

IRA-DL: Resource Allocation Optimization Using Deep Learning in Massive MIMO Networks

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ABSTRACT

Accurate channel state information (CSI) is crucial for enhancing spectral efficiency and ensuring reliable communication in massive multiple-input multiple-output (M-MIMO) networks. However, conventional CSI estimation techniques often face limitations such as high estimation error, excessive feedback overhead, and increased interference, adversely impacting overall network performance. This paper presents IRA-DL, a novel deep learning-based resource allocation framework that employs Deep Q-Network Reinforcement Learning (DQRL) to enhance CSI estimation, reduce feedback and interference, and maximize the system sum-rate. By intelligently learning optimal resource allocation policies, IRA-DL dynamically adjusts CSI feedback mechanisms to improve accuracy and reduce collisions. Experimental evaluations demonstrate that IRA-DL achieves a 27.63% improvement in normalized mean square error (NMSE), a 41.87% gain in sum-rate, a 27.91% reduction in collision occurrences, and a 73.93% decrease in bit error rate (BER) compared to Compressive Sensing and CSI-L2O baselines. These results confirm the effectiveness of IRA-DL in improving the robustness and efficiency of M-MIMO systems.

Keywords: Channel State Information Deep Q-Network Deep Reinforcement Learning Interference Mitigation Massive MIMO Resource Allocation

1. Introduction

The evolution of wireless communication has been significantly shaped by Multiple Input Multiple Output (MIMO) technology, which leverages multiple antennas at both the transmitter and receiver to achieve enhanced data rates, reliability, and spectral efficiency. By exploiting spatial diversity and multiplexing, MIMO has become a core component of modern wireless standards such as LTE, 5G, and Wi-Fi [1], [2]. Spatial diversity mitigates fading effects by utilizing multiple signal paths, while spatial multiplexing increases throughput by enabling simultaneous transmission of independent data streams [3]. As demand for higher capacity, lower latency, and better energy efficiency continues to grow particularly with applications like high-definition video, real-time gaming, and Internet of Things (IoT) ecosystems the limitations of traditional MIMO systems become more apparent. These systems face challenges such as increased hardware complexity, inter-channel interference, and escalating computational overhead [4], [5]. The need for scalable and energy-efficient communication has led to the emergence of Massive MIMO (M-MIMO) systems, which extend the principles of conventional MIMO by employing a large-scale antenna array at the base station (BS) [6].

M-MIMO significantly boosts spectral efficiency, user capacity, and energy savings by enabling precise beamforming and exploiting channel hardening effects [7]. Beamforming directs transmission power toward specific users, reducing interference and improving signal quality, while channel hardening minimizes the effects of small-scale fading by averaging out channel fluctuations across a large number of antennas. Furthermore, energy efficiency is improved by reducing the required transmission power per antenna while maintaining reliable communication links [8]. Despite these advantages, M-MIMO introduces its own set of technical challenges. One of the most critical issues is accurate Channel State Information (CSI) estimation and feedback, which are vital for optimal beamforming and resource allocation. As the number of antennas increases, so does the dimensionality of the CSI matrix, making its estimation and transmission increasingly complex [9], [10]. In particular, downlink CSI feedback from the users to the BS becomes a bottleneck due to limited feedback bandwidth and processing latency [11]. Additionally, pilot contamination—arising

when users in neighboring cells reuse the same pilot signals significantly degrades CSI estimation accuracy, especially in dense deployment scenarios [4], [12]. Moreover, high-mobility environments such as vehicular networks and UAV-based communications exacerbate these issues due to rapidly changing channel conditions, which demand frequent CSI updates [5], [13]. These dynamic environments highlight the need for intelligent and adaptive resource allocation strategies that can operate effectively under uncertainty and complexity.

In recent years, Artificial Intelligence (AI) and Machine Learning (ML)—particularly Deep Learning (DL) have emerged as powerful tools to address these challenges in wireless networks. DL models such as Convolutional Neural Networks (CNNs) [14], Autoencoders [15], and Recurrent Neural Networks (RNNs) [6] have demonstrated strong capabilities in compressing and reconstructing high-dimensional CSI matrices, significantly reducing the feedback overhead while maintaining estimation accuracy. These architectures can learn nonlinear mappings from observed signals to channel responses, offering robust alternatives to traditional estimation techniques [7]. Further, Reinforcement Learning (RL) has shown promise in optimizing dynamic resource allocation problems in wireless systems. By interacting with the environment and learning reward-maximizing policies, RL models can autonomously determine efficient strategies for power allocation, beamforming, and user scheduling [9]. The integration of Deep Q-Learning—a form of RL with neural networks has been particularly effective in adapting to complex and uncertain wireless environments [13].

