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BiLSTM Using Wiener Filter Online Training for Spectral Efficiency Enhancement in IRS-Assisted MU-MISO Systems

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Abstract*: These Intelligent Reflecting Surface (IRS)-assisted Multi-User Multiple-Input Single-Output (MU-MISO) communication has gained considerable attention due to its capability to enhance spectral efficiency by intelligently reshaping the wireless propagation environment through passive signal reflection. Despite recent progress, most existing deep learning-based IRS optimization techniques rely on offline training, which limits their robustness under time-varying and noisy channel conditions. To address this limitation, this paper proposes an online adaptive Bidirectional Long Short-Term Memory (BiLSTM) framework combined with a Wiener filter to improve noise robustness and spectral efficiency performance. The Wiener filter enables effective noise suppression, while the Bi-LSTM model continuously updates its parameters in real time to track dynamic channel variations. Extensive simulations are conducted in Python using the Google Colab platform under three different scenarios, including two baseline models for performance comparison. Quantitative results demonstrate that the proposed method achieves a spectral efficiency of 26.13 bits/s/Hz and a training loss of 0.62 at 30 dB SNR, consistently outperforming baseline approaches across the entire SNR range. These results confirm that the integration of online learning with Wiener filtering significantly enhances system stability and adaptability, making the proposed approach a promising solution for future IRS-assisted wireless communication systems.*

Keywords: Intelligent Reflecting Surface (IRS), MU-MISO Systems, Spectral Efficiency (SE), BiLSTM, Wiener Filter

1. Introduction

The rapid growth of wireless applications and the evolution toward sixth-generation (6G) communication systems have increased the demand for higher spectral efficiency (SE), improved reliability, and wider coverage. Intelligent reflecting surfaces (IRSs) have emerged as an effective technology to address these requirements by enabling control over the wireless propagation environment. By adjusting the electromagnetic characteristics of a large number of passive reflecting elements, IRSs can modify signal propagation and enhance overall system performance without requiring complex hardware structures [1].

The basic idea of IRS-assisted wireless communication is based on regulating the phase, amplitude, and polarization of incoming signals to reduce unfavorable propagation effects. In contrast to traditional wireless systems, where the channel behavior is largely uncontrollable, IRSs provide configurable control over the radio environment, enabling more flexible communication system design [2]. This capability has led to significant research interest in IRS-based networks for future wireless systems, covering performance analysis, system modeling, and practical application scenarios envisioned for 6G communications [3].

From a system performance perspective, one of the key goals of IRS deployment is the maximization of spectral efficiency in multi-user communication systems. In IRS-assisted multi-user multiple-input single-output (MU-MISO) systems, SE improvement is generally achieved through joint optimization of the base station beamforming and the IRS phase shift matrix. However, such optimization problems are often highly non-convex and require significant computational effort. Conventional approaches attempt to address these challenges by transforming the problem into convex forms or by adopting minimum mean square error (MMSE)-based techniques, which provide performance gains but suffer from scalability and adaptability issues under dynamic channel conditions [4]. Furthermore, practical hardware impairments at both the base station and IRS elements create central limitations on achievable SE, especially at high signal-to-noise ratio (SNR) levels, highlighting the need for more robust and adaptive solutions [5].

To address the drawbacks of conventional optimization-driven approaches, learning-based methods have gained attention in IRS-assisted wireless communication systems. Among these, recurrent neural network (RNN) architectures are effective in modeling time-dependent behavior in dynamic wireless channels. Several studies indicate that Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Gated Recurrent Unit (GRU) models enhance signal estimation and detection performance by learning sequential channel information from past and future observations [6]. Furthermore, deep learning approaches that combine convolutional neural networks with recurrent models improve decoding accuracy and training efficiency, highlighting the usefulness of deep learning techniques in complex IRS-enabled communication environments [7]. Additionally, LSTM-based frameworks have been successfully applied to improve energy efficiency and transmission power in IRS-assisted networks, indicating their adaptability to large-scale and variable systems [8].

While most existing learning-based approaches rely on offline training, real-world wireless environments are naturally changing, requiring continuous model adaptation. Online learning has therefore gained attention as an effective framework for updating model parameters sequentially as new data become available, allowing systems to adapt to changing channel conditions in real time [9]. Compared with offline learning, online learning offers improved flexibility and reduced storage requirements, making it particularly suitable for time-dependent wireless environment [10]. Within this framework, online training methods for LSTM networks have been investigated, where filtering-based training algorithms such as Kalman filtering enable faster training stabilization and reduced computational complexity compared to conventional gradient-based methods [11].

