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OPTIMIZATION SPECTRUM EFFICIENCY AND BER OF MASSIVE MIMO SYSTEMS USING MACHINE LEARNING

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Abstract: The fifth era of portable correspondence frameworks (5G) guarantees exceptional degrees of network and nature of administration to fulfill the unremitting development in the quantity of versatile savvy gadgets and the colossal expansion in information interest. One of the essential ways 5G organization innovation will be achieved is through network densification, specifically expanding the quantity of radio wires per site and sending increasingly small cells. Monstrous MIMO, where MIMO represents different info various result, is broadly expected to be a key empowering influence of 5G. This innovation influences a forceful spatial multiplexing, from utilizing countless sending/getting radio wires, to duplicate the limit of a remote channel. The passages (Aps) are associated, through a fronthaul network, to a CPU which is liable for planning the intelligible joint transmission. Such a dispersed design gives extra-large scale variety, and the co-handling at various APs altogether smothers the between cell impedance. Contingent upon slow/quick channel blurring conditions, a few creators recommended versatile LMS, RLS and NLMS based channel assessors, which either require factual data of the channel or are not proficient enough concerning execution or calculations. To conquer the above impacts, the work centers around the machine learning based channel estimation technique for Massive MIMO system with 16-QAM, 32-QAm and 64-QAM modulations. The 32×32 Massive MIMO system is simulated MARLAB software and simulated spectrum efficiency and bit error rate (BER).

***Index Terms* - Massive MIMO, Channel State Information, Machine Learning, QAM Modulation**

I. INTRODUCTION

Due to the special features of antenna diversity space time block code is suitable for high transmission rates as in OFDM. It is important to note that for any wireless mobile system inter block interference is and inter carrier interference play important role.
The former is selected to time variation of channel dispersion whereas the latter is due to temporal channel variations .IBI can be eliminated by CP cyclic Prefix. ICI reduction is also possible by alternate means but as the complexity of receiver increases. Cancellations of interference need the very accurate channel estimation. So the performance methods for mitigation of ICI is Space block code which gives enhanced spatial diversity for selective channel with fading [1, 2]. Conventional Alamouti Space time block coding is applicable for blocks of data symbols and not on individual symbols [3].
For eliminating the problems due to variation of speedy channels with respect to time, orthogonally designed symbols may be transmitted in adjacent subcarriers instead of on the same sub carriers of the successive system of OFDM. The additional advantage is the reduction of delay in transmission. This applies to channels with relatively in low frequency. Moreover a large number of subcarriers can be adopted making space very close. Basically SFBC [4, 5] eliminates the effect of time variants. The demerit is that the overall performance is lowered when frequency selectivity is high in which the steadiness of the channel coefficients can be taken for granted.

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.

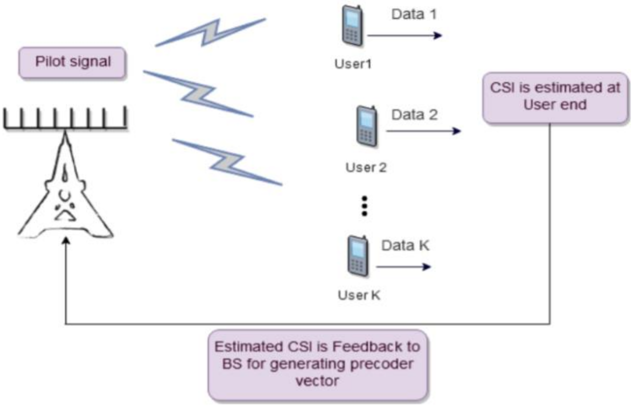

Fig. 1: Channel Estimation

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.

