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Wireless Networks with Large Intelligent Surfaces: Partial CSI Reconstruction through SNR-Aware Deep Learning

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Abstract

The growing demand for high data rates, widespread connectivity and intelligent network services in future wireless communication systems has accelerated the evolution from fifth-generation (5G) systems to sixth-generation (6G) networks. Large Intelligent Surface (LIS) has emerged as a key enabling technology for 6G. It is considered as a potential solution for increasing coverage, spectral efficiency and energy efficiency by intelligently controlling the wireless signal propagation environment. However, high-dimensional cascaded channels are created in LIS-based systems due to the large number of reflecting elements, which makes collecting accurate Channel State Information (CSI) or channel state information a challenging task. Conventional full-CSI detection methods incur excessive pilot overhead, computational complexity and sensing requirements, limiting their large-scale application. To address these challenges, this paper proposes an SNR-aware deep learning framework for partial CSI reconstruction in LIS-assisted wireless networks. Instead of relying on full channel observations, the proposed method reconstructs high-dimensional CSI from a limited number of measurements, thereby reducing sensing complexity and pilot overhead. From noisy partial observations, full channel information is recovered using a convolutional neural network (CNN) with residual learning. In addition, signal-to-noise ratio (SNR) information is incorporated into this learning method to increase robustness to changing channel conditions. During training, a joint loss function is used to improve the reconstruction quality, combining reconstruction fidelity and measurement-domain consistency. According to thorough simulations conducted using the DeepMIMO dataset, the proposed framework can successfully reconstruct high-dimensional channels with much fewer observations than conventional methods. According to research results, this approach ensures an optimal balance between sensing complexity and spectral efficiency, maintains robustness of performance at different SNR settings, and reaches similar performance to ideal full-CSI systems. These results demonstrate the potential of the proposed framework as a scalable and energy-efficient solution for realistic LIS-based 6G wireless networks.

Keywords: Deep Learning, Channel Reconstruction, Large Intelligent Surface, DeepMIMO, Convolutional Neural Network, Rayleigh fading, Rician fading, AWGN.

1. Introduction

New technologies such as artificial intelligence (AI), virtual reality (VR) and the Internet of Everything (IoE) [1] have led to an unprecedented increase in wireless data flow rates. This has resulted in a radical change in the functioning and requirements of modern communication systems. The wireless networks of the future will not only connect a large number of devices, but also guarantee fast data exchange, ultra-low latency, greater stability and fair use of spectrum. These growing and demanding requirements have further accelerated the continuous development of wireless transmission technology. Massive multiple-input multiple-output (MIMO) [3] and millimeter-wave (mmWave) communication systems—these two technologies have helped fifth-generation (5G) wireless systems [2] increase network capacity. These new concepts made the exchange of large amounts of data (throughput) much easier. Nevertheless, there are still some challenges or problems in using 5G networks in real cases. Some of the significant problems are signal or path loss at high frequencies, signal disruption in densely populated cities, hardware complexity and high power consumption. Researchers are now focusing on developing sixth-generation (6G)[4] wireless networks, as it is becoming increasingly clear that current systems have some limitations. 6G networks aim to ensure extremely high-speed data exchange, ubiquitous connectivity, and massive machine-to-machine communication and automated network management. They are considered the basis of an intelligent and fully connected society. To achieve these ambitious goals, we must move away from outdated communication methods and fully transform to wireless systems that are environment-aware and data-driven. The 'Large Intelligent Surface' (LIS)[5]—also known as the 'Reconfigurable Intelligent Surface' (RIS)—has become a very important technology that will help the 6G network achieve its high performance goals by making it more intelligent and environment-aware. A LIS essentially consists of a large array of passive but programmable reflector elements [6], which can intelligently change the pattern of wireless signal propagation. By instantaneously changing the 'phase response' of these components, LIS can shape the wireless environment in ways that improve coverage, spectral efficiency, signal interference, and power efficiency. LIS gives you the ability to actively control the signal propagation medium; this allows you to better optimize or improve your wireless network than with traditional communication methods (where only the sender and receiver devices are changed). However, while these advantages are theoretically possible, in practice LIS-based wireless systems are extremely difficult to implement. The presence of a large number of reflector elements results in high-dimensional cascaded channels, which makes accurate channel estimation and channel state information (CSI) [7] collection extremely difficult. Conventional channel estimation techniques usually require extensive pilot signalling and full CSI collection, resulting in excessive sensing overhead, excessive computational complexity, and increased power consumption. Furthermore, optimization-based methods designed for high-dimensional channel estimation often involve iterative processes, which become computationally impractical as the size of LIS increases. As a result, achieving full CSI is often impractical in large-scale LIS deployments.

These limitations have motivated the search for alternative techniques, which are able to maintain satisfactory communication performance based on monitoring only a limited number of channels. In this context, partial CSI (Channel State Information) reconstruction has emerged as a potential solution. Instead of directly determining the entire channel through extensive measurements, the partial CSI reconstruction method attempts to estimate the overall characteristics of the channel based on a limited number of observations. Such an

approach significantly reduces pilot signal-related tasks, sensor requirements, and hardware complexity. This makes it an excellent solution for large scale wireless networks with intelligent surfaces. Recent advances in deep learning (DL) have shown that it is capable of solving very complex signal processing problems in radio communications. While traditional model-based methods rely on precise mathematical formulas, deep learning techniques can master complex relationships between signals and channel intrinsic properties directly from data. The availability of realistic datasets such as DeepMIMO [9] has further accelerated the development of data-driven wireless solutions. Because it makes it possible to train and evaluate learning algorithms in realistic propagation situations. Motivated by these advances, this paper proposes an SNR [10]-aware deep learning framework for partial CSI reconstruction in LIS-assisted wireless networks. The proposed framework uses a convolutional neural network (CNN)[11] with residual learning to recover high-dimensional channel information from noisy and incomplete observations obtained with a limited number of active measurements. By explicitly incorporating signal-to-noise ratio (SNR) information into the learning process, the framework adapts to changing channel conditions and achieves improved robustness and reconstruction accuracy in different operating environments. Furthermore, a joint loss function combining reconstruction fidelity and measurement-domain consistency is introduced to improve the quality of the recovered channels. Detailed simulations conducted using the DeepMIMO dataset show that the proposed method achieves near-optimal spectral efficiency despite requiring far fewer measurements than conventional full-CSI based methods. The results highlight a useful balance between the complexity of sensing and the performance achieved. Besides, it indicates the potential of the proposed SNR-aware framework as a scalable and energy-efficient solution for future LIS-enabled 6G wireless networks.

