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Optimization Analysis of Massive MIMO System using Channel Estimation and Machine Learning Technique

Srishty Sinha¹, Mr. Manoj Singh Tomar²

M. Tech. Scholar, Department of Electronics and Communication, SORT, People's University, Bhopal, India¹

Associate Professor, Department of Electronics and Communication, SORT, People's University, Bhopal, India²

ABSTRACT: Massive Multiple-Input Multiple-Output (MIMO) technology is a key enabler for next-generation wireless communication systems, offering enhanced spectral efficiency, increased data rates, and improved network reliability. However, optimizing the performance of massive MIMO systems presents significant challenges, particularly in channel estimation and resource allocation. In this research, we investigate the optimization analysis of massive MIMO systems by integrating advanced channel estimation techniques with machine learning algorithms. Traditional estimation methods such as Least Squares (LS) and Minimum Mean Square Error (MMSE) suffer from high computational complexity and noise sensitivity. To address these limitations, we propose a data-driven approach leveraging machine learning-based estimators to enhance accuracy and reduce overhead. Various machine learning models, including support vector machine, decision tree are explored for efficient channel prediction and noise mitigation. Performance metrics such as bit error rate (BER), and spectral efficiency are analyzed to evaluate the effectiveness of the proposed methods. Simulation results demonstrate that integrating machine learning with channel estimation significantly improves system performance, offering a robust solution for real-world massive MIMO deployments.

KEYWORDS: Massive MIMO, Channel State Information, Machine Learning, QAM Modulation

I. INTRODUCTION

Massive Multiple-Input Multiple-Output (MIMO) technology has emerged as a cornerstone for next-generation wireless communication systems, particularly in 5G and beyond. By deploying a large number of antennas at the base station, massive MIMO significantly enhances spectral efficiency, increases data throughput, and improves network reliability. However, despite its advantages, the performance of massive MIMO systems is heavily dependent on accurate channel state information (CSI), which plays a crucial role in beamforming, signal detection, and interference mitigation [1, 2]. Traditional channel estimation techniques, such as Least Squares (LS) and Minimum Mean Square Error (MMSE), suffer from high computational complexity, increased training overhead, and sensitivity to noise, making them inefficient for large-scale antenna deployments. To address these limitations, machine learning (ML)-based approaches have gained attention due to their ability to learn complex channel characteristics and improve estimation accuracy with reduced computational burden [3]. Deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated promising results in predicting and optimizing channel parameters, leading to enhanced system performance. This research explores the integration of machine learning with channel estimation to optimize massive MIMO systems, focusing on reducing estimation errors, improving spectral efficiency, and minimizing processing latency [4, 5]. Through comprehensive simulations and performance evaluations, this study aims to provide a robust framework for intelligent channel estimation, making massive MIMO systems more adaptive and efficient for future wireless networks [6].

II. CHANNEL ESTIMATION

For rapidly-varying channels, pilot assisted channel estimation methods are popular and reliable. For a pilot assisted channel estimation method to OFDM systems, arrangement of the pilot subcarriers and their values is crucial for the overall performance. The subcarriers transmitting pilot information Symbols Subcarriers are often called pilot tones [6].

The pilot information is used at the receiver end to estimate the wireless channels. Pilot information, implies the position of the pilot subcarriers, and the values which modulate those subcarriers. Increasing the number of pilot tones improves estimation of the wireless channel, but the final throughput of the system decreases. Here different pilot arrangements of practical important are described [7, 8].

Here we are using wireless mobile OFDM transmit diversity Symbols with Alamouti code and double transmit, receive antennas at the respective stations in transmission link.

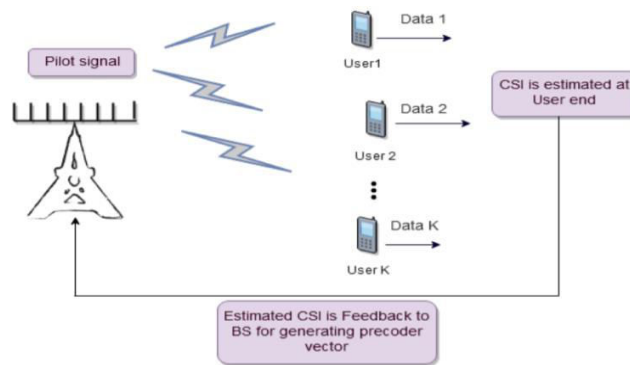


Fig. 1: Channel Estimation

The discrete-time baseband equivalent system models of the 2-parts STBC-OFDM [9] and SFBC-OFDM systems are shown in fig. 1 is implemented. The transmitter system designed depending on the one in [10], but the receiver system is different. At first, random numbers (the data to be transmitted) are created in Mat lab and mapped onto a various constellation such that the possible symbol values for example for QPSK are: $1 + j$, $1 - j$, $-1 + j$, and $-1 - j$. The modulated sequence (X) is formatted by dividing it to two blocks (X_1 and X_2) cumulatively each of them is passed through an M -point IFFT. The output of the IFFT block is M time-slotted impulses, corresponding to an OFDM frame.