Beyond sequence modeling, deep learning has also been applied to predictive beamforming in IRS-assisted multi-user systems to reduce channel estimation load. By learning historical channel characteristics, deep neural networks can estimate IRS phase shifts and beamforming vectors, achieving improved weighted sum-rate performance with lower signaling cost [12]. Similarly, deep reinforcement learning (DRL) approaches such as deep deterministic policy gradient (DDPG) and twin delayed DDPG (TD3) have been introduced to address the joint optimization of active and passive beamforming in IRS-assisted systems, showing significant SE gains under complex non-convex conditions [13]. DRL-based solutions have also been adapted to secure IRS-assisted communications, where adaptive beamforming policies are derived under changing channel and service requirement limitations [14].

Despite these advancements, learning-based IRS systems remain susceptible to noise and imperfect channel observations, particularly under low SNR conditions. Traditional signal processing techniques, such as the Wiener filter, provide an effective means of noise suppression and minimum mean square error estimation by utilizing statistical characteristics of the signal and noise. The Wiener filter has long been established as a powerful tool for smoothing, interpolation, and prediction in noisy environments, making it a suitable preprocessing stage for learning-based wireless systems [15].

Building on these insights, this work presents an online-trained learning approach for IRS-assisted MU-MISO communication that integrates a Bidirectional Long Short-Term Memory (BiLSTM) network with a Wiener filter. In the proposed approach, the received channel signals are first processed using a Wiener filter to reduce noise and improve signal quality. The processed observations are then provided to the BiLSTM model, which learns temporal patterns from both past and future signal information. This bidirectional learning ability enables more accurate channel predictions and results in improved spectral efficiency, especially under severe noisy conditions.

The main aim of this work is to examine the adaptability and stability of the proposed online learning approach across varying signal-to-noise ratio (SNR) levels using three distinct simulation cases. The first two cases are designed to establish reference performance and enable comparative analysis, whereas the third case demonstrates the effectiveness of the proposed online BiLSTM–Wiener filter method in a practical wireless environment.

Scenario 1: The impact of different base station antenna configurations on spectral efficiency is investigated using BiLSTM-based offline training. Systems with 2, 4, and 8 base station antennas are considered, showing that the 8-antenna configuration achieves superior spectral efficiency due to improved signal quality.

Scenario 2: The spectral efficiency performance is compared among multiple learning-based approaches, including BiLSTM with Wiener filter, BiLSTM without Wiener filter, Deep Deterministic Policy Gradient (DDPG), and Deep Learning-Based Beamforming (DL-BF). Under offline training conditions, the BiLSTM combined with the Wiener filter achieves the highest spectral efficiency, highlighting the effectiveness of noise suppression at the receiver.

Scenario 3: The proposed BiLSTM with Wiener filter model is initially trained offline at an SNR of 10 dB and then further improved through online training across varying SNR levels. This case highlights the ability of the proposed approach to adapt to time-varying noise conditions while maintaining improved spectral efficiency, representing the main contribution of this work.

2. System Model

Figure 1 shows the IRS-assisted multi-user multiple-input single-output (MU-MISO) communication system considered in this work. A base station (BS) equipped with multiple antennas communicates with multiple single-antenna user equipments (UEs). The direct line-of-sight (LoS) link between the BS and the UEs is assumed to be obstructed by surrounding obstacles such as buildings or dense urban structures. To support reliable transmission, an intelligent reflecting surface (IRS) with a fixed number of passive reflecting elements is positioned between the BS and the UEs. Each IRS element applies a predetermined phase shift to the incident signals, reflecting them toward the UEs and establishing an indirect cascaded communication path formed by the BS–IRS and IRS–UE channels.

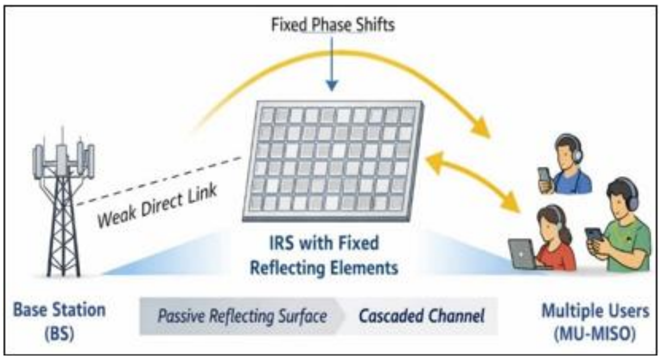

Figure 1: IRS-Assisted MU-MISO communication system

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2.1 Received Signal Model with Online Training

In [1], all system parameters were assumed to be static, and the analysis focused on offline training scenarios. In contrast, the present work considers BiLSTM with wiener filter using online training, which enables the model to adapt to dynamic noise variations across different SNR levels, thereby improving spectral efficiency in the IRS-assisted MU-MISO system.