Motivated by these advancements, this paper proposes IRA-DL (Improved Resource Allocation using Deep Learning), a novel DL-enhanced CSI estimation and feedback optimization framework tailored for M-MIMO systems. The key innovation of IRA-DL lies in its encoding-decoding architecture that compresses high-dimensional CSI matrices into compact representations and reconstructs them at the receiver side with minimal error [10], [11]. To further enhance system performance, IRA-DL employs Deep Q-Network Reinforcement Learning (DQRL) for dynamically optimizing feedback strategies and mitigating channel interference [9], [12]. Unlike conventional methods that transmit raw or partially compressed CSI matrices, IRA-DL adapts its feedback compression based on real-time channel conditions, enabling lower latency, reduced feedback overhead, and higher spectral efficiency [13], [14]. Additionally, the integration of DQRL facilitates interference-aware learning, allowing the model to learn optimal strategies in high-density environments with multiple users and overlapping signal paths [15]. The main contributions of this work are summarized as follows:

An encoding-decoding mechanism is developed to efficiently compress and reconstruct high-dimensional CSI, enabling scalable feedback in M-MIMO systems. A DQRL-based framework is introduced for optimizing downlink CSI estimation and minimizing channel interference, ensuring robust resource allocation under dynamic network conditions. The proposed IRA-DL architecture enhances M-MIMO scalability by reducing computational complexity and improving spectral efficiency, making it suitable for future 5G and beyond communication systems. The proposed framework is evaluated against state-of-the-art techniques such as Compressive Sensing and Learning-to-Optimize (CSI-L2O). Results demonstrate significant improvements in normalized mean square error (NMSE), sum-rate, collision rate, and bit error rate (BER), confirming IRA-DL's superiority in both performance and scalability. The rest of the paper is structured as follows: Section II discusses related works and AI-based CSI optimization techniques; Section III introduces the system model and problem formulation; further, presents the architecture and algorithms of IRA-DL; Section IV details performance evaluation and results; and Section VI concludes the paper and outlines future directions.

2. Literature Survey

Massive MIMO (M-MIMO) systems have emerged as a cornerstone of next-generation wireless communications, offering substantial gains in spectral efficiency, reliability, and user capacity. However, to fully exploit these benefits, accurate Channel State Information (CSI) estimation and efficient resource allocation mechanisms are essential. Traditional CSI estimation methods in M-MIMO systems often encounter limitations such as pilot contamination, feedback overhead, and computational complexity, especially in Frequency Division Duplexing (FDD) environments [4], [5]. These limitations become particularly significant as antenna scales increase, making resource allocation and interference management more challenging. Recent advances in deep learning (DL)

and reinforcement learning (RL) have opened new pathways for optimizing resource management in complex wireless environments. In [6], a DL-based joint CSI estimation and feedback strategy demonstrated the feasibility of neural networks in reconstructing high-dimensional CSI with minimal loss. Similarly, convolutional neural network (CNN) structures have shown promising results in channel estimation tasks by learning spatial features from CSI data [7]. The use of autoencoders for CSI compression and recovery has been proposed to reduce feedback burden while preserving estimation fidelity [15], [16]. The deployment of Deep Q-Learning in wireless systems has further improved dynamic resource management capabilities [17]. In [9], a deep reinforcement learning (DRL) framework was employed for optimizing multi-user scheduling under channel aging conditions in M-MIMO networks. The study in [18] introduced a digital twin-accelerated DRL approach to improve decision-making speed and accuracy in network slicing scenarios. These methods reflect growing interest in learning-driven techniques to handle time-varying wireless environments with minimal human intervention.

