IJAREEIE

e-ISSN: 2278-8875
p-ISSN: 2320-3765

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

Volume 11, Issue 10, October 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.18

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE)

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 10, October 2022||

|DOI:10.15662/IJAREEIE.2022.1110008 |

mmWave-Massive-MIMO System and Hybrid Beamforming Design

Iftkhar Alam Khan[1], **Prof. Devendra Kumar Raghav**[2]

Research Scholar, Dept. of Electronics and Communication Engineering, RJIT, Gwalior, India[1]

Professor, Dept. of Electronics and Communication Engineering, RJIT, Gwalior, India[2]

ABSTRACT*:* Beamforming is a technique used to improve the signal-to-noise ratio of received signals, eliminate undesirable interference sources, and focus transmitted signals to specific locations. Beamforming is central to systems with sensor arrays, including MIMO wireless communications systems such as 5G, LTE, and WLAN. Implementation of mMIMO systems at mmWave frequencies resolve the issue of high path-loss by providing higher antenna gains. The motivation for this research work is that mmWave and mMIMO operations will be much more popular in 5G NR, considering the wide deployment of mMIMO in major frequency bands as per 3rd generation partnership project. In this paper, a downlink multi-user mMIMO (MU-mMIMO) hybrid beamforming communication system is designed with multiple independent data streams per user and accurate channel state information. It emphasizes the hybrid precoding at transmitter and combining at receiver of a mmWave MU-mMIMO hybrid beamforming system. Results of this research work give the tradeoff between multiple data streams per user and required number of BS antennas. It strongly recommends for higher number of parallel data streams per user in a mmWave MU-mMIMO systems to achieve higher order throughputs.

KEYWORDS*:* Radio transmitter, beamforming, precoding, deep learning, convolutional neural networks

I. INTRODUCTION

Modern wireless communication systems use spatial multiplexing to improve the data throughput within the system in a scatterer rich environment. In order to send multiple data streams through the channel, a set of precoding and combining weights are derived from the channel matrix. Then each data stream can be independently recovered. Those weights contain both magnitude and phase terms and are normally applied in the digital domain. One example of simulating such a system can be found in the Improve SNR and Capacity of Wireless Communication Using Antenna Arrays example. In the system diagram shown below, each antenna is connected to a unique transmit and receive (TR) module.

The ever growing demand for high data rate and more user capacity increases the need to use the spectrum more efficiently. As a result, the next generation, 5G, wireless systems will use millimeter wave (mmWave) band to take advantage of its wider bandwidth. In addition, 5G systems deploy large scale antenna arrays to mitigate severe propagation loss in the mmWave band. However, these configurations bring their unique technical challenges.

Compared to current wireless systems, the wavelength in the mmWave band is much smaller. Although this allows an array to contain more elements with the same physical dimension, it becomes much more expensive to provide one TR module for each antenna element. Hence, as a compromise, a TR switch is often used to supply multiple antenna elements. This is the same concept as the subarray configuration used in the radar community. One such configuration is shown in the following figure.