In the proposed model, the intelligent reflecting surface (IRS) contains N passive elements arranged in a uniform planar array (UPA). The base station (BS) is furnished with M antennas arranged linearly in a uniform configuration, while each user equipment (UE) has a single antenna. The network accommodates I users in total, and the signal received by the i-th UE is i = 1, 2, 3, …. I can be written as

$$y_i'(t) = h_{2,i}^H \, \Phi \, H_1 \, x + n_i(t) \tag{1}$$

The channel vector from the IRS to Ith UE is denoted by $h_{2,i} \in C^{N\times 1}$, while the channel matrix from BS to the IRS is represented as $H_1 \in C^{N\times M}$. The IRS phase shift matrix is defined as $\Phi = \text{diag}\,(e^{j\omega_1}, e^{j\omega_2}, \dots, e^{j\omega_N})$, where $\omega_n \in [0,2\pi]$ corresponds to the phase shift applied by the n-th reflecting element. The combined IRS to UE channel matrix is expressed as $H_2=[h_{2,1}, h_{2,2}, \dots, h_{2,I}]^H \in C^{I\times N}$. The transmitted signal vector x is represented as $x = \sum_{i=1}^{I} v_i s_i$, where $s_i \sim CN(0,1)$ represents the data symbol for the i-th user, $V = [v_1, v_2, \dots, v_I] \in C^{M\times I}$ is the precoding matrix, and $n_i(t) \sim CN(0,\sigma^2(t))$ denotes the additive white Gaussian noise (AWGN) with noise variance $\sigma^2(t)$.

2.2 Online Adaptive Cascaded Channel Model

In this work, the direct transmission link between BS and UEs is neglected due to severe propagation loss and non-line-of-sight (NLoS) conditions commonly observed in practical millimeter-wave (mmWave) environments. Considering the high frequency propagation characteristics of mmWave signals, the reflected and scattered components dominate the transmission. Therefore, a three-dimensional (3D) Saleh-Valenzuela channel model with L scatters is adopted to accurately represent the multipath environment. The complex channel matrix between BS and IRS, denoted as H_1, can thus be expressed as

$$H_1=\sqrt{\frac{M\,N}{L_1}}\ \sum_{l_1=0}^{L_1-1} \beta_{l_1}\, a_u\left(\phi_{u,l_1}, \Theta_{u,l_1}\right) a_b^H(\phi_{b,l_1}) \tag{2}$$

Here, $\sqrt{\frac{M\,N}{L_1}}$ serves as the normalization factor, $\beta_{l_1} \sim CN(0,1)$ denotes the complex gain associated with the lth scatter. The term $a_b^H\left(\phi_{b,l_1}\right)$ and $a_u(\phi_{u,l_1}, \Theta_{u,l_1})$ corresponds to the array response vector of the BS and IRS, respectively. Furthermore, (ϕ_{u,l_1}), (Θ_{u,l_1}) and (ϕ_{b,l_1}) indicate the azimuth angles of arrival (AOA) and departure (AOD), as well as the zenith angles of departure (ZOD). The array response vector for the UPA comprising N reflecting elements can thus be represented as

$$a_u(\phi, \Theta) = \frac{1}{\sqrt{N}}\ [\,1, \dots, e^{j\left(\frac{2\pi}{\lambda}\right)d(\beta\sin\phi\sin\theta+\gamma\cos\theta}, \dots, e^{j\left(\frac{2\pi}{\lambda}\right)((N_x-1)d\sin\phi\sin\theta+(N_y-1)\cos\theta}\,]^T \tag{3}$$

Here, β and γ represent the indices of the reflecting elements along the horizontal and vertical axes, respectively, with $N = N_x N_y$, $0 \le \beta \le N_x-1$ and $0 \le \gamma \le N_y-1$. The spacing between reflective elements is denoted by d, while λ corresponds to the signal wavelength. Based on these definitions, the array response vector of the uniform linear array (ULA) at the base station (BS) can be formulated as

$$a_b(\phi) = \frac{1}{\sqrt{M}}\left[1, e^{j\left(\frac{2\pi}{\lambda}\right)d\sin\phi}, \dots, e^{j\left(\frac{2\pi}{\lambda}\right)(M-1)d\sin\phi}\right]^T \tag{4}$$

The channel connecting the IRS to the i-th UE, denoted by $h_{2,i}$, can be represented mathematically as

$$h_{2,i}^H = \sqrt{\frac{N}{L_2}}\ \sum_{l_2'=0}^{L_2-1} \beta_{l_2'}\ a_b^H\,(\phi_{b,l_2'}, \Theta_{b,l_2'}) \tag{5}$$