The major contributions of this paper are summarized below:

- A deep learning-based framework for channel reconstruction based on partial observations in high-dimensional wireless systems.
- SNR-aware convolutional neural network architecture with residual learning for robust performance across varying channel conditions.
- A joint optimization strategy that combines reconstruction loss and measurement consistency to enhance estimation accuracy.
- A comprehensive performance evaluation using realistic DeepMIMO data, demonstrating near-optimal achievable rate with significantly reduced sensing overhead.
- A detailed analysis of the trade-off between sensing complexity and spectral efficiency, enabling practical system design insights.

The remainder of this paper is organized as follows. The second part (Section II) describes the related research work, and the third part (Section III) presents the system model and methodology. Section IV presents the simulation setup and performance evaluation metrics; these include the maximum rate achievable and the normalized mean square error (NMSE). Full results and discussion of the study are in Section V, where signal-to-noise ratio (SNR), number of active receivers, and Rician K-factor affect system performance. The sixth part (Section VI) presents the comparison with the baseline. In the last part of the paper or the seventh part (Section VII), possible directions for future research in deep learning-based channel estimation for beyond-5G and 6G wireless systems are provided. Fig 1 presents an overview of this research work.

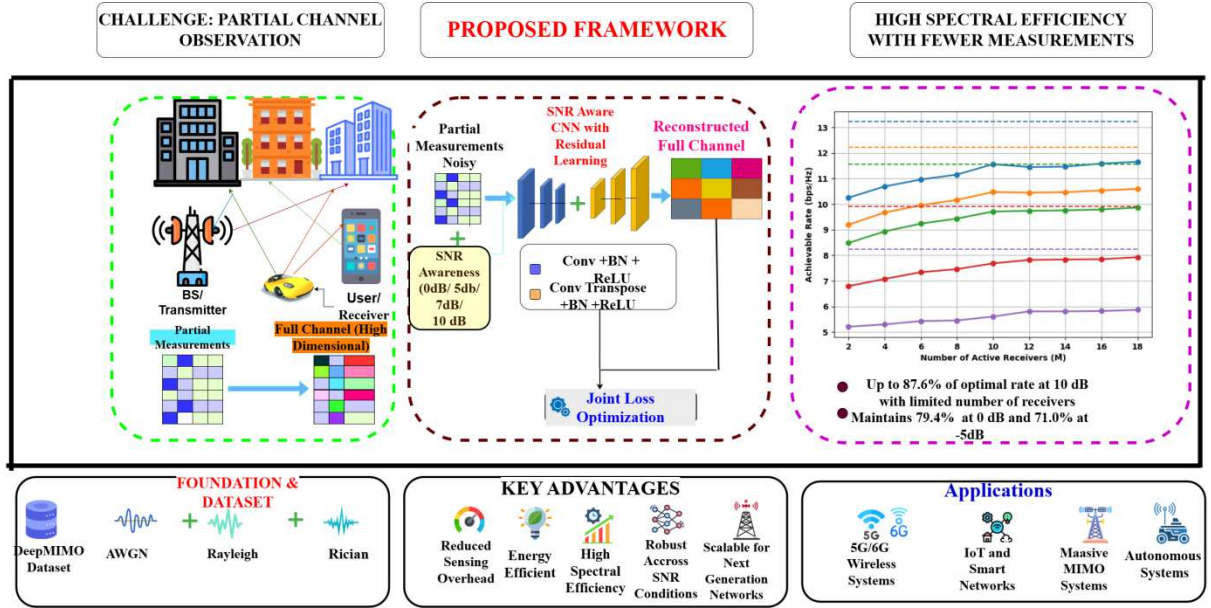


Fig. 1: Overview of research work

2. Related Work

Recent advances in wireless communication technology have made people interested in finding better ways to rearrange channels and use airwaves more efficiently for next-generation networks. Conventional methods of channel perception or measurement are largely dependent on accurate 'Channel State Information' (CSI). But in the case of high-dimensional (high-dimensional) systems it is quite difficult to collect this information; Reasons for this include the additional workload on the sensors, hardware or equipment limitations, and the computational complexity involved. Several analytical, optimization-based, and deep learning (DL)-based approaches have been looked into in the literature to try to solve these problems.

Traditional channel estimation methods, like Least Squares (LS) [18] and Minimum Mean Square Error (MMSE) [19], are widely used in wireless communication systems because they are easy to understand and are based on well-established theories. It is easy to implement LS estimation, but it doesn't work well in noisy environments, especially when the signal-to-noise ratio (SNR) is low. MMSE estimation is more accurate because it uses channel statistics, but you need to know about statistics ahead of time and it involves matrix inversion operations, which makes it hard to use on large systems [20]. These methods work well when there are enough pilot measurements, but they don't work as well when the number of measurements is much lower than the channel dimension. This means that standard estimation methods can't be used for high-dimensional wireless systems that can't sense much.

For reconstructing sparse wireless channels, techniques [21] based on compressive sensing (CS) have been looked into to cut down on the processing power needed for sensing. These methods use the fact that wireless channels are naturally sparse and turn channel estimation into an optimization problem. Iterative algorithms such as Orthogonal Matching Pursuit (OMP), Basis Pursuit (BP), and Sparse Bayesian Learning have been shown to be viable when not many channels are available. Although optimization-based methods work well, they have some problems. First, their computational complexity increases as the number of channels and iterations increases. Second, how well they perform depends largely on the sparseness assumptions and how well the sensing matrices are designed. Third, the

performance of these methods often deteriorates in variable propagation and highly noisy environments. For this reason, it is still difficult to use optimization-based methods in real time in real wireless systems. For sparse wireless channel reconstruction, compressive sensing (CS) based techniques [21] have been researched to reduce the processing power required for sensing. Iterative algorithms such as Orthogonal Matching Pursuit (OMP), Basis Pursuit (BP), and Sparse Bayesian Learning have been shown to be viable when not many channels are available. Although optimization-based methods work well, they have some problems. First, their computational complexity increases as the number of channels and iterations increases. Second, how well they perform depends largely on the sparseness assumptions and how well the sensing matrices are designed. Third, the performance of these methods often deteriorates in variable propagation and highly noisy environments. For this reason, it is still difficult to use optimization-based methods in real time in real wireless systems. For sparse wireless channel reconstruction, compressive sensing (CS) based techniques [21] have been researched to reduce the processing power required for sensing. New advances in deep learning have made it possible to use data to solve problems related to wireless signal processing, such as channel estimation, beamforming, and improving spectral efficiency. Deep learning methods don't need explicit channel models to learn complex nonlinear relationships; they can do this directly from data, unlike traditional model-based methods. Fully connected neural networks and convolutional neural networks (CNNs) have been used in a number of studies to use pilot observations to reconstruct wireless channels. CNN-based [23] architectures are especially appealing because they can effectively capture the spatial and temporal correlations and structural features that are present in wireless channels. Also, techniques for residual learning have been added to make training more stable and help deep architectures converge. Traditional estimation methods don't work as well as deep learning methods, especially in environments with a lot of noise and nonlinearity. However, a lot of the current deep learning methods depend on full or high-dimensional CSI observations for training and inference, which makes them less useful in systems with strict sensing requirements. Also, a lot of the current methods were trained with fixed SNR, which makes them less reliable when channel conditions change quickly.