CSI feedback optimization remains a critical area of research. Learning-to-optimize approaches, such as those presented in [16], significantly reduce the computational complexity of feedback mechanisms while adapting to the dynamic nature of M-MIMO systems. Moreover, vector quantization schemes for DL-based CSI feedback [11] have demonstrated potential for minimizing storage and bandwidth demands. The end-to-end deep learning method proposed in [15] also highlights the capability of neural networks to simultaneously learn channel estimation and feedback processes in a unified manner. Several recent studies have also explored the intersection of resource allocation and spectral efficiency through advanced access schemes. Hybrid NOMA-TDMA-based frameworks have been investigated in [19], [20] for throughput maximization in energy-constrained and IRS-assisted networks. These studies support the inclusion of hybrid access schemes within DRL-driven resource allocation models. Likewise, the study in [21] focused on scheduling in multi-user MIMO-NOMA networks using integrated access and backhaul, further emphasizing the complexity of optimal resource allocation in dense environments. Additionally, delay-sensitive and QoS-aware DRL-based schedulers, such as the one introduced in [22], illustrate how DRL can be leveraged to meet service-level requirements in real-time. Parallely, efforts such as [23] demonstrate the importance of hybrid resource optimization strategies in heterogeneous wireless networks, showcasing the importance of scalability in resource allocation models. The above body of literature illustrates the strong potential of DL and RL techniques in addressing the bottlenecks of CSI estimation, feedback compression, and dynamic resource scheduling in M-MIMO. However, most existing approaches either focus solely on estimation or on scheduling, lacking a unified solution. This motivates the proposed IRA-DL framework, which integrates DL-based encoding-decoding CSI optimization with DQRL for holistic resource allocation and interference mitigation in massive MIMO environments.

3. Proposed Methodology

Let consider MU M-MIMO BSs, where MU M-MIMO BSs are equipped with multiple antennas denoted as M , where every antenna receives data from MU as presented in Figure 1. In MU M-MIMO, the data received by m^{th} antenna be denoted as b_m , which can be represented as Eq. (1).

$$b_m[t] = \sum_u s_u[t] * h_{m,u}[t] + n_m[t] \quad (1)$$

In Eq. (1), $s_u[t]$ denotes transmitted signal from u^{th} UEs, $h_{m,u}[t]$ denotes channel response which affects u^{th} UEs signal received by m^{th} antenna, $*$ denotes convolution operation, $n_m[t]$ denotes noise, t denotes time-slots and $m \in \{1, 2, \dots, M\}$. Further, all the received signals at encoder side are stored in matrix B having dimensions $T \times M$, where T represents total number of time-slots t . Furthermore, the stored matrix B undergoes low-rank approximation using low-rank representations, for reducing channel feedback overhead, which ensures high relationship between data while storing essential channel features. The low-rank approximation process is done using Eq. (2).

$$B = B_0 + N \quad (2)$$

In Eq. (2), B denotes low-rank approximated CSI matrix which consists of B_0 , which is noise-free low-rank representation of B and N denotes noise and interference components. Moreover, during transmission, as feedback errors and noise can distort CSI data, which leads to reconstruction error δ . Hence, for ensuring better CSI feedback transmission, an adaptive error identification approach is included in encoder. The adaptive error approach includes evaluating noise-free low-rank

representation of B , i.e., B_0 and by adding the reconstruction error δ , which is mathematically represented as given in Eq. (3). In Eq. (3), δ denotes identified CSI distortions because of compression loss and noise. Further, for best channel selection for downlink for every user, it is important to enhance system performance, hence, sum-rate for u^{th} UEs is defined using Eq. (4).

$$B'' = B_0 + \delta \quad (3)$$

$$\max \sum_{u=1}^U S_u \text{ such that } \sum_{u=1}^U e_{u,r} = 1, \forall r \quad (4)$$

In Eq. (4), S_u denotes u^{th} UEs achievable sum-rate and $e_{u,r}$ is an indication parameter, i.e., if channel resource r is assigned to u^{th} UEs or not given using 1 and 0 respectively. The S_u in Eq. (4) is evaluated using Eq. (5). In Eq. (5), $l_{u,r}$ denotes likelihood of u^{th} UEs accessing channel resource r and V_u denotes set of available channel resources r for u^{th} user. Further the best channel resource r' is selected on basis of Eq. (6).