III. PROPOSED METHODOLOGY

Since this work focused on supervised machine learning task classification (twitter sentiment analysis), we have used three state-of-the-art supervised machine learning models including Support Vector Machine, Naive Bayesian Classifier, and Decision Tree Classifier. These algorithms analyze the training data and produce an inferred function which can be used for making new predictions. Put simply, supervised models are firstly trained on the features extracted in the previous step, and then trained model is used for making the predictions on test set. Figure 2 presents the general model for supervised learning. Thus, classification is a two-step process including learning and prediction as shown below in figure. Importantly, training set must be labelled for supervised machine learning task. Though test set is also labelled but labels of test instances are not known to models. Models are exposed to the known labels of only training data. Thus, it is essential to always have separate train and test data. It is important to note that, for benchmark dataset that we have used in this work has separate training and test set. That is, we used 80% of corpus for training and 20% for testing. It is important to note that, 20% testing corpus is unseen during the classifier training. After splitting only, models are trained on train set only. Moreover, we would be presenting the experimental results of each classifier with both real-time and benchmark dataset.

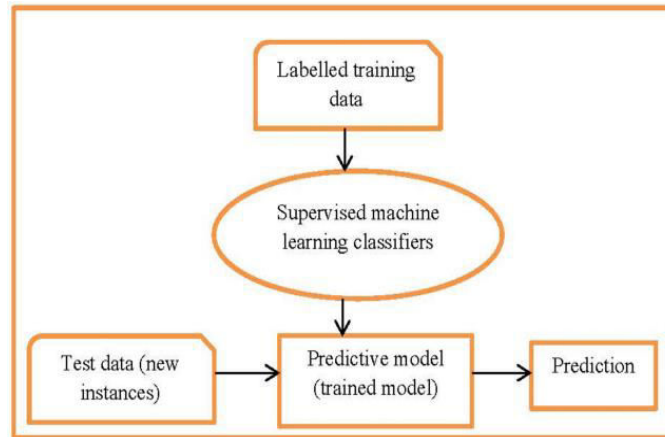


Fig. 2: General model of supervised classifiers

Support Vector Machine

SVM is the most popular and widely used supervised machine learning model (algorithm) for the task of classification (outputs a discrete class) and regression (outputs continuous value) both. Though it can be used for the regression, but it is most popular for the classification task. It has been used by many of the earlier works in their sentiment analysis task. Even the most popular SemEval-tasks also witnessed the usage of SVM by the top participants. The main goal of SVM is to generate a hyperplane (in N-dimensional space) to segregate dataset into classes. Hyperplane can be seen as decision boundary that classifies the data points distinctly. Importantly, it tries to find a hyperplane that have maximum margin from nearest elements of classes. The points closest to the hyperplane are known as support vectors. Support vectors affect the orientation and position of hyperplane. When margin gets maximum, then we get the optimal hyperplane. Figure 3 shows the SVM model. Put simply, SVM aim is to widen the distance among the classes through generating well defined hyperplane (decision boundary). If the no. of dimensions are 2, then decision boundary (hyperplane) is a line. If no. of dimensions (features) are 3, then hyperplane is 2- dimensional. For more than 3 features, it's decision boundary is hyperplane.

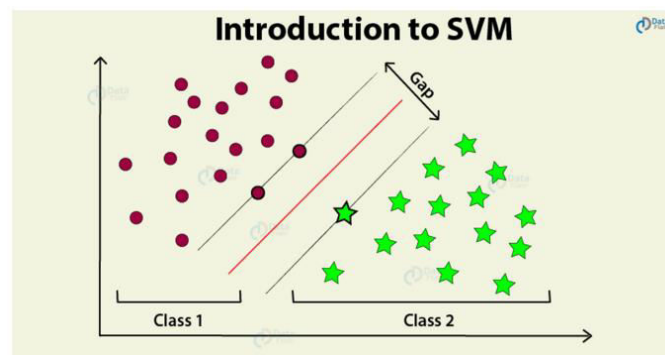


Fig. 3: SVM Model working

Decision Tree Classifiers

Decision Tree model is popular and easiest non-parametric supervised algorithm, used for both regression and classification. Decision tree is just like a tree having internal nodes, branches, and leaf node. Each internal node epitomizes feature, branches signifies a decision rule, and finally labels or classes are represented by the leaf node.