In this expression, $\sqrt{\frac{N}{L_2}}$ serves as the normalization factor, $\beta_{l_2'}^2 \sim CN(0,1)$ denotes the complex gain corresponding to the lth scatter, and L_2 represents the total number of propagation paths between the IRS and the UEs. Based on this, the overall cascaded channel H_{eff} linking the BS to the IRS and subsequently to the UEs can be expressed as

$$H_{eff} = H_2\ \phi\ H_1 + n_i(t) \tag{6}$$

The overall downlink spectral efficiency, denoted by X', for the proposed system can be expressed as

$$X' = \sum_{i=1}^{I} log\ \left(1 + \frac{|H_{eff}\, v_i|^2}{\sum_{l\neq i}|\, H_{eff}\, v_i|^2 + \sigma^2(t)}\right) \tag{7}$$

2.3 Online Wiener Filter for Noise-Adaptive Weight Update

In this work, the IRS contains 16 passive reflecting elements with fixed phase shifts; therefore, no IRS phase optimization is performed. Instead, the Wiener filter is employed to generate noise-adaptive linear combining weights based on the cascaded channel. The Wiener filter is designed to minimize the mean square error (MSE) between the received signal and the desired signal, ensuring optimal noise suppression. Since the channel remains static while the noise variance changes across different SNR levels, the Wiener filter produces updated complex weights that vary with the instantaneous noise level. This enables the system to maintain stable signal quality despite dynamic noise conditions. The noise-adaptive Wiener weight update is computed as

$$W_{online}(t) = (H_{eff}H_{eff}^H\ + \sigma^2(t)\ I)^{-1}\ H_{eff}^H \tag{8}$$

Where H_{eff} represents the cascaded channel matrix corresponding the BS, IRS and users. The term $\sigma^2(t)$ denotes the instantaneous noise variance during the adaptation process, while I refers to the identity matrix included to maintain numerical stability.

The complex-valued weight matrix $W_{online}(t)$ adapts automatically as noise variance changes, providing improved robustness and enhanced spectral efficiency across varying SNR levels. Since the IRS phases remain fixed, the obtained Wiener weights are used only for adaptive signal enhancement, without reconfiguring the IRS.

3. Deep Learning Framework

3.1 BiLSTM-Based Network Architecture

The Bidirectional Long Short-Term Memory (BiLSTM) network is an advanced form of recurrent neural network architecture that models long-range temporal patterns by processing sequence data in both forward and backward directions. Unlike a conventional LSTM that relies solely on information from earlier time steps, a BiLSTM combines the outputs of two independently trained LSTM layers to utilize information available from both past and future directions. This bidirectional processing enables sequence representations and improves learning performance for time-dependent signals.

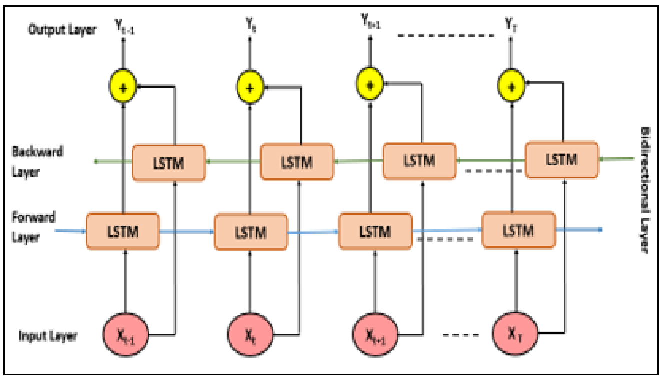

Figure 2: Architecture of the BiLSTM network

The architecture of the BiLSTM network, illustrated in Figure 2, begins by feeding the input sequence simultaneously into a forward LSTM layer that processes the data from X_{t-1} to X_T, and backward LSTM layer that processes the same sequence in reverse, from X_T to X_{t-1}. Each LSTM cell uses the input, forget, and output gates to manage the flow of information, keeping important temporal features while reducing the influence of irrelevant components. The outputs from the forward and backward directions are then combined, either through concatenation or summation, to form a unified context vector that is passed to the output layer to produce the final prediction.

3.2 Dataset Generation and Preprocessing

The dataset is generated using a simulated multi-user multiple-input single-output (MU-MISO) system assisted by 16 IRS elements. The Saleh–Valenzuela channel model is adopted to capture multipath propagation between the BS, IRS, and users. The SNR range is varied from 0 dB to 30 dB, with equal spacing of 5 dB. Additive White Gaussian Noise (AWGN) is applied to all generated channels. Each input sequence is represented using 10 time steps, with real and imaginary components concatenated during preprocessing. Before training, all inputs are normalized to ensure stable learning.