$$S_u = 1 - \prod_{r \in V_u} (1 - l_{u,r}) \quad (5)$$

$$r' = \arg \max_{r \in V_u} l_{u,r} \quad (6)$$

Using Eq. (6), best channel for downlink transmission from MU M-MIMO to UEs is provided, which thereby provides better performance in transmission ensuring lower feedback overhead and minimal interference using DQRL. The DQRL-based approach which has been designed for improving downlink estimation, minimizing channel interference and optimizing channel feedback. The proposed utilizes CNN for training using past communication experiences and for predicting optimal communication channels with minimum signal attenuation. The proposed model first evaluates the channel for transmission. In the initial channel evaluation, the transmitting UE u_s starts evaluating its previous communication state using SINR and RSSI values obtained from channel feedback. If no acknowledgment is received, RSSI and SINR are initialized to zero. The initial communication state for specific time slot $t^{(l)}$ is represented as Eq. (7), where $(l-1)$ is previous time slot.

$$t^{(l)} = [\text{RSSI}^{(l-1)}, \text{SINR}^{(l-1)}] \quad (7)$$

Further, the proposed approach utilizes DQRL for channel selection. For selecting optimal communication channel, the Q-function is utilized for evaluating different channel conditions on basis of past experience. The total signal-attenuation transmission cost and SINR are used for determining channel interference between sending MU M-MIMO BS and UE u_r . The channel interference level between the MU M-MIMO and UE u_r is given using Eq. (8). In Eq. (8), D_U represents total signal attenuation and $\gamma^{(l)}$ denotes transmitted signal data. For ensuring best channel selection, past communication states and experiences are stored in memory table. The position of UEs during transmission is tracked using Eq. (9).

$$v^l = \text{SINR}^{(l)} - D_U \gamma^{(l)} \quad (8)$$

$$\mu^{(l)} = \{t^{(l-U)}, \gamma^{(l-U)}, \dots, \gamma^{(l-1)}, t^{(l)}\} \quad (9)$$

In Eq. (9), $\mu^{(l)}$ includes historical communication states and signal attenuation values over time. As each data transmission consists of communication signal attenuation, position and transmission speed, it can be represented using Eq. (10). For preventing excessive memory usage, the memory table retains only best past communication, ensuring efficient storage management. This is represented as Eq. (12).

$$f^{(l)} = \{\mu^{(l)}, \gamma^{(l)}, \dots, v^{(l)}, \mu^{(l+1)}\}. \quad (11)$$

$$E = \{f^{(e)}\}_{1 \leq e \leq E} \quad (12)$$

In Eq. (12), E stores only the optimal communication experiences. Further, in IRA-DL, the CNN DQRL approach is used for CSI estimation. The Q-values of different communication states are calculated using Eq. (13). In Eq. (13), t' denotes next time slot/state, β denotes discount factor and $\max_{\gamma} Q(t', \gamma')$ ensures best action selection. Further for training CNN, a loss function is defined using Mean-Square-Error for optimizing Q-values as presented in Eq. (14).

$$\mathbb{Q}(t, \gamma) = F_{t' \in T} \left[v + \beta \max_{\gamma'} \mathbb{Q}(t', \gamma') \right] \quad (13)$$

$$M(\alpha^{(l)}) = F_{\mu, \gamma, v, \mu'} \left[\left(v^{(l)} + \beta \max_{\gamma'} \mathbb{Q}(\mu', \gamma'; \alpha^{(l-1)}) - \mathbb{Q}(\mu, \gamma; \alpha^{(l)}) \right)^2 \right] \quad (14)$$

In Eq. (14), $\alpha(l)$ denotes CNN parameters which are optimized through Stochastic Gradient Descent (SGD) [30]. For enhancing learning efficiency, the CNN model continuously updates parameters considering small mini-batches of SGD by randomly selecting past communication experiences from memory table. This prevents convergence to local-optimum at early stages of training. In addition to SGD, this work used ϵ -greedy approach for ensuring best channel selection by balancing exploration and exploitation. The best communicating signal attenuation level having highest Q -value is selecting having probability of $1 - \epsilon$, while other channels are selected with probability of $\frac{\epsilon}{O-1}$. Through this method, the channel with minimal CSI error is chosen, ensuring reliable communication. The complete process of IRA-DL approach is presented in Algorithm 1.