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 10, October 2022||

|DOI:10.15662/IJAREEIE.2022.1110008 |

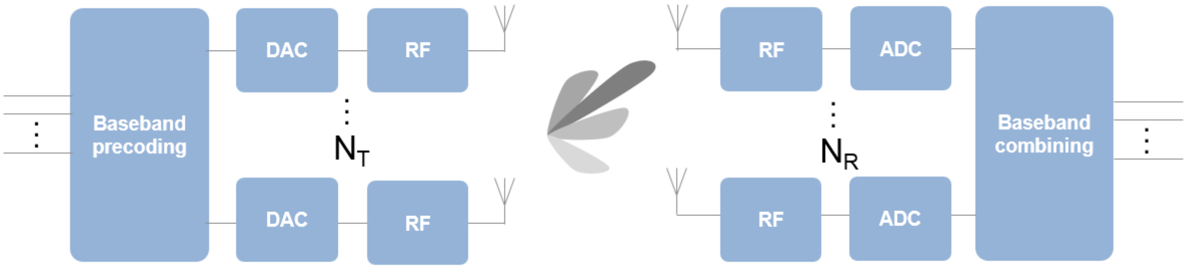

Fig.1 : System diagram for MIMO-OFDM hybrid beamforming

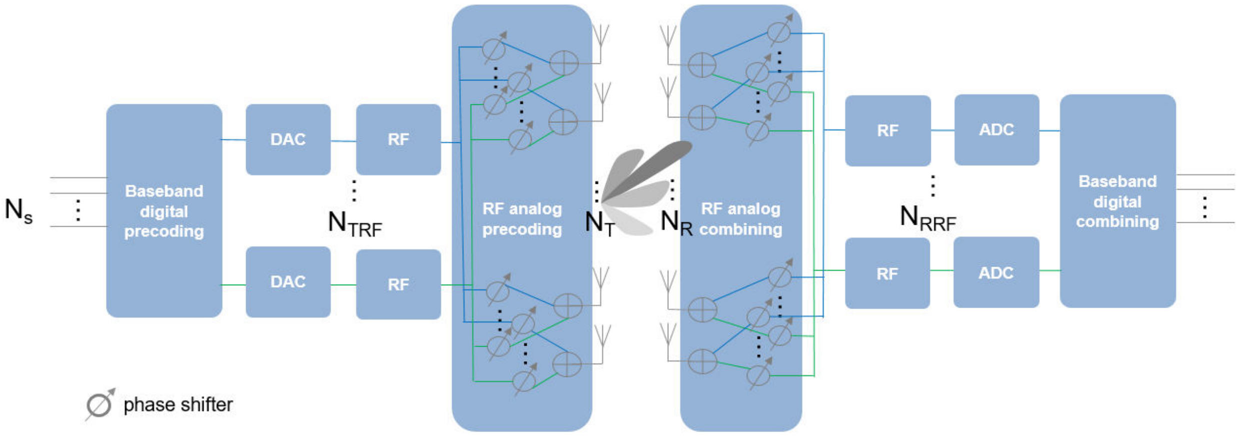

Fig.2 : System diagram for MIMO-OFDM hybrid beamforming with phase shifter connections

The figure above shows that on the transmit side, the number of TR switches, N_T^{RF}, is smaller than the number of antenna elements, N_T. To provide more flexibility, each antenna element can be connected to one or more TR modules. In addition, analog phase shifters can be inserted between each TR module and antenna to provide some limited steering capability. The configuration on the receiver side is similar, as shown in the figure. The maximum number of data streams, Ns, that can be supported by this system is the smaller of N_T^{RF} and N_R^{RF}. In this configuration, it is no longer possible to apply digital weights on each antenna element. Instead, the digital weights can only be applied at each RF chain. At the element level, the signal is adjusted by analog phase shifters, which only changes the phase of the signal. Thus, the precoding or combining are actually done in two stages. Because this approach performs beamforming in both digital and analog domains, it is referred to as hybrid beamforming.

II. SYSTEM MODEL

This section simulates a 64 x 16 MIMO hybrid beamforming system, with a 64-element square array with 4 RF chains on the transmitter side and a 16-element square array with 4 RF chains on the receiver side. In this simulation, it is assumed that each antenna is connected to all RF chains. Thus, each antenna is connected to 4 phase shifters. Such an array can be modeled by partitioning the array aperture into 4 completely connected subarrays. To maximize the spectral efficiency, each RF chain can be used to send an independent data stream. In this case, the system can support up to 4 streams.

Next, assume a scattering environment with 6 scattering clusters randomly distributed in space. Within each cluster, there are 8 closely located scatterers with an angle spread of 5 degrees, for a total of 48 scatterers. The path gain for each scatterer is obtained from a complex circular symmetric Gaussian distribution.

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 10, October 2022||

|DOI:10.15662/IJAREEIE.2022.1110008 |

III. RESEARCH METHODOLOGY

In this work we have calculated the precoding and combining weights in following steps.

A. Hybrid Weights Computation

In a spatial multiplexing system with all digital beamforming, the signal is modulated by a set of precoding weights, propagated through the channel, and recovered by a set of combining weights. Mathematically, this process can be described by Y = (X*F*H+N)*W where X is an Ns-column matrix whose columns are data streams, F is an Ns × Nt matrix representing the precoding weights, W is an Nr × Ns matrix representing the combining weights, N is an Nr-column matrix whose columns are the receiver noise at each element, and Y is an Ns-column matrix whose columns are recovered data streams. Since the goal of the system is to achieve better spectral efficiency, obtaining the precoding and combining weights can be considered as an optimization problem where the optimal precoding and combining weights make the product of F*H*W' a diagonal matrix so each data stream can be recovered independently.