Scenario 1: For BS antenna configurations of 2, 4, and 8 antennas, 3000 channel realizations are generated for each configuration. Samples are equally distributed across the SNR range of (0–30) dB. The dataset is partitioned using an 85% training, with the remaining 15% used for both validation and testing split.

Scenario 2: For comparing different deep learning methods, an MU-MISO system with 8 BS antennas is simulated. A total of 3000 realizations are generated and uniformly distributed across all SNR levels. The dataset is divided as 80% for training and remaining 20% divided between validation and testing.

Scenario 3: For the BiLSTM with Wiener filter using online training, an MU-MISO system with 8 BS antennas and 4 users is simulated. 5000 realizations per SNR level (0–30 dB) are generated. The dataset is split into 68% training, 20% testing, and 12% validation.

3.3 Proposed Deep Learning Model

In this work, Scenarios 1 and 2 utilize an offline BiLSTM framework that includes an input layer, a single BiLSTM layer, a fully connected stage, and a final output layer. Scenario 3 differs by employing online training, where two BiLSTM layers are stacked to capture more detailed temporal patterns and adjust to changing channel conditions during operation. The focus of the study is mainly on Scenario 3, as it demonstrates stronger adaptability when the channel experiences noise fluctuations.

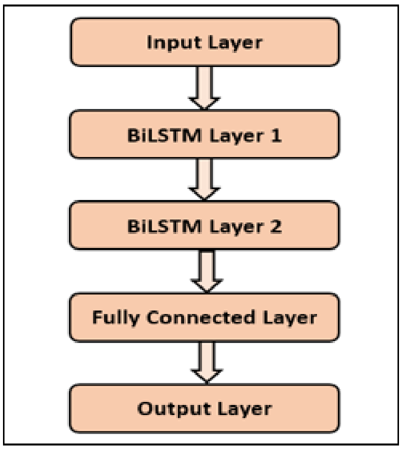

Figure 3: Layered architecture of the proposed BiLSTM based online training model

The proposed deep learning model consists of an input layer followed by two stacked Bidirectional Long Short-Term Memory (BiLSTM) layers with 64 hidden units each, a fully connected (dense) layer, and a linear output layer, as shown in Figure 3. The input layer receives time-sequenced channel features derived from the real and imaginary components of the channel coefficients along with fixed IRS parameters. The first BiLSTM layer captures temporal dependencies in both forward and backward directions, learning short-term and long-term patterns in the channel data. The second BiLSTM layer further refines these temporal features, producing a high-dimensional sequential representation that preserves the dynamics of the time-varying channel. The output of the second BiLSTM layer is passed through the fully connected layer, which transforms the sequential features into a fixed-length vector. This vector is then processed by the linear output layer to generate continuous-valued predictions of the effective channel coefficients in a regression-based framework. During training, feedback in the form of prediction error is backpropagated through the network to update all trainable parameters, minimizing the regression loss. When integrated with the Wiener filter, this architecture supports noise-aware online adaptation and enhanced spectral efficiency in time-varying wireless environments.

3.4 Training and Evaluation Procedure

The deep learning models are trained using the Adam optimizer with a learning rate of 0.001, batch size 128, and MSE (loss). Model performance is evaluated using spectral efficiency (SE) and mean squared error (MSE) across SNR levels from 0–30 dB. Each scenario follows the dataset splits defined in sub-heading 3.2.

Scenario 1: For MU-MISO systems with 2, 4, and 8 BS antennas, a BiLSTM model with one hidden layer of 32 units is trained for 10 epochs under offline training. A Wiener filter is applied at the preprocessing stage to enhance noise suppression before the BiLSTM processes each input sequence, which consists of 10 time steps. Model performance is evaluated using SE and MSE across all SNR levels, and results show that spectral efficiency improves as the number of BS antennas increases.

Scenario 2: To compare different DL methods, simulations are performed for an MU-MISO system with 8 BS antennas and 16 IRS elements. The four deep learning methods are trained offline, including BiLSTM with Wiener filter using 64 units, BiLSTM without Wiener filter using 64 units, supervised deep learning based beamforming (DL-BF), and the Deep Deterministic Policy Gradient (DDPG) method. Each method is trained for 5 epochs. Model performance is evaluated across all SNR levels using spectral efficiency and mean squared error. The results demonstrate that the BiLSTM model equipped with the Wiener filter provides the highest spectral efficiency and the lowest MSE among the compared methods.