The availability of realistic wireless datasets like DeepMIMO has sped up research in data-driven wireless communications even more. DeepMIMO provides 'ray-tracing'-based channel data that accurately reflects signal propagation patterns—such as multipath effects, spatial correlations, and obstruction conditions in real-world wireless environments. Recent studies have shown the use of DeepMIMO in beam detection [24], channel assignment [25] and smart communication system design [26]. Compared to artificial or synthetic channel models, DeepMIMO-based evaluation allows for more realistic performance analysis [27] and increases the generalization capability of deep learning models. Nevertheless, a large part of existing research focuses mainly on beam selection or fully observable channel conditions; On the other hand, channel reconstruction from severely compressed observations has received relatively little attention [28].

Despite significant progress in wireless channel reconstruction and deep learning-based estimation, several important challenges remain unresolved:

- Existing LIS-assisted communication systems face significant CSI acquisition overhead due to the large number of reflector elements.
- Deep learning-based channel reconstruction for LIS environments using highly compressed observations is still insufficiently explored.
- The effect of partial CSI reconstruction on spectral efficiency in LIS-assisted wireless systems using realistic propagation datasets has not been extensively investigated.

- The trade-off between sensing complexity and achievable spectral efficiency has not been comprehensively analysed using realistic wireless datasets.

The next section presents the system model and workflow of the proposed deep learning-based channel reconstruction framework. To reduce the overhead of CSI acquisition in large-scale LIS/RIS-assisted wireless systems, this work proposes a deep learning-based framework for channel reconstruction from partial observations. A high-dimensional wireless communication system is considered, where only partial channel monitoring is available due to sensing and hardware limitations. The proposed method uses realistic channel data generated from the DeepMIMO dataset and applies a residual CNN architecture to reconstruct the full channel from compressed measurements. The reconstructed channel is then used for beamforming and spectral efficiency evaluation. The overall workflow depicts the sequence of channel creation, partial observation acquisition, deep learning-based reconstruction, and performance evaluation under different channel and noise conditions.

3. System Modelling

3.1 Modelling the Wireless System

A downlink wireless communication system is considered, where data is transmitted from a base station (BS) to a single-antenna user over a high-dimensional wireless channel. The system operates under a partial observation framework, where only a limited number of measurements are available for channel reconstruction.

Let $h \in \mathbb{C}^{N \times 1}$ denote the complex channel vector with dimension N . Due to hardware and sensing constraints, the receiver acquires only $\bar{M} \ll N$ linear measurements of the channel using a sensing matrix.

The transmitted signal is given by

$$x = \sqrt{P} s \dots\dots\dots (1)$$

where P denotes the transmit power and s is the unit-power data symbol, i.e. $E[|S^2|] = 1$.

3.2 Modelling the Channel and Acquiring Measurements

To capture realistic propagation conditions, the channel are generated using the DeepMIMO [14] dataset and further incorporates small-scale fading. The DeepMIMO dataset is a ray-tracing-based wireless communication dataset, designed for the development and evaluation of machine learning algorithms for mmWave and massive MIMO systems. It generates realistic channel data from simulated propagation environments, providing information such as channel co-efficient, user location and beamforming parameters. Specifically, the channel is modelled as

$$\check{h} = h \cdot g \dots\dots\dots (2)$$

where $g \sim \mathcal{CN}(0,1)$ represents Rayleigh fading.

In scenarios with a dominant line-of-sight (LOS) component, the channel follows a Rician distribution:

$$h_{ric} = \sqrt{\frac{K}{K+1}} h_{LOS} + \sqrt{\frac{1}{K+1}} h_{NLOS} \dots\dots\dots (3)$$

Where K is the Rician K -factor representing the ratio of LOS to scattered power, h_{LOS} is the deterministic LOS component, and $h_{NLOS} \sim \mathcal{CN}(0, I)$ represents the scattered component. In this work, the original channel h serves as the LOS component, and random Gaussian noise models the NLOS part. A sensing matrix $\Phi \in \mathbb{C}^{N \times \bar{M}}$ is used to obtain compressed measurements of the channel. Each row of Φ is normalized to unit norm to ensure stable measurements. The observed signal is expressed as

$$y = \tilde{h}\Phi^T + n \dots\dots\dots (4)$$

where $n \sim \mathcal{CN}(0, \sigma^2 I)$ denotes additive white Gaussian noise.

3.3 Computing the SNR and Achievable Rate

The signal-to-noise ratio (SNR) is defined as:

$$SNR = \frac{P\|h\|_2^2}{\sigma^2} \dots\dots\dots (5)$$

In practice, noise variance is adjusted according to a target SNR value (in dB):

$$SNR_{linear} = 10^{\frac{SNR_{dB}}{10}} \dots\dots\dots (6)$$

The achievable rate is computed as:

$$R = \log_2(1 + SNR) \dots\dots\dots (7)$$

These metrics are used to evaluate system performance under different sensing configurations and noise conditions.

3.4 Deep Learning-Based Channel Reconstruction

To recover the high-dimensional channel from partial observations, a deep learning model is employed. The input to the neural network is constructed from the real and imaginary parts of the noisy measurements:

$$x = [\Re(y), \Im(y)] \dots\dots\dots (8)$$

A convolutional neural network (CNN) with residual learning is designed to estimate the channel:

$$\hat{h} = \mathcal{F}(x, \gamma; \Theta) \dots\dots\dots (9)$$

where γ denotes the SNR, Θ represents the trainable parameters, and $\hat{h}$ is the reconstructed channel.

3.5 Optimizing the Reconstruction Process

To ensure accurate reconstruction and measurement consistency, a joint loss function is defined as:

$$\mathcal{L} = \frac{\|\tilde{h} - \hat{h}\|_2^2}{\|\hat{h}\|_2^2} + \lambda \|y - \hat{h}\Phi^T\|_2^2 \dots\dots\dots (10)$$

where λ regularization parameter that balances reconstruction accuracy and measurement-domain consistency.