In a hybrid beamforming system, the signal flow is similar. Both the precoding weights and the combining weights are combinations of baseband digital weights and RF band analog weights. The baseband digital weights convert the incoming data streams to input signals at each RF chain and the analog weights then convert the signal at each RF chain to the signal radiated or collected at each antenna element. Note that the analog weights can only contain phase shifts.

Mathematically, it can be written as $F=F_{bb}*F_{rf}$ and $W=W_{bb}*W_{rf}$, where F_{bb} is an Ns × N_t^{RF}matrix, F_{rf}an N_t^{RF} × N_t matrix, W_{bb} an N_r^{RF} × Ns matrix, and W_{rf}an N_r × N_r^{RF} matrix. Since both F_{rf} and W_{rf} can only be used to modify the signal phase, there are extra constraints in the optimization process to identify the optimal precoding and combining weights. Ideally, the resulting combination of $F_{bb}*F_{rf}$ and $W_{rf}*W_{bb}$ are close approximations of F and W that are obtained without those constraints.

Unfortunately, optimizing all four matrix variables simultaneously is quite difficult. Therefore, many algorithms are proposed to arrive at suboptimal weights with a reasonable computational load. This example uses the approach proposed in [1] which decouples the optimizations for the precoding and combining weights. It first uses the orthogonal matching pursuit algorithm to derive the precoding weights. Once the precoding weights are computed, the result is then used to obtain the corresponding combining weights.

Assuming the channel is known, the unconstrained optimal precoding weights can be obtained by diagonalizing the channel matrix and extracting the first N_t^{RF} dominating modes. The transmit beam pattern can be plotted.

A. Signal Propagation

The example offers an option for spatial MIMO channel and a simpler static-flat MIMO channel for validation purposes. The scattering model uses a single-bounce ray tracing approximation with a parametrized number of scatterers. For this example, the number of scatterers is set to 100. The 'Scattering' option models the scatterers placed randomly within a sphere around the receiver, similar to the one-ring model [6]. The channel models allow path-loss modeling and both line-of-sight (LOS) and non-LOS propagation conditions. The example assumes non-LOS propagation and isotropic antenna element patterns with linear or rectangular geometry. The same channel is used for both sounding and data transmission. The data transmission has a longer duration and is controlled by the number of data symbols parameter, prm.numDataSymbols. The channel evolution between the sounding and transmission stages is modeled by prepending the preamble signal to the data signal. The preamble primes the channel to a valid state for the data transmission, and is ignored from the channel output. For a multi-user system, independent channels per user are modeled.

