi.org/10.1109/ICDSP.2014.6900841

[13] Mishra, R. (2023). An overview of backbone technology behind the latest advanced gadgets in use: 4G & 5G. *Spatial Information Research*, *31*(1), 15-26. https://doi.org/10.1007/s41324-022-00474-1.

[14] Oyedare, T., Shah, V. K., Jakubisin, D. J., & Reed, J. H. (2022). Interference suppression using deep learning: Current approaches and open challenges. *IEEE access*, *10*, 66238-66266. https://doi.org/10.1109/ACCESS.2022.3185124

[15] Riadi, A., Boulouird, M., & Hassani, M. M. R. (2021). ZF and MMSE Detectors Performances of a Massive MIMO System Combined with OFDM and M-QAM Modulation. *Wireless Personal Communications*, *116*(4), 3261-3276.https://doi.org/10.1007/s11277-020-07848-4

[16] Siddiqui, M. U. A., Qamar, F., Ahmed, F., Nguyen, Q. N., & Hassan, R. (2021). Interference management in 5G and beyond network: Requirements, challenges and future directions. *Ieee Access*, *9*, 68932-68965. https://doi.org/10.1109/ACCESS.2021.3073543

[17] Sumathi, S., Ramesh, T. K., & Ding, Z. (2023). Low complex analog beamforming design in multi-user mmWave non-orthogonal multiple access (NOMA). *Journal of Circuits, Systems and Computers*, *32*(13), 2350219.https://doi.org/10.1142/S0218126623502195

[18] Van Luong, T., Shlezinger, N., Xu, C., Hoang, T. M., Eldar, Y. C., & Hanzo, L. (2022). Deep learning based successive interference cancellation for the non-orthogonal downlink. *IEEE transactions on vehicular technology*, *71*(11), 11876-11888. https://doi.org/10.1109/TVT.2022.3193201.

[19] Zhan, J., & Dong, X. (2021). Interference cancellation aided hybrid beamforming for mmWave multi-user massive MIMO systems. *IEEE Transactions on Vehicular Technology*, *70*(3), 2322-2336. https://doi.org/10.1109/TVT.2021.3057547

[20] Zheng, Q., Zhu, P., Li, J., Wang, D., & You, X. (2023). Energy efficiency enhancement in user-centric and cell-free millimeter-wave massive MIMO systems with hybrid beamforming. *IEEE Transactions on Vehicular Technology*, *73*(4), 5484-5499. https://doi.org/10.1109/TVT.2023.3336071

[21] Kim, Y., Kim, H.-S., Lee, H., & Jeon, S. (2026). Energy-Efficient Hybrid Beamforming Architecture for Millimeter-Wave Massive MIMO Communication Systems. *Journal of Wireless Intelligence and Spectrum Engineering, 3*(2), 37–43.

Authors Biography



Sagar Basavaraju received the B.Tech. degree in Electronics and Communication Engineering from Vidya Vardhaka College of Engineering, Mysore and the M.Tech. degree in Digital Electronics and communication from NMAMIT, Nitte, Mangaluru, Karnataka, India. He is currently working as Senior Assistant Professor with the Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru, India. He has published his research works in 20 reputed international conferences and journals. His research interests include mmWave communication, cybersecurity, sustainable development, and societal development projects.



T.K. Ramesh received the Ph.D. degree in optical networks from Amrita Vishwa Vidyapeetham. He is currently the Professor and HOD of the Department of Electronics and Communication Engineering, Amrita School of Engineering, Bengaluru. He has 30 years of teaching and research experience. He has successfully guided eight Ph.D. students so far. He has published more than 80 research publications in peer-reviewed journals and conferences. His areas of research interests include communication networks and applications, analog and digital devices and circuits, functional safety, artificial intelligence, and network-on-chip. He is a Lifetime Member of Indian Society for Technical Education and a member of Electronics and Telecommunication Engineers.