Scenario 3: For the proposed BiLSTM model with the Wiener filter using online training, two BiLSTM layers with 64 hidden units each are employed, and the training process is carried out in two stages. The first stage involves offline pretraining at an SNR of 10 dB for 5 epochs, while the second stage performs online adaptation across all SNR levels with 5 epochs for each SNR. The Wiener filter is incorporated to enhance noise suppression and stabilize the online learning process. Model performance is evaluated across all SNR levels using spectral efficiency and mean squared error.

4. Results and Discussion

4.1 Simulation Setup

The proposed system's performance is evaluated under three scenarios which are antenna configuration, DL methods, and the BiLSTM with Wiener filter using online training. Scenarios 1 and 2 serve as baselines for comparison, validating the effectiveness of the proposed BiLSTM with wiener filter framework using online training (scenario 3). Spectral efficiency (SE) is analyzed using the simulation parameters in Table 1 for consistent evaluation.

Table 1: Simulation Parameters of the Proposed System under Three Scenarios

Parameters	Antenna Configuration	Deep Learning Methods	BiLSTM Online Training
No. of BS antennas	[2,4,8]	8	8
No. of IRS elements	16	16	16
No. of Samples	3000	3000	5000
SNR range	(0-30) dB	(0-30) dB	(0-30) dB
No. of LSTM hidden layer	1 (32 units)	1 (64 units)	2 (64 hidden units per layer)
No. of epoch	10	5	(5 offline & 5 online)
Batch Size	128	128	128
Learning rate	0.001	0.001	0.001
Time step	10	10	10
Optimizer	Adam	Adam	Adam

The parameter values are carefully selected to achieve reliable and meaningful performance comparisons across all scenarios. The results are presented in the following subheadings with respective graphs.

4.2 Antenna Configuration

Figure 4 illustrates the variation of spectral efficiency (SE) with respect to SNR for different base station antenna configurations. As the SNR increases, SE improves consistently across all configurations, confirming the expected gain in system performance under higher signal quality. Among the evaluated configurations, the 8-antenna configuration achieves the highest SE, reaching approximately 15 bits/s/Hz at 30 dB, whereas the 4-antenna and 2-antenna cases attain around 14 bits/s/Hz and 12.8 bits/s/Hz, respectively. These results indicate that increasing the number of transmit antennas leads to improved throughput, making larger antenna arrays more suitable for high-capacity wireless communication systems.

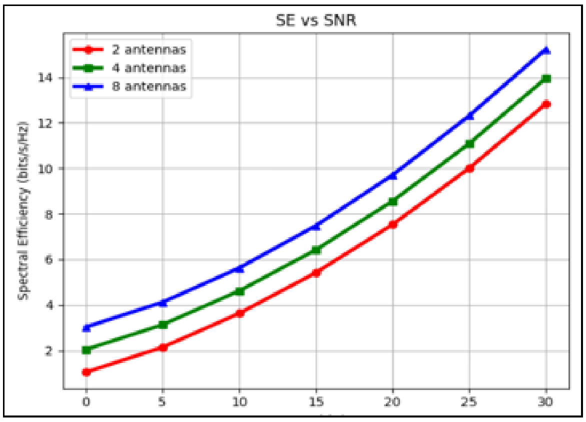

Figure 4: SE vs SNR for different BS antenna configurations

Figure 5 illustrates the variation of mean squared error (MSE) with respect to SNR for different base station antenna configurations. The MSE decreases consistently as the SNR increases for all configurations, reflecting improved estimation accuracy under higher signal quality. At 30 dB, the 8-antenna configuration achieves the lowest loss of approximately 0.68, while the 4-antenna and 2-antenna cases attain higher losses of about 0.77 and 0.85, respectively. This trend demonstrates that increasing the number of antennas enhances training stability and robustness, leading to more reliable learning and accurate signal estimation in MU-MISO systems.

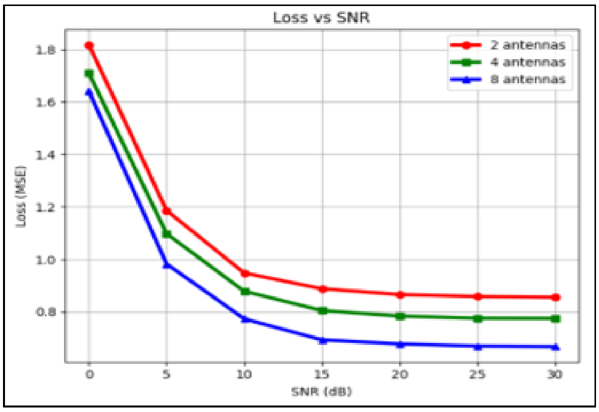

Figure 5: loss vs SNR for different BS antenna configurations

4.3 Comparison of Deep Learning Methods

Figure 6 presents the spectral efficiency (SE) versus SNR performance for different deep learning–based methods. For all approaches, SE improves as the SNR increases; however, the proposed BiLSTM–Wiener model consistently achieves the highest performance across the entire SNR range. At 30 dB, it attains an SE of approximately 15.81 bits/s/Hz, significantly outperforming the BiLSTM model without the Wiener filter with about 9.10 bits/s/Hz, the DL-based beamforming method with nearly 4.21 bits/s/Hz, and the DDPG approach with around 2.00 bits/s/Hz. These results confirm that integrating the Wiener filter with the BiLSTM network effectively enhances noise suppression and feature learning, leading to superior spectral utilization, higher data rates, and improved overall communication efficiency.