3.6 Evaluating the Achievable Rate Using Reconstructed Channels

Using the reconstructed channel, a beamforming vector is defined as

$$\Psi = \frac{\hat{h}^*}{\|\hat{h}\|} \dots\dots\dots (11)$$

The effective channel gain is computed as

$$g = |h^H \Psi|_2^2 \dots\dots\dots (12)$$

and the corresponding achievable rate is

$$R_{DL} = \log_2(1 + \gamma g) \dots\dots\dots (13)$$

To verify the effectiveness of the proposed deep learning-based channel reconstruction framework, extensive simulations were conducted using realistic wireless channel environments generated from the DeepMIMO dataset. The simulation setup was designed to evaluate the performance of the proposed model under different channel conditions including AWGN, Rayleigh fading and Rician fading environments. Various system parameters such as number of active measurements, signal-to-noise ratio (SNR) and Rician K-factor were varied to investigate their effect on channel reconstruction accuracy and spectral efficiency. Furthermore, the proposed CNN architecture was trained and tested using realistic channel observations to evaluate its robustness, convergence behaviour, and ability to achieve near-optimal performance with significantly reduced sensing overhead.

4. Simulation setup and CNN Architectural design

To efficiently reconstruct the high-dimensional wireless channel from limited observations, this work employs a deep convolutional neural network (CNN) with residual learning. The proposed architecture is specifically designed to capture the spatial correlations and structural dependencies present in wireless channel measurements generated from the DeepMIMO dataset. Compared with conventional fully connected architectures, CNN-based models provide better feature extraction capability, lower parameter complexity, and improved generalization performance in high-dimensional channel reconstruction problems. The real and imaginary parts of the compressed received measurements are sent to the network as input. When there are M active measurements from a sensor, the complex observation vector is turned into a real-valued representation of dimension $2M$. After being reshaped into a two-channel feature map, the input goes through several convolutional layers to be processed.

This representation lets the network learn how real and imaginary channel components relate to each other in space at the same time.

The proposed CNN structure has three convolutional layers and then a learning block that is left over. From the compressed observations, the first convolutional layer pulls out low-level channel features. Later, deeper convolutional layers capture more general channel features and multipath propagation patterns. It uses residual learning to keep training stable and fix the degradation problem that deep neural networks often have. The network converges faster and gets better reconstruction accuracy by learning residual mappings directly. Signal-to-noise ratio (SNR) and Rician K-factor information are added as extra inputs to the fully connected layers to make them more stable when the channel conditions change. The network can automatically adjust to different fading and noise environments because the design takes both SNR and channel awareness into account. This means that the network doesn't need separate models for each operating condition. The convolutional outputs are flattened and sent through two fully connected layers to build back up the full channel vector after the features have been extracted. The last layer predicts both the real and imaginary parts of the high-dimensional channel that has been rebuilt. The reconstructed channel is then used to figure out the achievable rate and rate the performance.

The proposed CNN architecture, Fig.2, offers several important advantages for high-dimensional channel reconstruction. First, it efficiently extracts meaningful features from compressed channel measurements, enabling accurate learning even under limited observation conditions. Incorporation of residual learning increases the accuracy of reconstruction by facilitating the learning of complex channel features while also mitigating the problem of training degradation. Moreover, this architecture exhibits strong robustness to variable signal-to-noise ratio (SNR) levels and different fading environments, which ensures stable performance in different wireless channel conditions. By accurately reconstructing channel information from a small number of measurements, the proposed framework significantly reduces sensing overhead while maintaining near-optimal spectral efficiency. Also, compared to conventional iterative optimization-based methods, the proposed deep learning framework achieves lower computational complexity and faster inference, which makes it more suitable for practical real-time wireless communication systems.

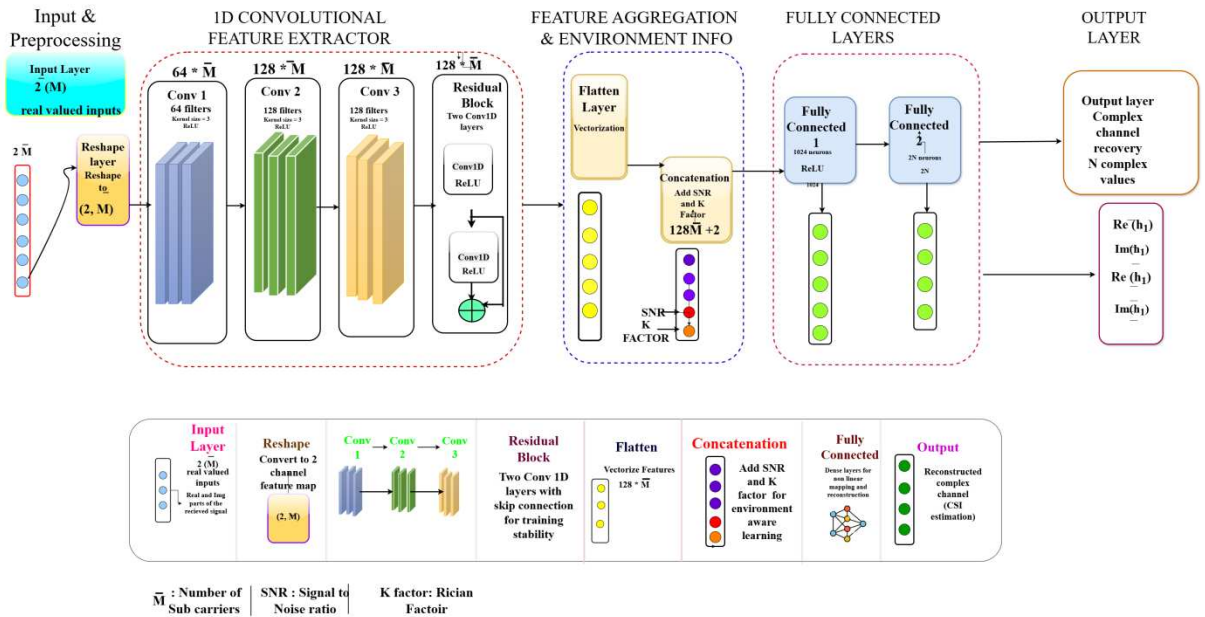


Fig.2: CNN architecture of the proposed model

4.1 Simulation Parameters

The DeepMIMO dataset, which has realistic ray-tracing-based wireless channel environments good for beyond-5G and 6G communication research, was used to test how well the proposed deep learning-based channel reconstruction framework worked. The simulations were run in the O1_28 outdoor scenario, which had a bandwidth of 0.1 GHz and 512 OFDM subcarriers. 64 of these subcarriers were chosen to create and reconstruct the channel. The base station had a 32×32 uniform planar antenna array that created a channel vector with dimensions $N=1024$. The user equipment, on the other hand, only had one antenna.

