Minimize NMSE of Massive System using Machine Learning based Channel Estimation Technique

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Abstract—In the recent years more research is going on in 5G technology. Massive MIMO (large-scale antenna systems, covering hyper MIMO) is more attractive and different from current practice in 4G technology, through the preferred use of more service antennas over active terminals and time-division, frequency division duplex operations. More number of Antennas can be used for the channel state information (CSI) estimation, which directly affects the normalized mean square error (NMSE). To provide high performance in 5G cellular networks, Massive MIMO is one of the promising methods with simple transmit and receive operations. But it is possible only with accurate channel state information at the transmitter. Because of usage of large dimensional channels is one of the challenging issues in current research. Massive Multiple-Input Multiple-Output (MIMO) systems play a crucial role in next-generation wireless communication, offering enhanced spectral and energy efficiency. However, accurate channel estimation remains a key challenge due to high-dimensionality and hardware impairments. This paper explores machine learning-based channel estimation techniques to minimize the Normalized Mean Squared Error (NMSE) in massive MIMO systems. We review traditional estimation methods, highlight the advantages of ML-based approaches, and discuss future research directions.

Keywords— Massive MIMO, CSI, NMSE, Machine Learning, Channel Estimation

I. INTRODUCTION

With a vast array of uses ranging from mobile phones and satellite-based broadcasting systems to TV remote controls and cordless phones, wireless communications can be considered the most significant emerging field. One of the most promising approaches for high data rate wireless channel transmissions is MIMOOFDM technology [1, 2]. The space-time codes [4] can be successfully deciphered in the OFDM system with broadcast diversity [3] when the receiver has a better understanding of the channel information. The receiver must also be aware of the channel information for coherent detection in order to improve frequency efficiency. Thus, channel estimate and system performance are directly correlated. Accurate channel state information is obviously the foundation for the performance enhancement and capacity expansion [5], which is important for MIMO-OFDM systems. Real-time video transmissions have replaced phone services with low data rates as the primary demand for wireless communications. More sophisticated wireless systems are still being developed, and support for faster data rates [5] has become increasingly important. This has to do with the receiver's intricate signal processing [6] algorithms. 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.

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.

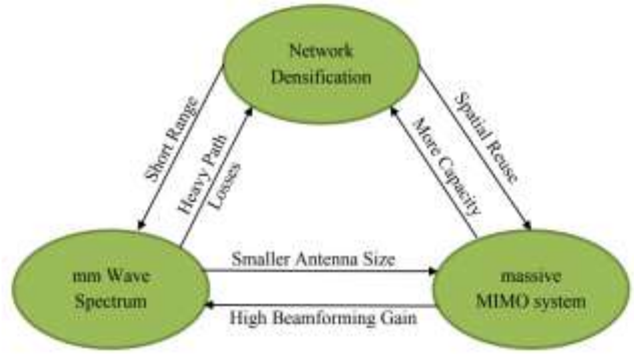

Figure 1: Relation between Three-design Aspects for Upcoming Wireless Communication Systems

- 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.

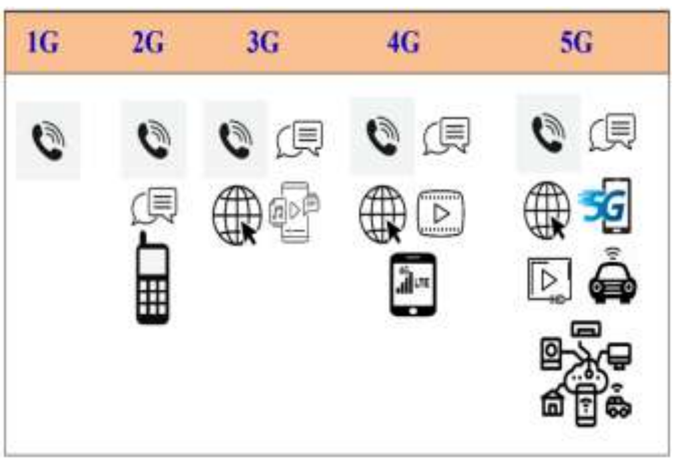

Figure 2: Evolution of Services form 2G to 5G

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

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.

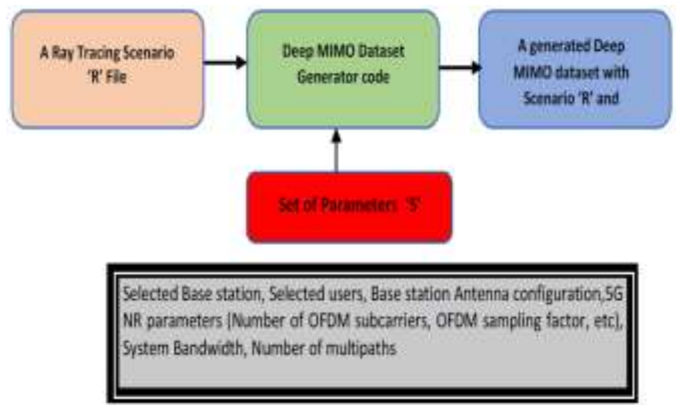

Figure 3: ML MIMO dataset generation framework

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.