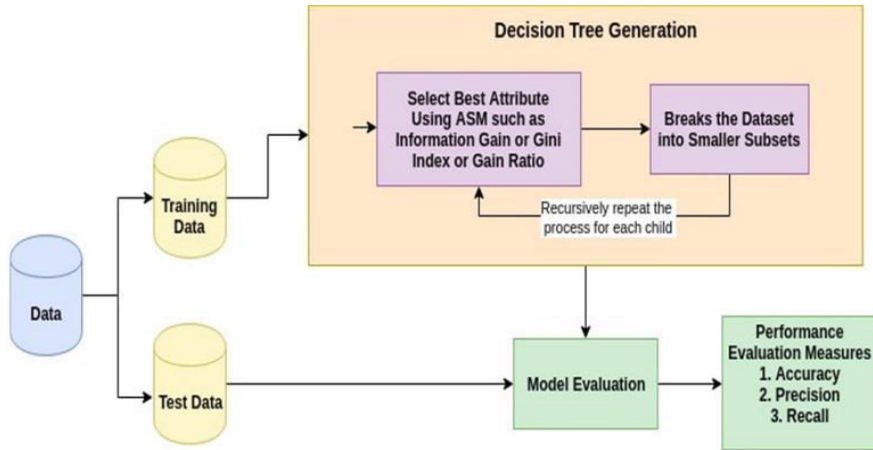


Fig. 4: Working of Decision Tree algorithm

Tree partitioning is done in a recursive manner and it learns to divide the tree based on the value of attribute. The main goal is to predict the target variable value through learning decision rules concluded from the features. The entire working of DTC is shown in below figure 4.

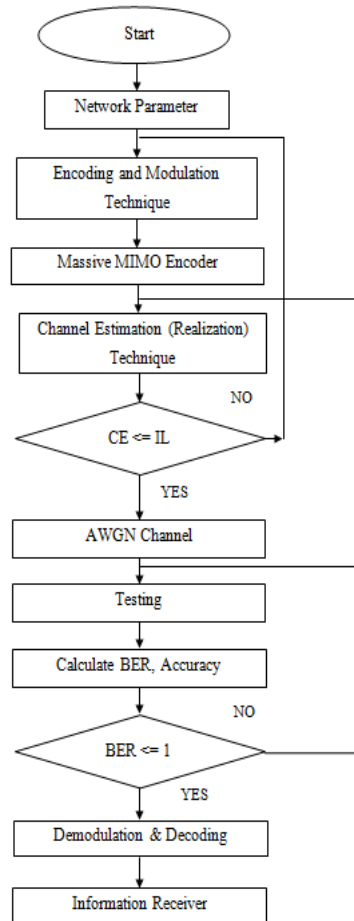


Fig. 5: Flow Chart of Proposed Methodology

- Step 1: Input
- Step 2: Enter network Parameter
- Step 3: Encoding and Modulation Technique
 - (3.1) Encoding with the help of non-return to zero (NRZ) technique
 - (3.2) Modulation with the help of QAM-64 and QAM-128 technique
- Step 4: Massive MIMO Encoder
- Step 5: Applied Channel Estimation
 - (5.1) Channel Estimation using RLS Technique
- Step 6: Channel
 - (6.1) if
 - (6.2) (Channel Estimation \geq Input Layer (IL))
 - (6.3) end if;
- Step 7: AWGN Channel
- Step 8: ANN (Testing)
- Step 9: Calculate BER, Accuracy
- Step 10: Error
 - (10.1) if
 - (10.2) (BER \leq 1)
 - (10.3) end if;
- Step 12: Demodulation & Decoding
- Step 13: Information received
- Step 14: Stop.

IV. SIMULATION RESULT

Fig. 6 represents the BER of 32×32 Massive system using machine learning based channel estimation with the help of QAM-16, QAM-32 and QAM-64. QAM -64 provide best BER compared to QAM-16. Zhitong Xing et al. [1] is provide BER 8.2 dB of 10^{-4} SNR for companding schemes, 9.3 dB for HCC, FHCC and MHCC scheme and 9.2 dB for SSPA schemes. The proposed scheme is provide 8.0 dB of QAM-16, 7.5 dB of QAM-32 and 7.0 dB QAM-64 for 10^{-4} SNR. Clearly that, the proposed schemes is 14.36% improvement compared to Zhitong Xing et al. [1].