The proposed framework included additive white Gaussian noise (AWGN), Rayleigh fading, and Rician fading channels to test how robust it was in real-world propagation settings. We did the tests with a signal-to-noise ratio (SNR) that ranged from -5 dB to 10 dB. Several K-factor values were looked at for the Rician fading model to see how line-of-sight propagation affected the performance that could be reached. To ensure the stability of the compressed measurements, the method of 'complex Gaussian random projections' has been used in generating the sensing matrix. To verify how the trade-off or 'trade-off' between sensing complexity and spectral efficiency affects each other, varying numbers of active measurements (M) from 2 to 18 have been considered. 5×10^{-4} learning rate, 512 batch size and 250 training epochs are used to train the proposed Convolutional Neural Network (CNN). Normalized mean square error (NMSE), achievable data rate and spectral efficiency—these metrics are used to evaluate performance. The proposed framework is compared with the best 'full-CSI' benchmark to verify how effective the channel reconstruction process is under partial observation conditions. Table 1 illustrates the list of simulation parameters used in this research work.

Table 1: Simulation parameters

Parameter	Value
Dataset	DeepMIMO
Scenario	O1_28
Channel Dimension (N)	1024
Base Station Antenna Array	$32 \times 32 \times 1$
User Antenna Configuration	$1 \times 1 \times 1$
Number of OFDM Subcarriers	512
Selected Subcarriers	64
Number of Paths	10
Active Measurements $\bar{M}$	2–18
SNR Range	(-5) dB to (10) dB
Channel Models	AWGN, Rayleigh, Rician
Optimizer	Adam
Learning Rate	5×10^{-4}
Batch Size	512
Number of Epochs	250
Loss Function	NMSE + Measurement Consistency
Framework	PyTorch
Hardware	GPU-enabled environment

5. Results and Discussion

In this section, it is verified how effectively the proposed deep learning-based channel reconstruction framework performs for different signal-to-noise ratios (SNR) and number of active measurements ($\bar{M}$). The performance is assessed in terms of achievable rate, normalized mean square error (NMSE), and efficiency relative to the optimal full-CSI benchmark.

5.1 Achievable Rate Performance

Fig. 4, Fig.5 and Fig.6 illustrate the achievable rate as a function of the number of active measurements $\bar{M}$ for different SNR levels. The dashed lines represent the optimal achievable rate obtained using perfect channel state information (CSI), while the solid curves correspond to the proposed deep learning (DL)-based method.

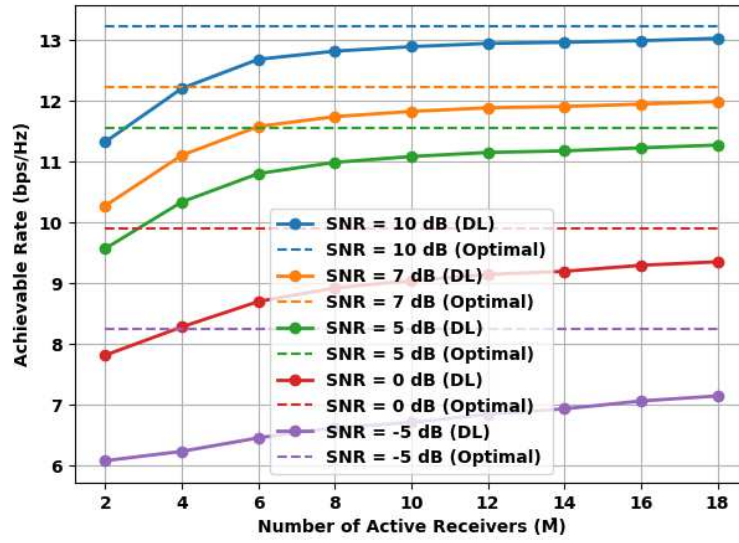


Fig 4: Achievable rates with respect to number of active receivers at AWGN channels

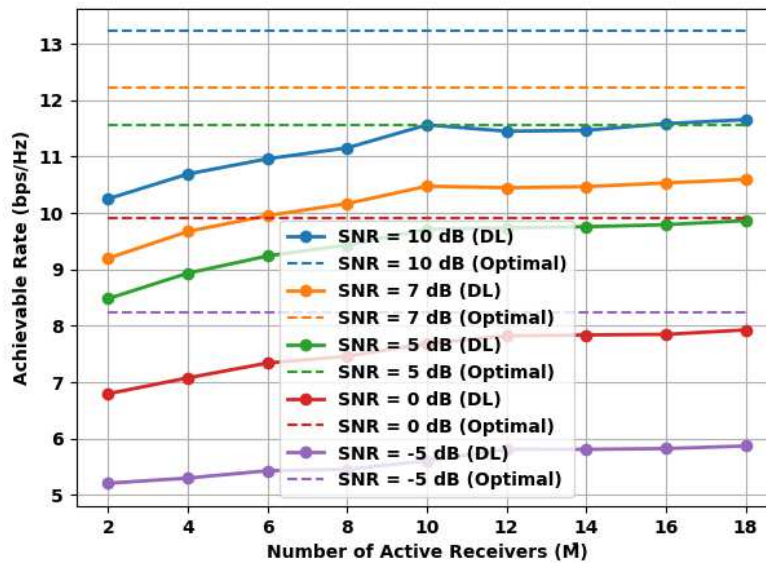


Fig 5: Achievable rates with respect to number of active receivers at Rayleigh channels

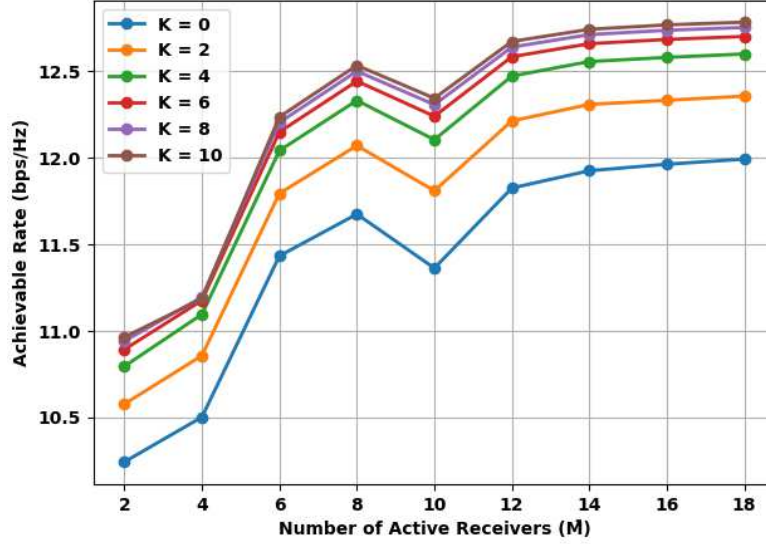


Fig 6: Achievable rates with respect to number of active receivers at Rician channels