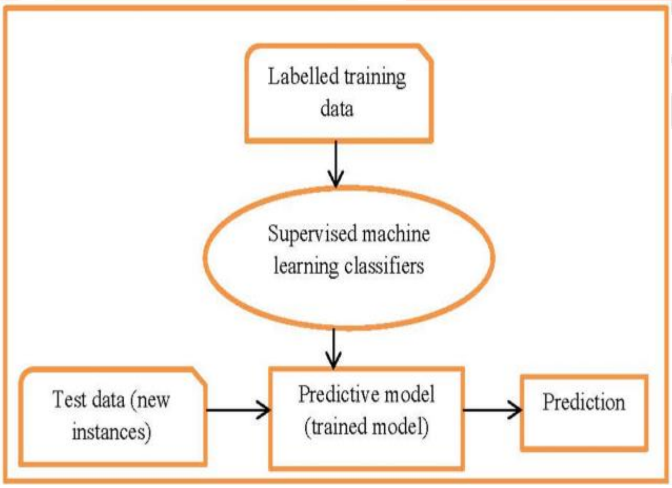

Fig. 2: General model of supervised classifiers

Naive Bayesian Classifier

It is a text classification model based on Bayes rule, which says that each feature is independent of each other i.e. there is no correlation between two features. It is simple and fast algorithm which can handle both real and discrete data. The NB fundamental assumption is that each feature contributes equally to the outcome. Though this assumption seems to be impractical in the real world scenario, but it works well quite often. Moreover, NB algorithm relies on the BOW representation of text. Bag-of-Words is collection of sentiment words and their count. The basic idea is to look a textual document (tweet in our case) by the list of words and count and throwing away everything else that is position of word and context.

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 positon 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.

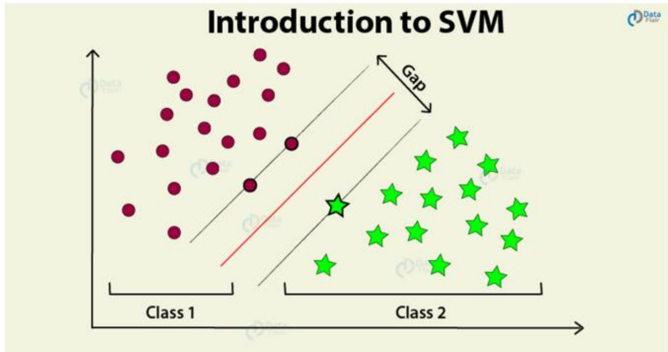

Fig. 3: SVM Model working

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. 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.

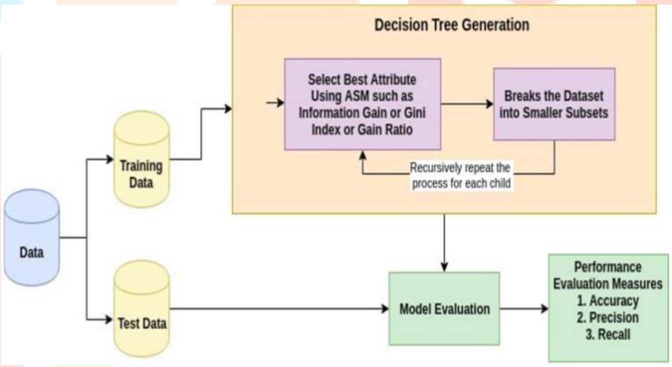

Fig. 4: Working of Decision Tree algorithm

Fig. 5 shows the Single-cell Massive MIMO system with M BS antennas serving single-antenna users and assuming that each antenna of BS has a single RF chain consisting of a 1-bit Analog to a Digital Converter (ADC). The channel model behaves as a multipath adding channel. After modulation, the signal travels through different L paths with complex gain and angle of arrival. The received is used as input to the proposed Deep Learning-based Fully connected neural Network architecture (DL-FCNN) and gives estimated channel as an output. Fig 4.7 the channel estimation process.

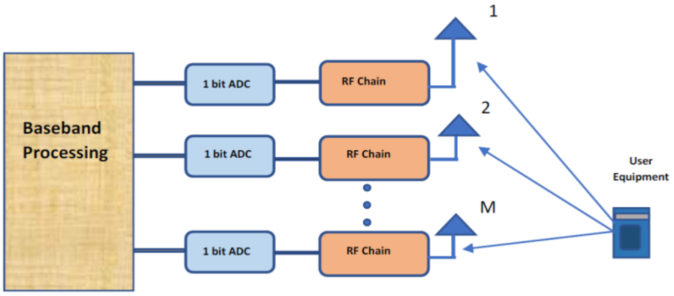

Fig. 5: Single-Cell Massive MIMO for channel estimation with a single user

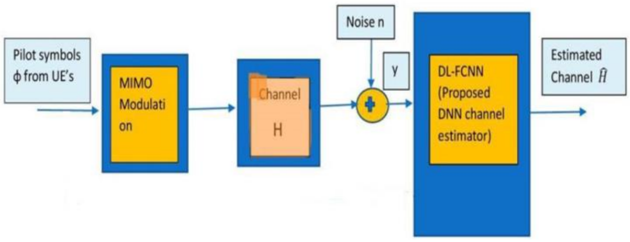

Fig. 6: Channel estimation process

IV. SIMULATION RESULT

Fig. 7 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].