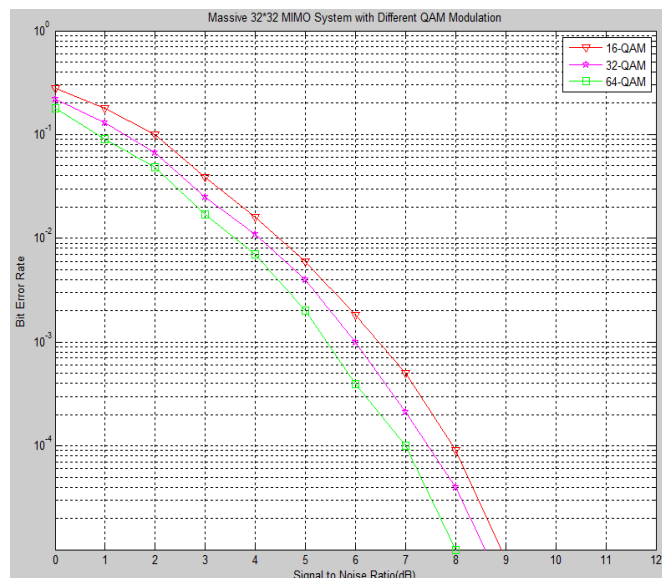


Fig. 6: BER of Massive 32×32 System with Machine Learning based Channel Estimation Technique

Fig. 7 represents the spectrum efficiency of 32×32 Massive system using machine learning based channel estimation with the help of QAM-16, QAM-32 and QAM-64. QAM -64 provide best spectrum efficiency compared to QAM-16. Mustafa S. Aljumaily et al. [2] is providing spectrum efficiency 22 bits/s/Hz of 15 SNR for 16×4 systems, 40 bits/s/Hz for 64×16 systems and 51 bits/s/Hz for 144×36 systems. The proposed scheme is provide spectrum efficiency 88 bits/s/Hz for QAM-64, 83 bits/s/Hz for QAM-32 and 81 bits/s/Hz for QAM-16. Clearly that, the proposed schemes is 12.06% improvement for QAM-64 compared to Mustafa S. Aljumaily et al. [2].

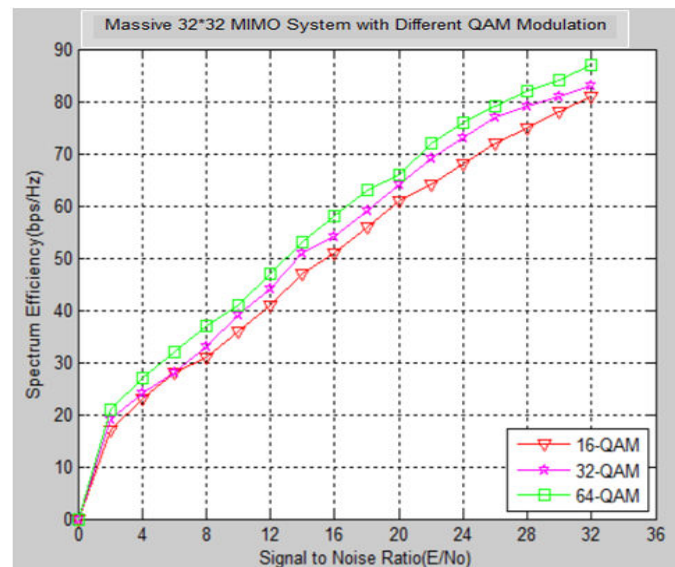


Fig. 7: Spectrum Efficiency of Massive 32×32 System with Machine Learning based Channel Estimation Technique

V. CONCLUSION

In this research, we analyzed the optimization of massive MIMO systems by integrating advanced channel estimation techniques with machine learning approaches. Traditional channel estimation methods, such as LS and MMSE, suffer from high computational complexity and reduced accuracy in dynamic wireless environments. To overcome these challenges, machine learning-based techniques, including deep learning models like CNNs and RNNs, were explored for efficient channel prediction and noise mitigation. Simulation results demonstrated that ML-driven channel estimation significantly enhances system performance by reducing estimation errors, improving spectral efficiency, and minimizing processing latency. The findings highlight the potential of artificial intelligence in optimizing massive MIMO networks, making them more adaptive to varying channel conditions and reducing overall computational overhead. Future research could explore hybrid ML models and real-time implementation to further enhance the robustness of these techniques in practical wireless communication scenarios.

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