It is observed that the achievable rate increases monotonically with $\bar{M}$, which is expected as more measurements provide richer channel information for reconstruction. At a high SNR (10 dB), the suggested method achieves up to 87.6% of the best rate with $\bar{M}=16$, showing that it can get very close to full-CSI performance with a lot fewer measurements. The model works 77.5% of the time even with very little sensing ($(\bar{M})=2$), which shows how stable it is when measuring conditions are very bad. When the SNR is moderate (0 dB), the rate that can be reached is about 79.4% of the best performance. When the SNR is low (-5 dB), the efficiency stays above 71%. The fact that the proposed model is effective under various conditions and does not vary much in performance with changes in the SNR level suggests that it is suitable for a wide range of applications. Furthermore, the rate of increase in efficiency does not increase further above $\bar{M}=14$. That is, increasing the number of measurements further diminishes the benefits. This is very important in building real systems, as it indicates an optimal performance range where sensing-related overhead can be kept to a minimum, yet overall performance is not greatly reduced.

5.2 NMSE Performance Analysis

Here are three figures (Figure 7, Figure 8 and Figure 9) that show how NMSE performs for a large number of active measurements. As expected, the value of NMSE decreases as the value of $\bar{M}$ increases. This proves that as the channel reconstruction accuracy improves, the performance of the system directly improves.

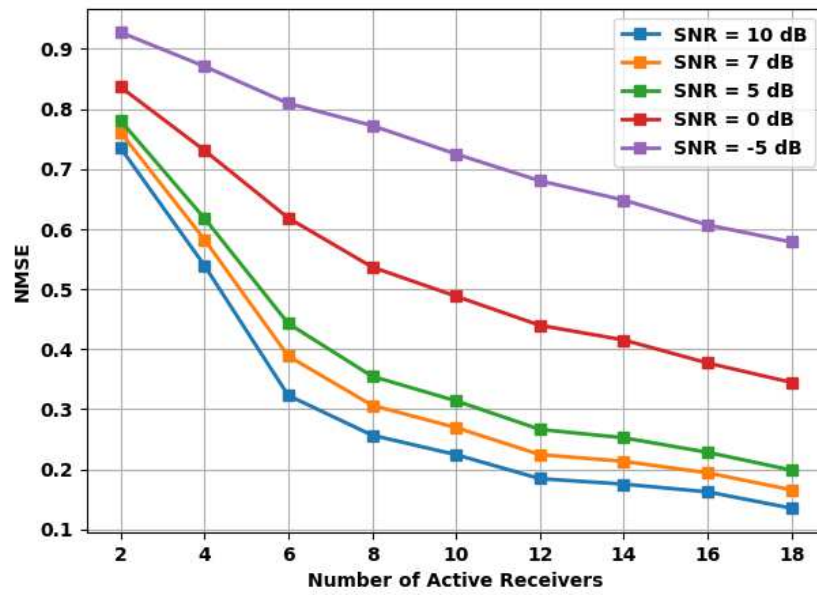


Fig 7: NMSE with respect to number of active receivers at AWGN channels

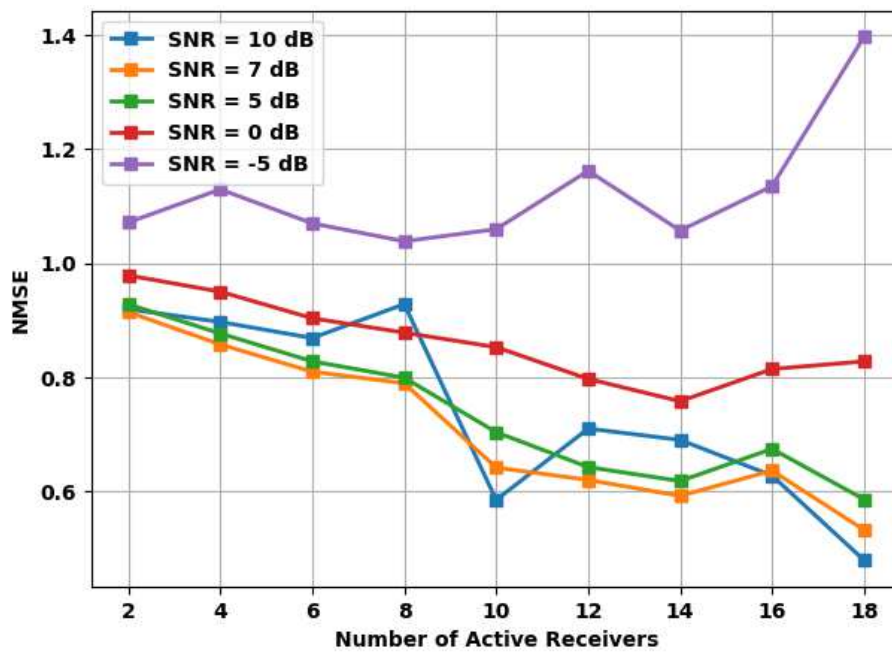


Fig 8: NMSE with respect to number of active receivers at Rayleigh channels

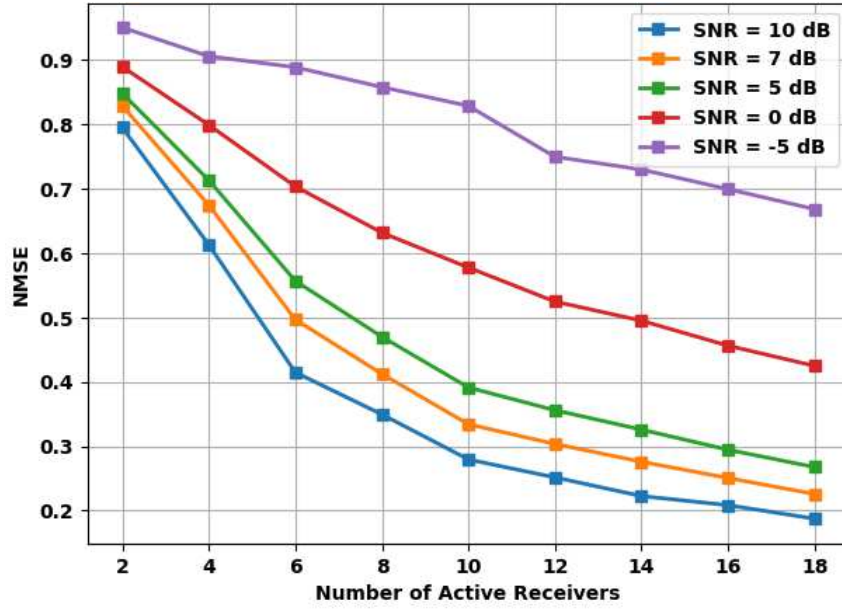


Fig 9: NMSE with respect to number of active receivers at Rician channels

A higher value of SNR results in a higher rate of decline in NMSE, as the model can then use relatively 'cleaner' or less-noisy observations. On the other hand, when the SNR value is low, the NMSE value is high due to the excess of noise, which makes the reconstruction process less accurate. Nevertheless, the proposed framework maintains a stable downward trend, which proves its effectiveness and robustness. The behavior of NMSE suggests that the joint loss function is performing very well. It balances both reconstruction accuracy and measurement consistency. This two-way objective optimization helps the model obtain accurate channel estimates, even when the observations are noisy or incomplete.

