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Optimize NMSE of Massive MIMO System using Machine Learning and Channel Estimation Technique

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ABSTRACT: Massive MIMO (Multiple-Input Multiple-Output) systems are key to meeting the high data rate and spectral efficiency requirements of 5G and beyond wireless networks. However, the performance of such systems largely depends on the accuracy of channel estimation. A critical performance metric in this context is the Normalized Mean Square Error (NMSE), which quantifies the accuracy of estimated Channel State Information (CSI). Traditional estimation methods such as Least Squares (LS) and Minimum Mean Square Error (MMSE) suffer from high complexity, pilot contamination, and limited adaptability to nonlinear and dynamic environments, leading to suboptimal NMSE performance. Recently, Machine Learning (ML) techniques have gained attention for enhancing channel estimation in massive MIMO. ML models, such as Convolutional Neural Networks (CNNs), Autoencoders, and Deep Neural Networks (DNNs), learn from data and can effectively capture complex channel behaviors, thereby reducing NMSE. This paper reviews the integration of ML with conventional estimation methods, highlighting architectures, training strategies, and performance improvements. It also discusses the key challenges in minimizing NMSE using ML, including data dependency, generalization, and real-time deployment. The review concludes that ML-based techniques offer promising solutions for NMSE optimization in massive MIMO systems, enabling more reliable and efficient wireless communication.

KEYWORDS: Massive MIMO, CSI, NMSE, Machine Learning, Channel Estimation

I. INTRODUCTION

Wireless communications can be regarded as the most important developing area that has an extremely wide range of applications from TV remote control and cordless phones to cellular phones and satellite-based broadcasting systems. MIMOOFDM technology has become one of the most promising solutions in the high data rate wireless channel transmissions [1, 2]. In the OFDM system with transmit diversity [3], when the receiver knows the channel information better, the space-time codes [4] can be decoded effectively. In order to enhance frequency efficiency, the receiver also needs to know the channel information for coherent detection. So channel estimation is directly related to the system performance. Clearly the performance improvement and capacity growth are based on accurate channel state information [5], which plays a significant role for MIMO-OFDM systems. The requirements of wireless communications have shifted from the low data rate voice services to real time video transmissions. Support for higher data rates [5] has become more essential and the development towards more advanced wireless systems is still ongoing. This involves the complexity of signal processing [6] algorithms in the receiver.

Among channel estimation algorithms the LS estimation is the simplest channel estimation. This algorithm has lower complexity. However, it has larger Mean Square Error (MSE) and it is easily influenced by noise and Inter Carrier Interference (ICI). LMMSE algorithm is a simplified algorithm of Minimum Mean Square Error (MMSE). Although they can achieve better performance than LS, they have higher computational-complexity and need to know the channel statistics which are usually unknown in real system. The method of least squares is a standard approach to the approximate solution of over determined systems, i.e., sets of equations in which there are more equations than unknowns. Least squares problems fall into two categories: linear or ordinary least squares and non-linear least squares, depending on whether or not the residuals are linear in all unknowns. The following discussion is mostly presented in terms of linear functions but the use of least-squares is valid and practical for more general families of functions.

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II. BACKGROUND

Industry experts as well as academicians/researchers in the communication field form all parts of the globe are working for increasing system capacity to meet the demands of new services with increased amount of data exchange, uninterrupted connectivity and seamless service quality. The three predominant design aspects listed as under are currently under investigation by industry experts to realize anticipated increase in system capacity as compared to current wireless standard.

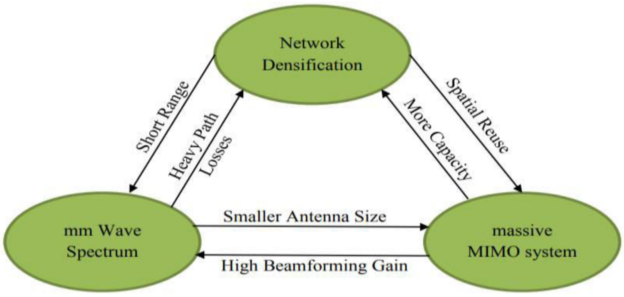

Figure 1: Relation between Three-design Aspects for Upcoming Wireless Communication Systems

- Millimeter Wave Spectrum - Shift towards higher available bandwidth
- Massive MIMO and Beamforming. - Higher Spectral Efficiency
- Small Cells - Network densification to overcome heavy path losses

The before stated three predominant design characteristics are technically interconnected with each other in several ways. The drift towards millimeter Waves will facilitate the utilization of reasonably large available bandwidth in licensed as well as unlicensed spectrum to realize anticipated system capacity. As millimeter Waves has relatively much shorter wavelengths, because of it the physical dimensions of an antenna and hence the antenna array will reduce significantly. Consequently, we will be able to fabricate the relatively large number of antenna elements in comparatively smaller physical dimensions and encourages for the utilization of large dimensional massive MIMO systems. In addition, the Small Cell Technology [3, 4] will enable us to conquer with hefty path losses linked with millimeter Wave communication. Industry experts/Academicians/Researcher are working on all three design aspects to realize anticipated increase in system capacity for 5G and other upcoming wireless communication applications/standards. The figure 1 presents a symbolic view of the evolution of associated user services from 2G to 5G.