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 10, October 2022||

|DOI:10.15662/IJAREEIE.2022.1110008 |

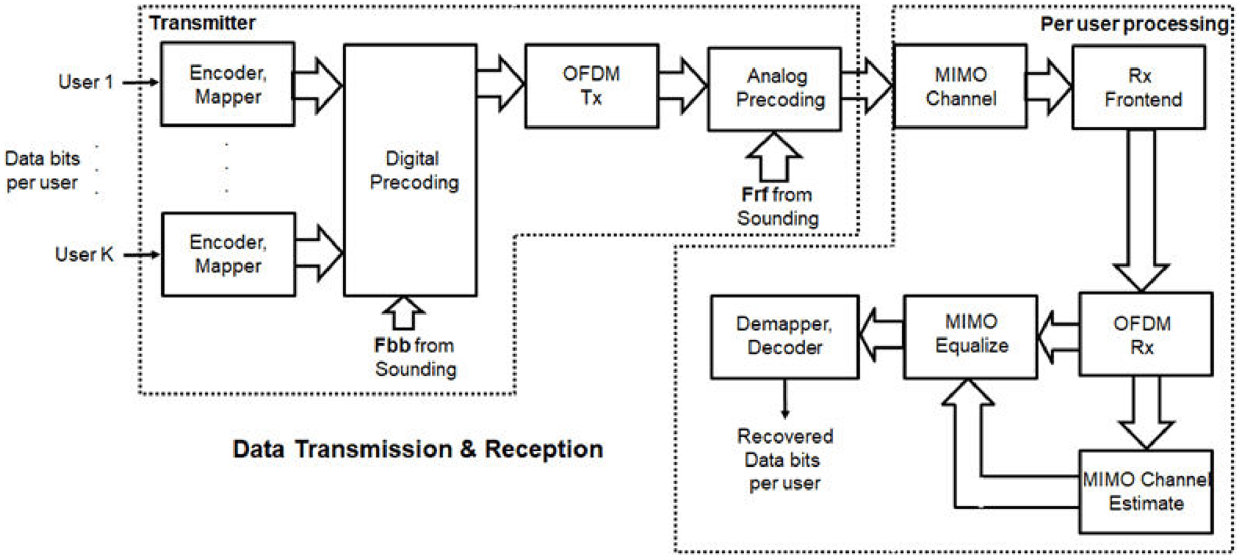

Fig. 3: System block diagram

The receiver modeled per user compensates for the path loss by amplification and adds thermal noise. Like the transmitter, the receiver used in a MIMO-OFDM system contains many stages including OFDM demodulation, MIMO equalization, QAM demapping, and channel decoding.

IV. RESULT AND DISCUSSION

Figures 21, 22 and 23 represent the signal radiation patterns in MU-mMIMO wireless systems with multiple BS antennas. The stronger lobes of 3D response pattern in mMIMO designs represent distinct data streams of users. These lobes indicate the spread achieved by hybrid beamforming. From these figures, it is clear that the radiation beams are becoming sharper for increasing number of BS antennas and this increases the reliability of signal there by throughput.