5.3 Efficiency Analysis

The efficiency that is, the ratio of the achieved rate to the optimal rate is displayed in Figures 10, 11 and 12 to show the extent of the performance gap between the proposed method and the optimal benchmark.

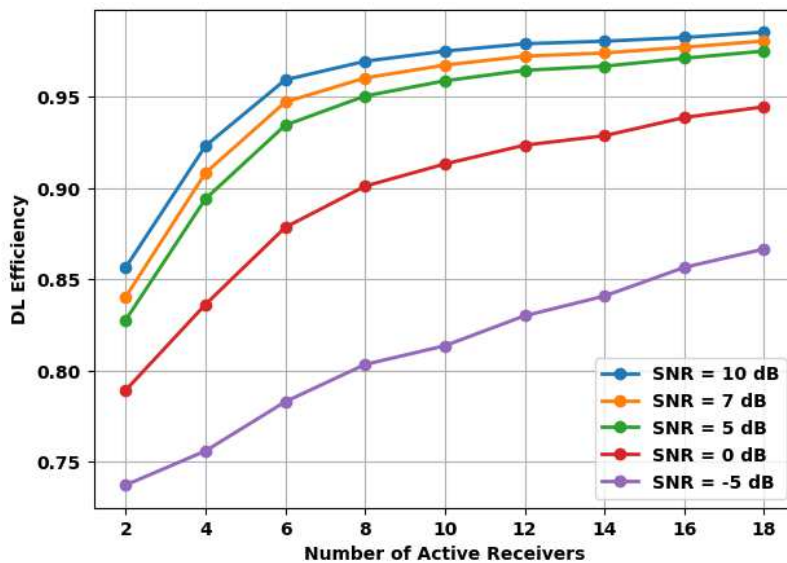


Fig 10: Deep learning efficiency with respect to number of active receivers at AWGN channels

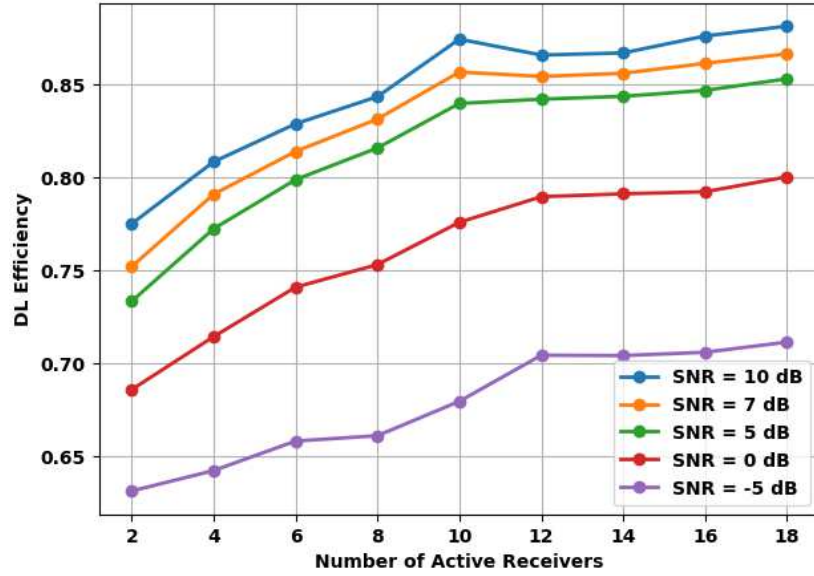


Fig 11: Deep learning efficiency with respect to number of active receivers at Rayleigh channels

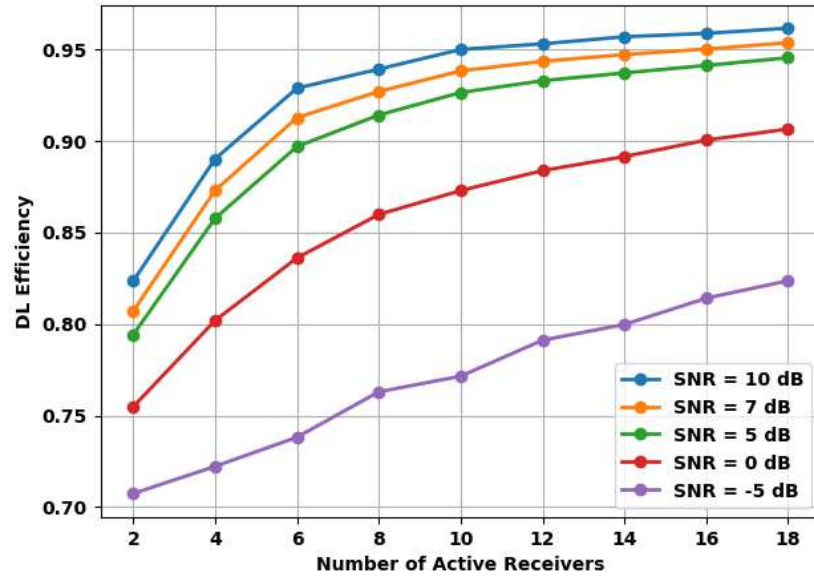


Fig 12: Deep learning efficiency with respect to number of active receivers at Rician channels

The results show that, regardless of the value of SNR or measurement format, the proposed method always achieves 70 to 88 percent of the maximum possible performance. Remarkably, the performance increases steadily as the value of $\bar{M}$ increases and reaches near-ideal levels in a fraction of the measurement compared to full channel dimensions $\bar{M} \leq N$. This is one of the best features of the proposed method: it greatly simplifies the sensing process while maintaining high spectral efficiency, which is crucial in building scalable or expandable wireless systems.