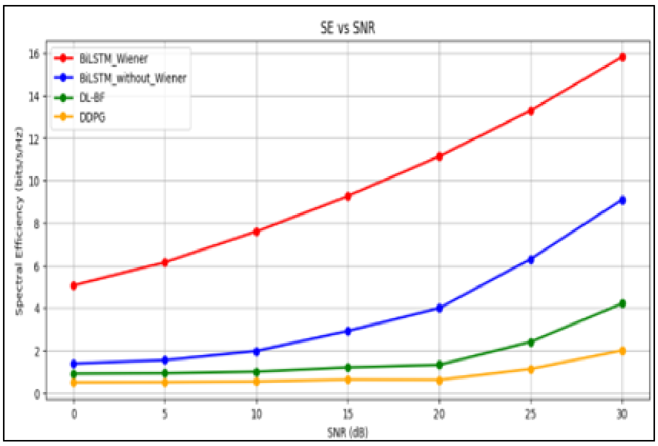

Figure 6: SE vs SNR for different DL methods

Figure 7 shows the mean squared error (MSE) versus SNR performance for different deep learning–based methods. For all approaches, the loss decreases as the SNR increases, indicating improved estimation accuracy under higher signal quality. The proposed BiLSTM–Wiener model achieves the lowest loss, reaching approximately 0.14 at 30 dB, followed by the BiLSTM without the Wiener filter at around 0.18, the DL-based beamforming method at nearly 0.25, and the DDPG approach at about 0.28. These results demonstrate the robustness and training stability of the BiLSTM–Wiener framework, highlighting its effectiveness in reducing noise and improving channel estimation performance.

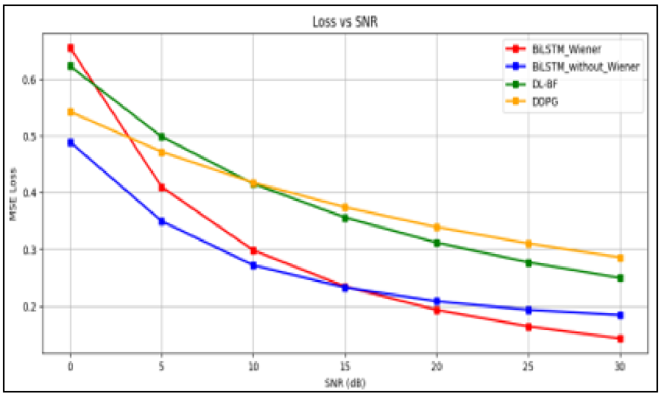

Figure 7: loss vs SNR for different DL methods

4.4 BiLSTM with Wiener Filter through Online Training

Figure 8 shows the spectral efficiency (SE) versus SNR performance of the BiLSTM model with a Wiener filter under online training. The SE increases steadily from approximately 2.55 bits/s/Hz at 0 dB to 26.13 bits/s/Hz at 30 dB, indicating a significant improvement in data transmission capability as the signal quality improves. This consistent growth confirms the effectiveness of the online BiLSTM–Wiener framework in adapting to noise variations, enabling efficient spectral utilization and enhanced throughput under dynamic wireless channel conditions.

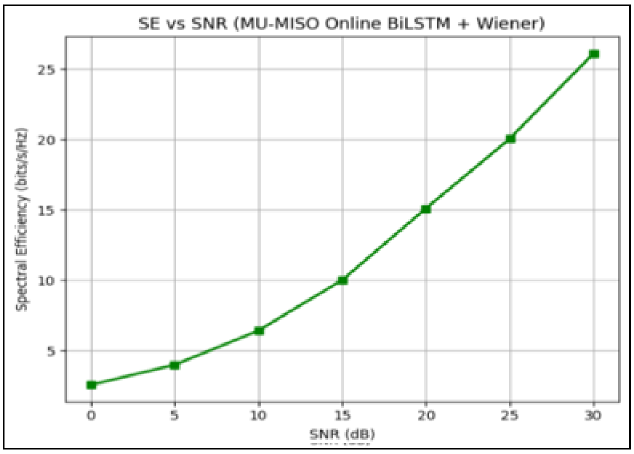

Figure 8: SE vs SNR for BiLSTM with Wiener Filter

Figure 9 shows the mean squared error (MSE) versus SNR performance of the BiLSTM model with a Wiener filter under online training. The loss decreases steadily from approximately 0.92 at 0 dB to 0.61 at 30 dB, indicating improved learning accuracy as the signal quality increases. This decreasing trend confirms the effectiveness of the online BiLSTM–Wiener framework in maintaining stable training, enhancing noise resilience, and achieving adaptive optimization under noise-varying channel conditions.