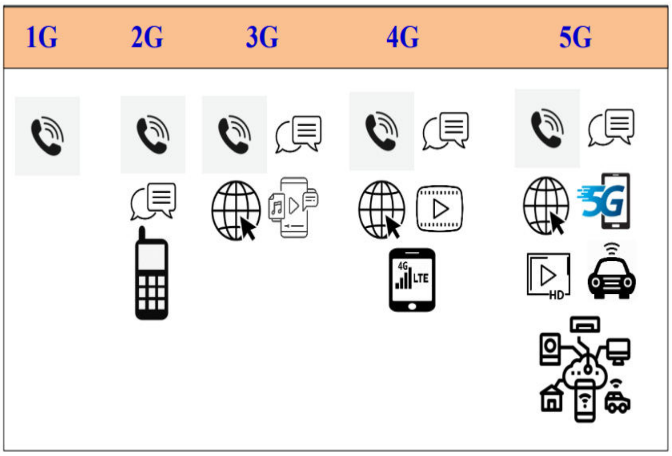

Figure 2: Evolution of Services form 2G to 5G

The upcoming wireless communication applications/standards targets both public and private sectors. These also support diverse nature of devices and associated technologies.

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III. PROPOSED METHODLOGY

The vast and accurate dataset is essential for the DL model in the data-driven mode, required for training, to evaluate the performance of the NN model. Remcom Wireless Insite provides the accurate ray-tracing scenarios dataset for different environmental conditions. The Deep MIMO dataset generation framework is utilized to construct the MIMO channels dataset. The original dataset is preferred. The data set is constructed using Deep MIMO, a Generic Deep Learning dataset for millimetre waves and Massive MIMO. It is easy to generate an accurate dataset using the framework.

A Ray tracing scenario ultimately defines the deep MIMO dataset. It was generated by an accurate 3D ray-tracing simulator wireless Insite Remcom is free to download. Ray tracing scenarios help evaluate and compare the Machine learning and deep learning algorithms. Using DL, these huge datasets help to implement MIMO signal processing like channel estimation, mm-wave beam prediction, optimum power allocation, etc. The dataset generation has two essential steps
Step 1: Select the Ray-tracing Scenario accurately obtained from Remcom Wireless Insite. It describes the nature of the environment on which the channel gain depends.
Step 2: Parameter setting for selecting the number of BS, UEs and multipaths, system bandwidth, OFDM parameters, etc.

Fig 3 shows the process of Deep MIMO dataset generation.

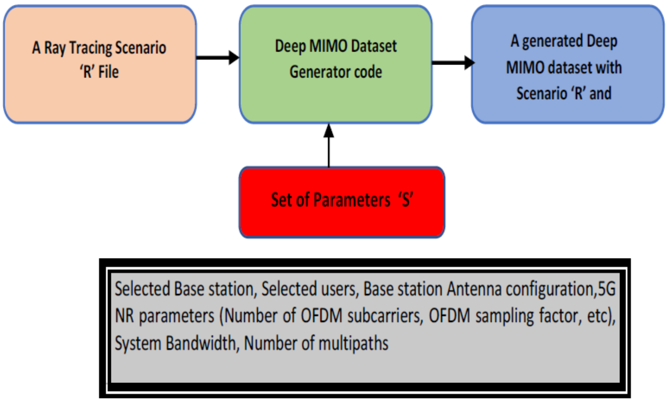

Figure 3: ML MIMO dataset generation framework

The generated dataset contains the channel gain matrix H and user location. The channel coefficients are complex and cannot be used as it is directly. The Deep Neural Network uses the labelled training and testing data, which must be real form. Thus, the pre-processing of a generated dataset is a must. Complex channel coefficients that use the maximum absolute channel value of the dataset are normalized within the range [-1 1]. The pilot symbols $\emptyset$ of length P are generated from UE and combined with the channel Coefficient matrix H. The noise w is added to the receiver. These received signals y with corresponding channel matrix H act as training data and labels. As a single UE is assumed, after Vectorizing, the received has dimension MPx1. The Channel matrix-vector and measured received vectors are separated into real and imaginary parts and then flattened to (2Mx1) and (2MP) vectors. This 70% of the processed dataset is considered for training, and the remaining 30% for testing the DL-FCNN for channel estimation.