VI. 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].

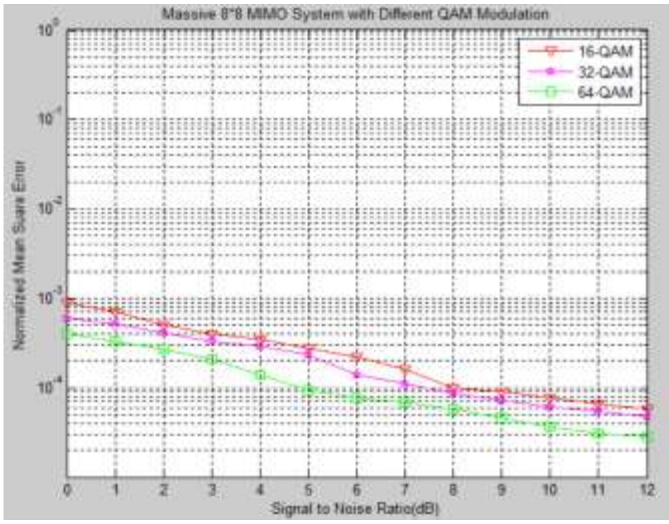

Figure 4: NMSE of Massive 8×8 System with Machine Learning based Channel Estimation Technique

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].

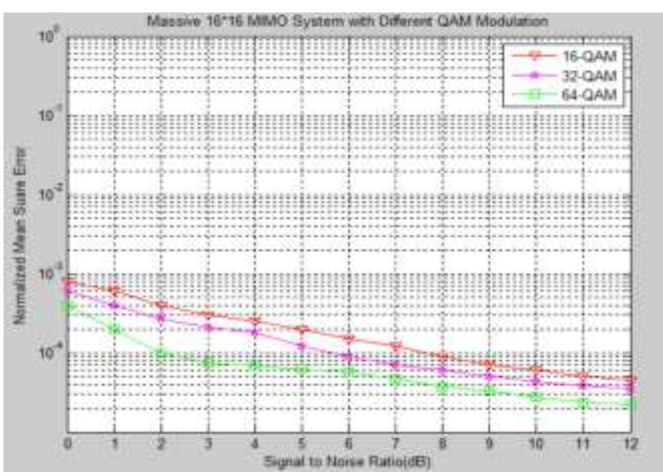

Figure 5: NMSE of Massive 16×16 System with Machine Learning based Channel Estimation Technique

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].

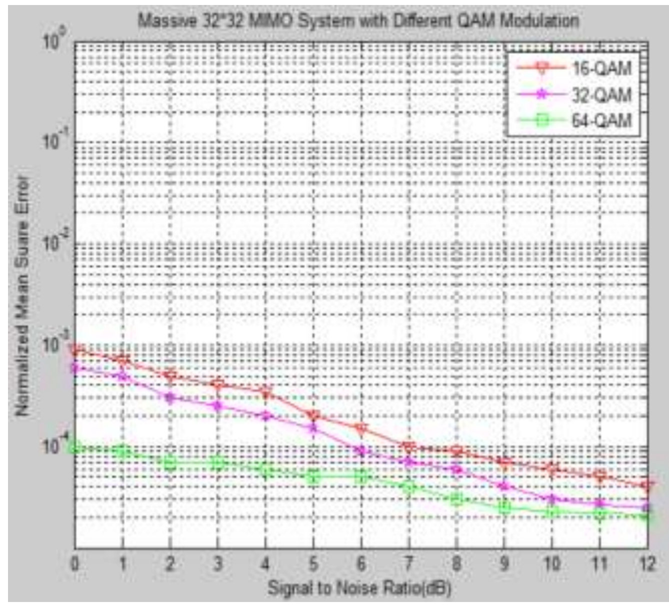

Figure 6: NMSE of Massive 32×32 System with Machine Learning based Channel Estimation Technique

VII. CONCLUSION

Machine learning-based channel estimation techniques show significant potential in minimizing NMSE for massive MIMO systems. By leveraging deep learning, unsupervised learning, and reinforcement learning, these methods outperform conventional techniques in accuracy and adaptability. Further research is required to optimize computational efficiency and enhance real-world deployment.

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