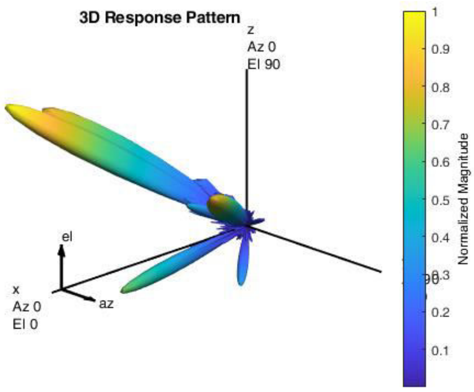

Fig4: Radiation pattern for N_t= 64, N_r = 4

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 10, October 2022||

|DOI:10.15662/IJAREEIE.2022.1110008 |

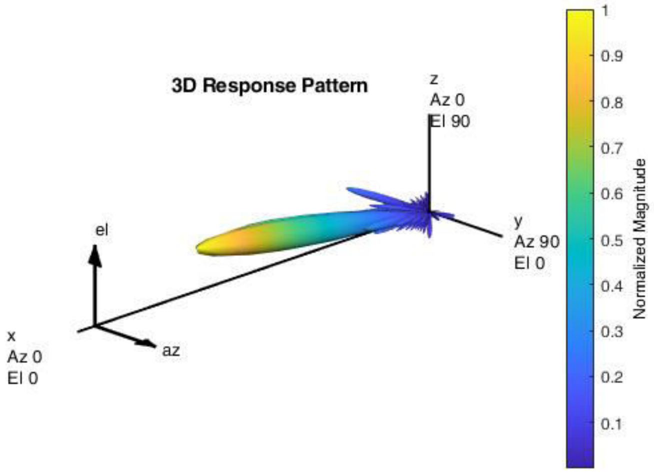

Fig 5: Radiation pattern for N_t= 256, N_r = 16

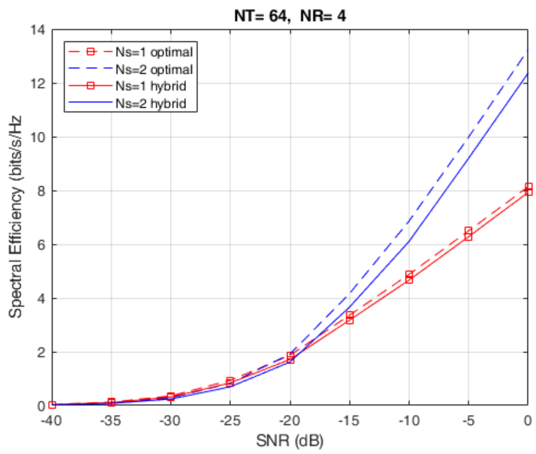

Fig. 6 :Sepectral efficiency Vs SNR(dB) for N_t= 64, N_r = 4

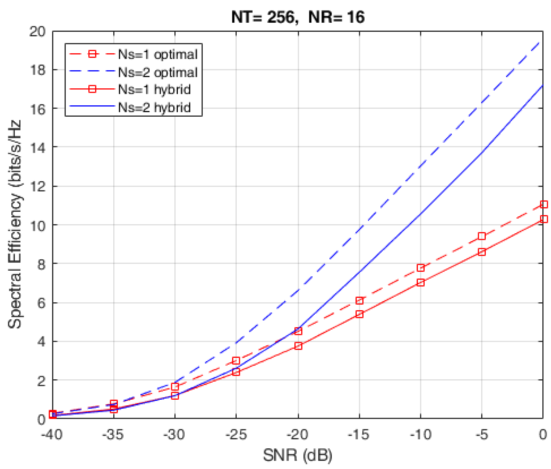

Fig. 7: Sepectral efficiency Vs SNR(dB) for N_t= 256, N_r = 16

| e-ISSN: 2278 – 8875, p-ISSN: 2320 – 3765| www.ijareeie.com | Impact Factor: 8.18|

||Volume 11, Issue 10, October 2022||

|DOI:10.15662/IJAREEIE.2022.1110008 |

The response pattern above shows that even in a multipath environment, there are limited number of dominant directions. From figure, 4 and 6 it is seen that with increase in the number of transmit and receive antenna pairs, the beams is more focused in the dominant direction and becomes narrower. From fig. 5 and 7 it could be inferred that the spectral efficiency of the MIMO-OFDM system increases with increase in number of transmit and receive antennas.

V. CONCLUSION

A mmWave DL MU-mMIMO hybrid beamforming communication system is designed with multiple independent data streams per user. From the overall results, it is observed that for users with lower number of independent data streams, RMS EVM values are higher and for more number of independent data streams, the RMS EVM is less. Therefore, the increasing number of data streams per user leads to decrease in RMS EVM values. For the given modulation scheme, as the number of BS antennas are increasing, the RMS EVM is decreasing. It gives trade-off between the number of Tx/Rx antenna elements and multiple data streams per user. It has been concluded that if the user data is divided into more number of parallel data streams then it requires less number of active antenna elements to transmit the signals. From the simulation results, it is concluded that 256×16 MIMO system is more suitable for eight users and 64×4 MIMO system for four users with multiple data streams.

REFERENCES

[1] J. Zhang, Y. Huang, J. Wang, X. You, and C. Masouros, "Intelligent interactive beam training for millimeter wave communications," IEEE Transactions on Wireless Communications, vol. 20, no. 3, pp. 2034–2048, 2021.
[2] A. . Kaya and H. Viswanathan, "Deep learning-based predictive beam management for 5g mmwave systems," in 2021 IEEE Wireless Communications and Networking Conference (WCNC), 2021, pp. 1–7.
[3] W. Xia, G. Zheng, Y. Zhu, J. Zhang, J. Wang, and A. P. Petropulu, "A deep learning framework for optimization of MISO downlink beamforming," IEEE Transactions on Communications, vol. 68, no. 3, pp. 1866–1880, 2020.
[4] J. Shi, W. Wang, X. Yi, X. Gao, and G. Y. Li, "Robust precoding in Massive MIMO: A deep learning approach," 2020.23
[5] H. Huang, W. Xia, J. Xiong, J. Yang, G. Zheng, and X. Zhu, "Unsupervised learning-based fast beamforming design for downlink MIMO," IEEE Access, vol. 7, pp. 7599–7605, 2019.
[6] K. Kong, W.-J. Song, and M. Min, "Knowledge distillation-aided end-to-end learning for linear precoding in multiuser MIMO downlink systems with finite-rate feedback," 2021.
[7] Z. Hu, J. Cheng, Z. Zhang, and Y.-C. Liang, "Performance analysis of collaborative beamforming with outdated CSI for multi-relay spectrum sharing networks," IEEE Trans. Veh. Technol., vol. 67, no. 12, pp. 11627–11641, 2018.
[8] D. Korpi, M. Honkala, J. M. J. Huttunen, and V. Starck, "DeepRx MIMO: Convolutional MIMO detection with learned multiplicative transformations," in IEEE International Conference on Communications (ICC), 14-23 June, 2021, pre-print available in arXiv:2010.16283.
[9] J. Pihlajasalo, D. Korpi, M. Honkala, J. M. J. Huttunen, et. al, "HybridDeepRx: Deep learning receiver for high-evm signals," in 2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC),, September 13-16, 2021.
[10] D. Korpi, M. Honkala, J. M. J. Huttunen, F. A. Aoudia, and J. Hoydis, "Waveform learning for reduced out-of-band emissions under a nonlinear power amplifier," 2022