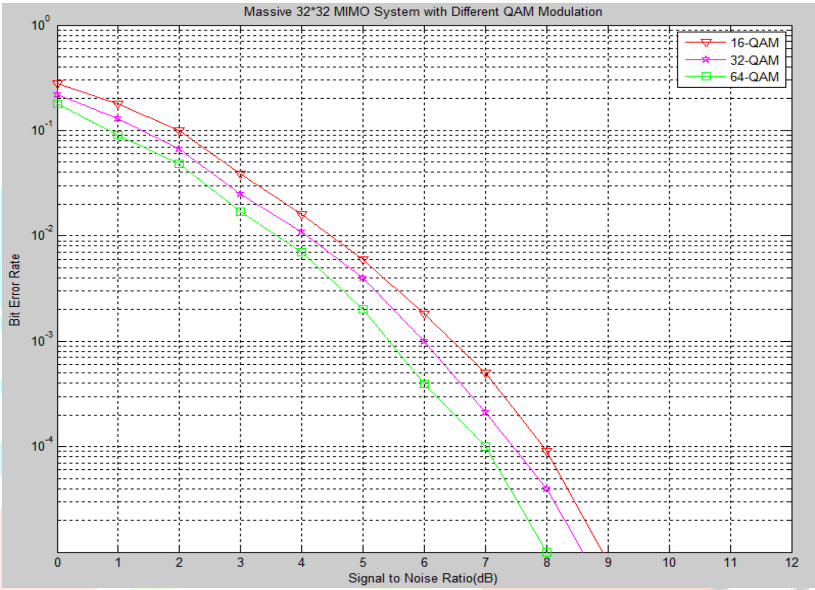

Fig. 7: BER of Massive 32×32 System with Machine Learning based Channel Estimation Technique

Fig. 8 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. [1] 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. [1].

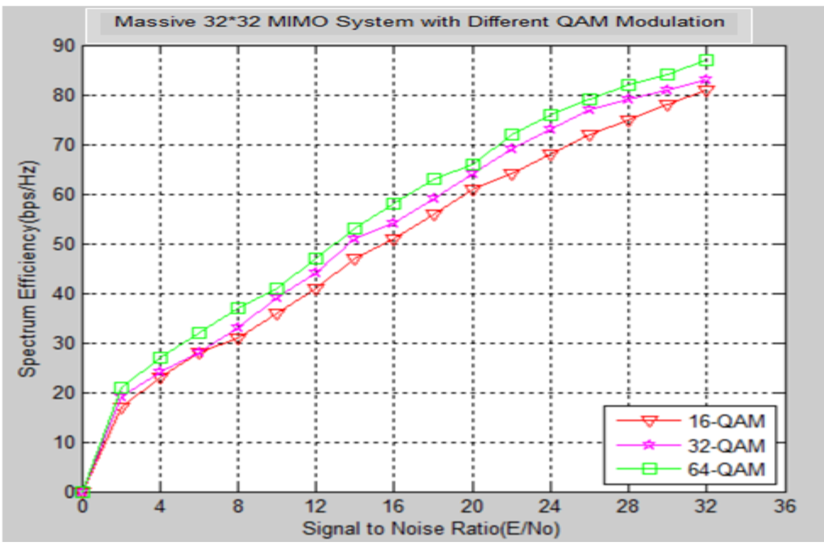

Fig. 8: Spectrum Efficiency of Massive 32×32 System with Machine Learning based Channel Estimation Technique

V. CONCLUSION

A scheme of massive MIMO is used and compared with the performance of previous design. By employing diversity schemes along with QAM-16, QAM-32 and QAM-64 for the channel estimation is performance of 32x32 massive MIMO systems. So as number of antennas used at the transmitter and receiver side increases BER decreases with respect to SNR. 16-QAM, 32-QAM and 64-QAM, modulation over a fading channel, Raleigh channel also are being considered.

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