5.4 Impact of SNR-Aware Learning

An important aspect of the proposed framework is the incorporation of SNR information into the neural network. The research results show that the model works effectively even with a lot of noise or other disturbances due to this unique design feature. Instead of training the model for a specific SNR, the proposed method gives good results for a wide range of SNRs, such as -5 dB (dB) to 10 dB (dB). This adaptability of the model, or ability to adapt to changing conditions, is very useful in real-life radio communication systems, where channel conditions are constantly changing.

5.5 Training Convergence

The 'training loss' for different values of M can be seen in Figures 7, 8 and 9. It can be seen that the model converges smoothly, and the loss reduction rate remains the same in all configurations. The convergence pattern suggests that the proposed architecture and training technique are quite effective for the discussed problem. Also, models with large $\bar{M}$ values generally converge somewhat faster; because they have access to more measurement data, which facilitates the learning process. The results obtained provide several important insights into the performance of the proposed framework. First, the proposed method achieves near-optimal spectral efficiency with significantly fewer channel measurements than conventional full-CSI methods, thereby reducing sensing overhead. The results also reveal a clear trade-off between sensing complexity and system performance, where the performance improvement gradually reaches a certain limit after a certain number of active measurements. Furthermore, the addition of SNR-aware learning increases the model's robustness to variable noise and fading conditions, enabling stable operation in a wide range of channel environments. In addition, the proposed joint loss function effectively balances the reconstruction accuracy and measurement consistency, resulting in improved channel estimation quality and higher achievable rate performance. The concise result of achievable rate and efficiency is depicted in Table 2.

Table 2: Achievable Rate and Efficiency

$\bar{M}$	10 dB Efficiency	0 dB Efficiency	-5 dB Efficiency
2	77.5%	68.6%	63.1%
6	82.4%	74.1%	65.6%
10	86.7%	77.5%	67.8%
16	87.6%	79.4%	71.0%

Overall, the proposed framework has great potential for creating wireless communication systems that are easily expandable and consume less power—especially when the entire channel cannot be used.

6. Performance Gains and Comparison with Baseline Methods

Conventional baseline methods such as full-CSI optimal beamforming, random phase/estimation methods, and standard estimation methods such as Least Squares (LS) are used to compare the performance of the proposed framework. It shows that it is effective.

6.1 Advantage over Full-CSI Optimal Benchmark

The best way to do this is when Channel State Information (CSI) is perfect and performance is at its peak. This requires full channel acquisition or full channel acquisition ($N = 1024$ elements). But this is not possible in real systems, as it increases the work of signal detection or sensing too much. On the other hand, the proposed method does 87.6% of the best rate at 10 dB, then around 79.4% at 0 dB and around 71.0% at -5 dB using only $\bar{M} \ll N$ measurements.

6.2 Advantage over Random or Naïve Estimation

Methods that are random or based on heuristics don't take advantage of channel structure and usually lead to low beamforming gain.

Unlike the proposed model, learns spatial correlations in the channel from DeepMIMO data along with recovers meaningful channel structure from highly compressed observations and achieves consistent performance improvement across all SNR values.

6.3 Advantage over Traditional Estimation Methods (LS/MMSE)

Standard approaches like LS or MMSE need a bunch of measurements $\geq$ channel size ($\bar{M} \geq N$) while inverting the matrix or iterative optimization and high computational complexity. These methods don't work well when the underdetermined regime ($\bar{M} \ll N$) is present. On the other hand, the suggested method works well even with very low measurement ratios and avoids matrix inversion as opposed to explicit modeling; it uses data-driven inference.

7. Comparison with Existing Methods

Table 3: Comparison of Proposed Method with Baseline Approaches

Method	CSI Requirement	Measurement Requirement	Computational Complexity	Robust to Low SNR	Partial Observation Support	Achievable Rate Performance
Optimal (Full-CSI) [29]	Full CSI	$\bar{M} = N$	High	Moderate	No	100% (Benchmark)
LS Estimation [30]	Full/Over determined	$\bar{M} \geq N$	High (matrix inversion)	Poor	No	Low–Moderate
MMSE Estimation [31]	Full CSI + Statistics	$\bar{M} \geq N$	Very High	Moderate	No	Moderate
Random/Heuristic [32]	No CSI structure	Low	Low	Poor	Yes	Very Low
DL-Based (Conventional) [33]	High/Full CSI	Moderate to High	Medium	Limited	Partial (limited)	Moderate to High
Proposed	Partial CSI	$\bar{M} \leq N$	Medium	Strong	Yes	88% of

Method			(offline training)			Optimal
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There is a comparison between the proposed method and standard baseline approaches described in Table 3. There is evidence that traditional estimation methods like LS and MMSE need full or over-determined measurements and are very hard to compute, which means they are not good for large systems with limited sensing capabilities. The suggested method, on the other hand, works well in the undetermined regime $\bar{M} \leq N$ achieving up to 87.6% of the optimal feasible rate. In addition, the proposed framework includes SNR-aware learning and joint optimization, which makes it work well across a wide range of SNR values. This is different from other deep learning methods that rely on a lot of CSI or fixed operating conditions. These features show that the suggested method is better in terms of being scalable, efficient, and useful in real life.

8. Conclusion

In this paper, an SNR-aware deep learning framework is proposed for partial channel state information (CSI) reconstruction in large intelligent surface (LIS)-assisted wireless networks. The proposed method addresses one of the major bottlenecks in real LIS-enabled communication systems, that is, obtaining accurate channel state information under limited sensing resources. Using only a subset of channel observations, this framework reconstructs high-dimensional CSI through a residual convolutional neural network and incorporates SNR information to increase robustness to changing channel conditions. In addition, a joint loss function combining reconstruction accuracy and measurement-domain consistency is implemented to improve the reliability of channel estimation. Fully implementing the proposed framework is particularly useful for large-scale LIS-supported 6G wireless networks. Because obtaining full CSI (Channel State Information) in such networks is usually difficult, as it requires more pilot signal exchanges, hardware complexity and power consumption. Due to the low sensing or measurement requirements and data-dependent nature, this approach can be used in intelligent communication systems where efficient extraction of CSI is essential, such as ultra-dense networks, extensive machine-type communication, and other power-constrained next-generation wireless systems. Research results show that the proposed framework is capable of accurately reconstructing channel information even from incomplete observations, and its performance remains stable for different channels and signal-to-noise ratio (SNR). It strikes the best balance between the complexity of sensing and the effectiveness of communication. Future researchers can focus on practical application areas and extend this framework to multi-user and antenna-specific LIS systems. In addition, advanced propagation environments featuring user movement, time-varying channels and more complex fading or signal decay can also be explored. In addition, developing small and easy-to-understand deep learning systems, suitable for real-time or instant use on resource-limited devices will be considered an important step in the practical implementation of future 6G wireless networks.

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