IV. SIMULATION RESULT

Fig. 4 represents the Normalized MSE of 8×8 Massive system using channel estimation and ANN with the help of QAM-16, QAM-32 and QAM-64. QAM -64 provide best Normalized MSE compared to QAM-16. Farzana Kulsoom et al. [6] is providing NMSE 9×10^{-4} dB for common support, 9.1×10^{-4} dB for number of users and 10^{-4} dB for number of antenna at each user. The proposed scheme is provide NMSE 3×10^{-5} dB for QAM-64, 5×10^{-5} dB for QAM-32 and 6×10^{-5} dB for QAM-16. Clearly that, the proposed schemes is 16.08% improvement compared to Farzana Kulsoom [6].

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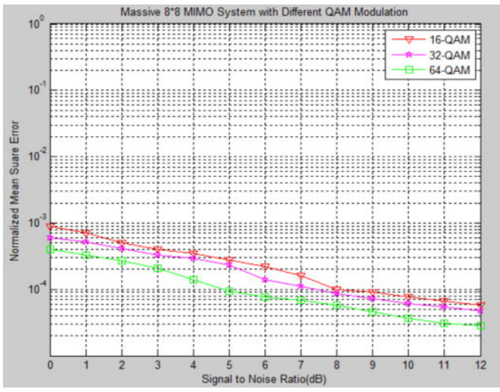

Figure 4: NMSE of Massive 8×8 System with Machine Learning based Channel Estimation Technique

Fig. 5 represents the Normalized MSE of 16×16 Massive system using channel estimation and ANN with the help of QAM-16, QAM-32 and QAM-64. QAM -64 provide best Normalized MSE compared to QAM-16. Farzana Kulsoom et al. [6] is providing NMSE 9×10^{-4} dB for common support, 9.1×10^{-4} dB for number of users and 10^{-4} dB for number of antenna at each user. The proposed scheme is provide NMSE 2×10^{-5} dB for QAM-64, 4×10^{-5} dB for QAM-32 and 5×10^{-5} dB for QAM-16. Clearly that, the proposed schemes is 19.8% improvement compared to Farzana Kulsoom [6].

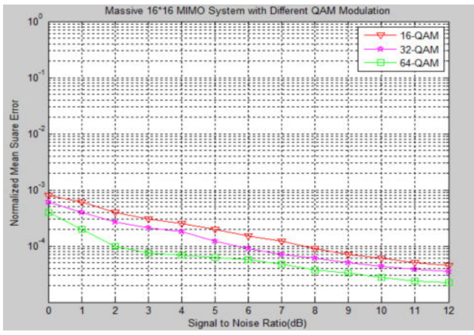

Figure 5: NMSE of Massive 16×16 System with Machine Learning based Channel Estimation Technique

Fig. 6 represents the Normalized MSE of 32×32 Massive system using channel estimation and ANN with the help of QAM-16, QAM-32 and QAM-64. QAM -64 provide best Normalized MSE compared to QAM-16. Farzana Kulsoom et al. [6] is providing NMSE 9×10^{-4} dB for common support, 9.1×10^{-4} dB for number of users and 10^{-4} dB for number of antenna at each user. The proposed scheme is provide NMSE 2×10^{-5} dB for QAM-64, 2.5×10^{-5} dB for QAM-32 and 4×10^{-5} dB for QAM-16. Clearly that, the proposed schemes is 24.6% improvement compared to Farzana Kulsoom [6].

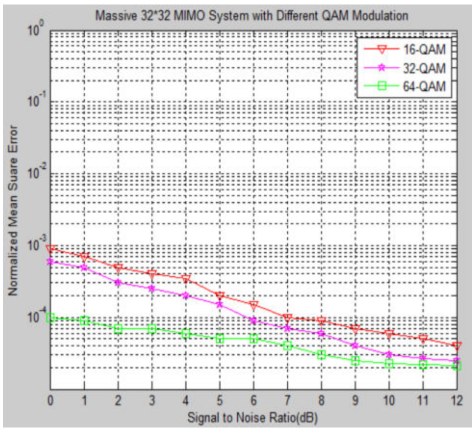

Figure 6: NMSE of Massive 32×32 System with Machine Learning based Channel Estimation Technique

V. CONCLUSION

Channel estimation plays a crucial role in the performance of massive MIMO systems, where accurate Channel State Information (CSI) directly influences system reliability, throughput, and spectral efficiency. Normalized Mean Square Error (NMSE) is a key metric used to assess the effectiveness of estimation techniques. Traditional approaches like LS and MMSE, while widely used, struggle in high-dimensional and dynamic environments due to pilot contamination, noise, and computational limitations.