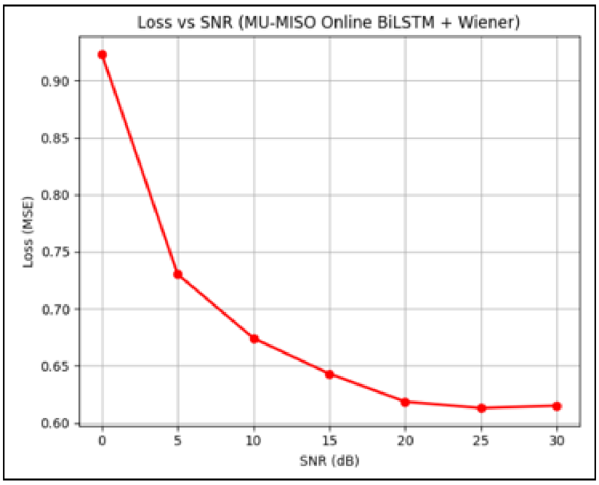

Figure 9: loss vs SNR for BiLSTM with Wiener Filter

The performance analysis of the proposed BiLSTM model integrated with the Wiener filter using online training, in terms of Spectral Efficiency (SE) and Loss across varying Signal-to-Noise Ratio (SNR) levels, is presented in Table 2.

Table 2 Spectral Efficiency (SE) and MSE (Loss) performance of the Proposed System

SNR (dB)	*Spectral Efficiency (bits/s/Hz)*	*MSE (Loss)*
0	2.55	0.92
5	3.98	0.73
10	6.41	0.67
15	10.00	0.64
20	15.11	0.62
25	20.06	0.61
30	26.13	0.61

Table 2 presents the spectral efficiency and loss performance of the proposed system. The proposed BiLSTM with Wiener filter model using online training demonstrates a consistent improvement relationship between spectral efficiency and signal quality, with spectral efficiency increasing from 2.55 bits/s/Hz to 26.13 bits/s/Hz as the SNR increases from 0 dB to 30 dB. Concurrently, the loss decreases from 0.92 to 0.61, indicating enhanced model accuracy and stable behavior during online training. These results confirm the effectiveness of the proposed framework in achieving adaptive spectral utilization and robust noise suppression under noise varying conditions. Such performance is particularly beneficial in static deployment environments such as indoor networks, fixed wireless access links, industrial communication setups, and backhaul systems, where the fixed IRS configuration and cascaded MU-MISO structure effectively improve multiuser connectivity and overall spectral efficiency.

5. Conclusion

This research investigated an online adaptive BiLSTM framework integrated with a Wiener filter to improve spectral efficiency in IRS-assisted MU-MISO communication under noisy conditions. Performance analysis indicates that the proposed online approach consistently performs better than conventional offline-trained deep learning models and different antenna configuration in terms of spectral efficiency, noise handling capability, and system stability. At an SNR of 30 dB, the system achieves a spectral efficiency of 26.13 bits/s/Hz with a low loss value of 0.61, confirming the effectiveness of the online learning approach. The Wiener filter supports noise-aware signal processing, while the BiLSTM structure captures temporal channel variations effectively, enabling adaptive and dependable performance across a wide range of SNR levels. Overall, the proposed framework offers a clear improvement compared to earlier offline learning-based methods.

6. Future Scope

Although the proposed framework provides notable improvements in spectral efficiency, it is currently tested under controlled simulation settings with fixed IRS configurations and ideal synchronization, which may not fully reflect practical wireless scenarios. In real deployments, factors such as hardware imperfections, user movement, inaccurate channel information, and processing limitations can influence system performance. While the online training strategy enhances adaptation to noise variations, extending this capability to fast-changing channel conditions remains an important area for future research. Further studies may focus on real-time implementation, reducing computational delay and power consumption, and jointly optimizing IRS phase control using reinforcement learning or combined deep learning approaches. Moreover, improving scalability and computational efficiency will be essential for applying the proposed framework to large-scale and dense 6G communication networks.

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