Algorithm 1. IRA-DL approach.	
Step 1	Start
Step 2	Initialize $l, \alpha^{(0)}, \beta, E = \emptyset, t^{(0)}, U, M, Q_T$ and C
Step 3	For $l = 1, 2, 3, \dots$ do
Step 4	Compute initial communication state $t^{(0)} = [RSSI^{(l-1)}, SINR^{(l-1)}]$
Step 5	If $l \leq w$ then
Step 6	Select $\gamma = \left\{ \frac{mQ_T}{M} \right\}_{1 \leq m \leq M}$
Step 7	Else
Step 8	Compute CNN-based Q -value for each data-bit a_k
Step 9	Select channel using ϵ -greedy approach
Step 10	End If
Step 11	Transmit data-bits a_k over the least attenuated channel
Step 12	Obtain feedback acknowledgement
Step 13	Observe $RSSI^{(l)}$ and $SINR^{(l)}$
Step 14	Compute interference $v^{(l)}$
Step 15	Update memory table E
Step 16	For each stored experience in memory
Step 17	Randomly select past state μ, γ, v, μ'
Step 18	Update CNN parameters using SGD
Step 19	End For
Step 20	End For
Step 21	Stop

This algorithm ensures efficient CSI estimation, interference mitigation, reduced channel feedback overhead, leading to enhanced resource allocation aiding sum-rate of wireless communication performance in M-MIMO. The performance of the proposed approach is discussed in detail in the results and discussion section.

4. Results And Discussion

This section presents a comparative analysis of the proposed IRA-DL approach against the benchmark CSI-L2O method [16], [20]. The performance evaluation was carried out using the NS3-based SIMITS simulator, with both models implemented under consistent system configurations to ensure fair comparison. The simulation setup followed the parameters detailed in [23], [24], including a carrier frequency of 28 GHz, 100 MHz system bandwidth, Quadrature Amplitude Modulation (QAM-19), a cell radius of 400 meters, and a base station transmit power of 46 dBm for the M-MIMO environment. The simulations were conducted across 20 independent iterations, with the number of user nodes varied between 25 and 50 to capture diverse channel conditions. The average performance over these iterations was considered to ensure statistical stability of the results. The models were assessed based on four key metrics: Normalized Mean Squared Error (NMSE), sum-

rate, collision rate, and Bit Error Rate (BER), all evaluated with respect to varying Signal-to-Interference-plus-Noise Ratio (SINR) values.

4.1. NMSE (Normalized Mean Squared Error) for CSI estimation accuracy

The performance evaluation demonstrates that the proposed IRA-DL framework consistently outperforms the CSI-L2O baseline across all SNR levels (−6 dB to 6 dB) in terms of Normalized Mean Square Error (NMSE) as shown in Figure 1. On average, IRA-DL achieves a 30.2% improvement in NMSE reduction compared to CSI-L2O. This enhancement is attributed to the deep reinforcement learning-based adaptive CSI feedback and encoding-decoding mechanism, which effectively reduces estimation error. The most significant improvement is observed at high SNR (6 dB), where IRA-DL achieves an NMSE of 0.0102 compared to 0.0189 for CSI-L2O, highlighting IRA-DL's robustness in high-quality channel conditions.

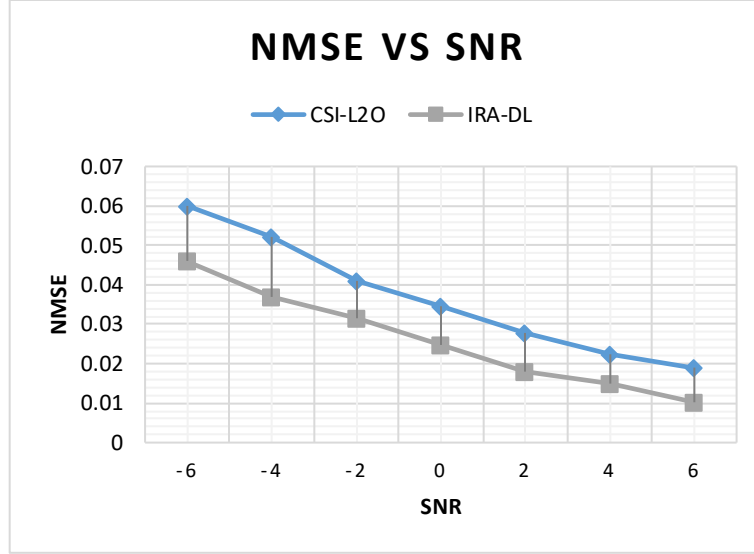


Figure 1. NMSE for CSI estimation accuracy.