Machine Learning (ML) offers a promising alternative by learning from data and modeling complex, nonlinear channel behaviors. ML-based techniques such as deep neural networks, CNNs, and autoencoders have demonstrated the ability to significantly reduce NMSE by capturing hidden patterns and efficiently reconstructing channel information, even under low SNR and high mobility conditions. Furthermore, hybrid models that combine ML with traditional methods show further potential in balancing performance and computational complexity.

Despite the advantages, challenges such as data dependency, model generalization, and real-time implementation remain. Continued research into lightweight models, transfer learning, and real-world dataset applications will be essential for practical deployment. In conclusion, optimizing NMSE using machine learning integrated with advanced channel estimation strategies holds great potential for the advancement of robust and intelligent massive MIMO communication systems.

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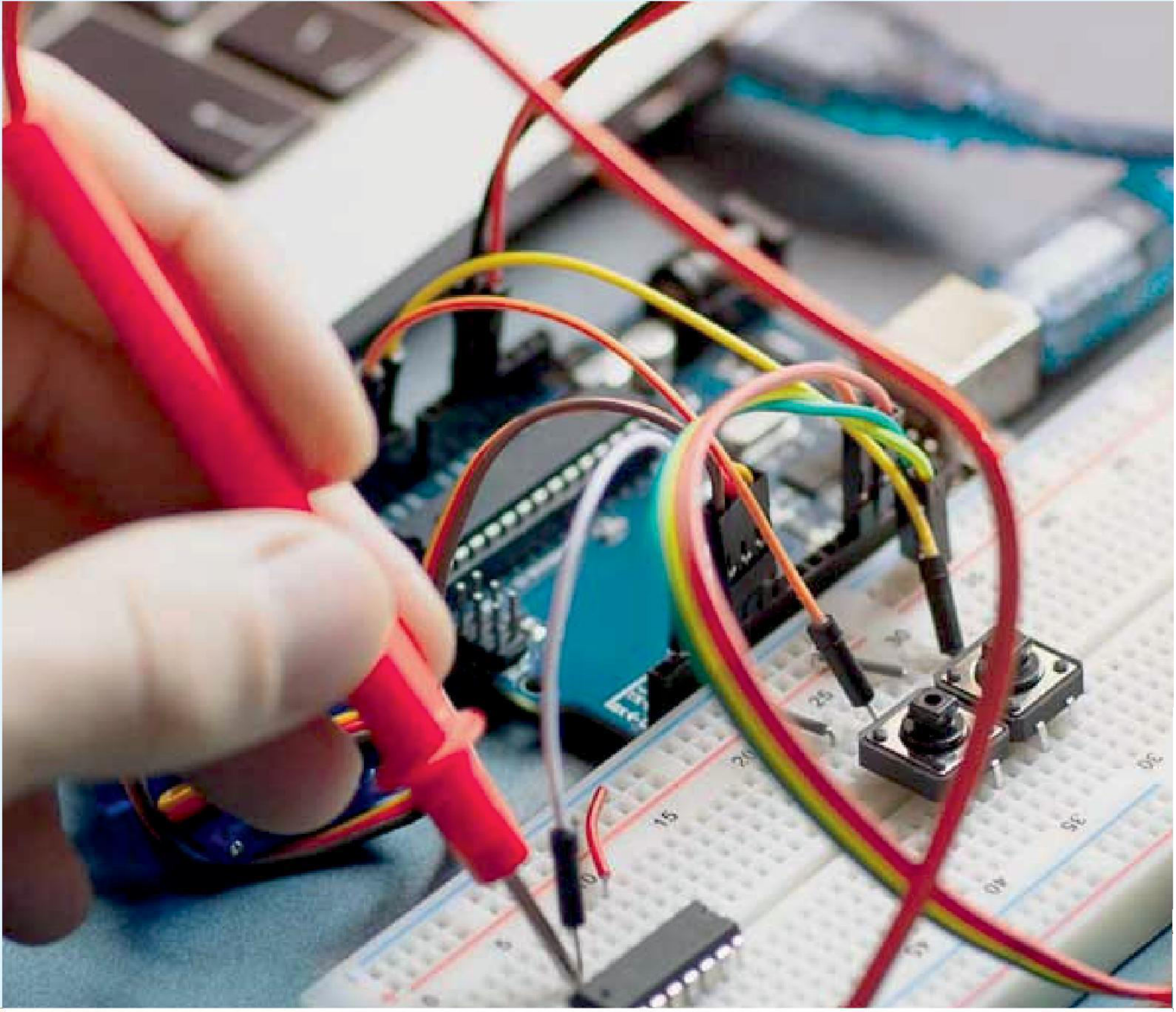

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