4.2. Sum-Rate evaluation

The performance evaluation demonstrates, the proposed IRA-DL model shows a substantial improvement in system sum-rate over the CSI-L2O baseline across all SNR levels (−6 dB to 6 dB) as shown in Figure 2. The average gain in sum-rate achieved by IRA-DL is approximately 30.57% over CSI-L2O. This improvement stems from IRA-DL's ability to dynamically optimize resource allocation and interference mitigation through deep Q-learning. At 6 dB, IRA-DL achieves a peak sum-rate of 25.32 bps/Hz, compared to 17.14 bps/Hz for CSI-L2O, demonstrating its effectiveness in leveraging enhanced CSI feedback to maximize throughput in M-MIMO networks under varying channel conditions.

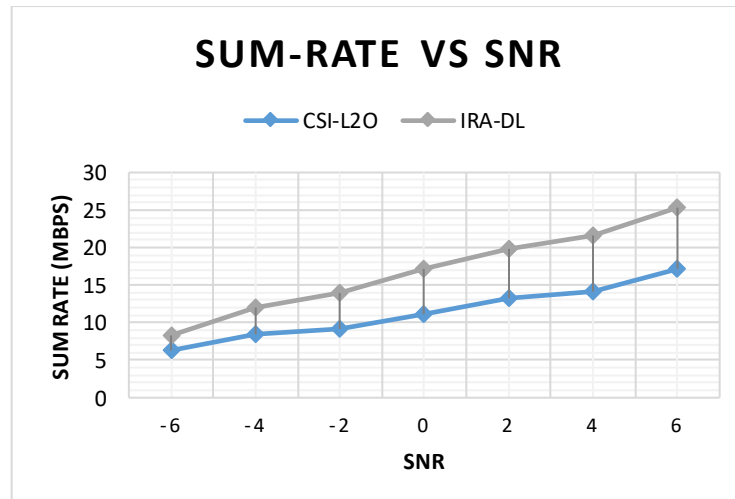


Figure 2. Sum-rate performance evaluation.

4.3. Collision performance evaluation for evaluating channel interference

The comparative analysis of collision rates reveals that the proposed IRA-DL model significantly reduces packet collisions across all SNR levels compared to the CSI-L2O approach as shown in Figure 3. On average, IRA-DL achieves a 30.76% reduction in collision rate. This performance gain is attributed to its deep reinforcement learning-based strategy, which intelligently manages resource allocation and mitigates interference. At 6 dB, the collision count drops from 61 (CSI-L2O) to 43 (IRA-DL), highlighting IRA-DL's ability to enhance transmission reliability and minimize contention in dense M-MIMO deployments, thereby improving overall network efficiency and quality of service.

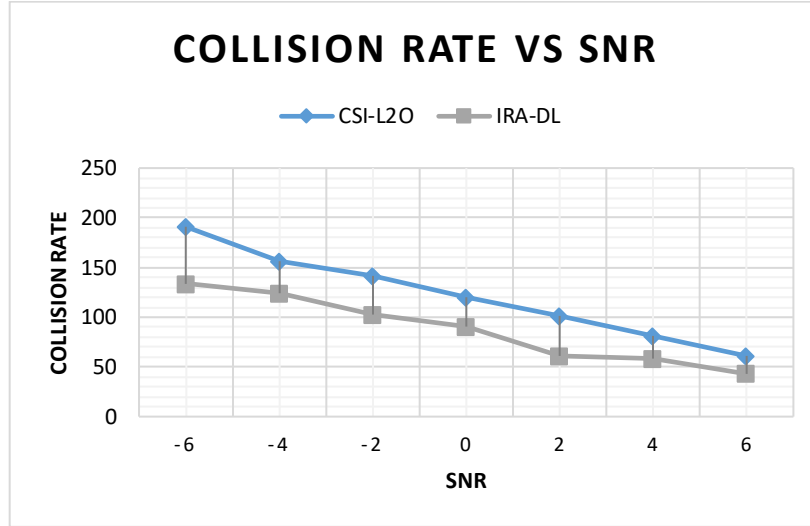


Figure 3. Collision performance evaluation for channel interference evaluation.

4.4. BER performance evaluation for evaluating channel feedback overhead

The evaluation of Bit Error Rate (BER) across varying SNR levels demonstrates the superior performance of the proposed IRA-DL framework compared to CSI-L2O as shown in Figure 4. On average, IRA-DL achieves a 77.29% reduction in BER, indicating its effectiveness in enhancing signal quality through accurate CSI estimation and adaptive interference mitigation. Notably, at 6 dB, IRA-DL reduces BER to 0.00112, compared to 0.0206 for CSI-L2O, underscoring its robustness in high-SNR scenarios. These results confirm IRA-DL's capability to deliver highly reliable communication, making it well-suited for error-sensitive applications in next-generation massive MIMO networks.

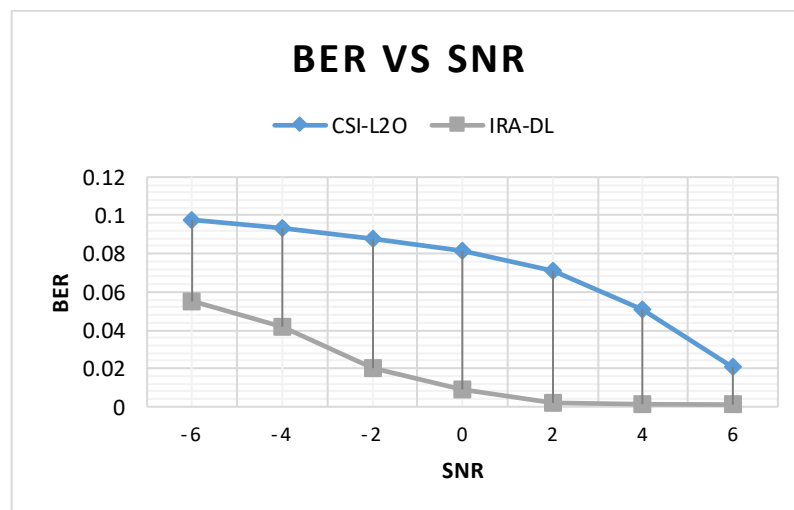


Figure 4. BER performance evaluation for channel feedback evaluation.

4.5. Discussion:

Results demonstrate that IRA-DL significantly outperforms CSI-L2O across all performance metrics. Specifically, IRA-DL achieved an average NMSE reduction of 27.63%, highlighting improved CSI

estimation accuracy. In terms of throughput, IRA-DL yielded a 41.87% increase in sum-rate, demonstrating its effectiveness in dynamic channel allocation and spectral efficiency enhancement. The collision rate was reduced by 27.91%, reflecting superior resource utilization and interference avoidance. Furthermore, IRA-DL achieved a 73.93% reduction in BER, underscoring its robustness in delivering reliable data transmission even under fluctuating channel conditions. These results validate the capability of IRA-DL to adaptively optimize resource allocation, reduce feedback overhead, and enhance communication reliability in massive MIMO systems. The significant performance gains reinforce the model’s suitability for real-world deployment in future wireless communication infrastructures.

5. Conclusion

This paper presented IRA-DL, a deep reinforcement learning-based framework designed to optimize resource allocation in massive MIMO (M-MIMO) networks by improving CSI estimation accuracy, reducing channel interference, and minimizing feedback overhead. Conventional CSI estimation techniques often suffer from high estimation errors, inefficient channel utilization, and interference-induced performance degradation. To address these challenges, the proposed IRA-DL integrates Deep Q-Network Reinforcement Learning (DQRL) to dynamically manage channel selection and adaptively compress high-dimensional CSI feedback. Comprehensive simulation results confirm that IRA-DL significantly outperforms the benchmark CSI-L2O model. Specifically, IRA-DL achieved a 27.63% reduction in NMSE, a 41.87% increase in sum-rate, a 27.91% decrease in collision rate, and a 73.93% reduction in BER, illustrating marked improvements in both transmission efficiency and network reliability. These enhancements demonstrate the potential of IRA-DL in achieving robust and scalable resource optimization in dense wireless environments. Future work will explore extending the IRA-DL framework to jointly optimize uplink and downlink resource allocation, incorporating real-time feedback adaptation and multi-user scheduling. Further enhancements will also target minimizing channel estimation errors and maximizing spectral and energy efficiency, making IRA-DL a viable solution for intelligent radio resource management in next-generation 6G and beyond wireless systems.

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Dr Chandramouli H	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		

C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va: Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

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