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

| 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.2022.1110009 |

Hybrid Beamforming Design for MIMO-OFDM System using Deep Learning

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ABSTRACT*:* Machine learning algorithms recently have been considered for many tasks in the area of wireless communications. Previously, we have proposed the use of a deep fully convolutional neural network (CNN) for receiver processing and shown it to provide considerable performance gains. In this study, we focused on machine learning algorithms (ML) for the transmitter.We specifically emphasized on beamforming and using it we proposed a CNN that, given an input uplink channel estimate, generates downlink channel data that will be used for beamforming. Here we have the CNN in a supervised way taking both the uplink and downlink transmissions into consideration with a UE receiver-based performance loss function. The neural network's primary goal is to forecast how the channel will evolve between both the slots of uplink and downlink, but it can also be trained to deal with inefficiencies and mistakes across the entire chain, which also includes the phase of actual beamforming. The enhanced beamforming performance can be seen by the provided numerical simulations

KEYWORDS*:* Precoding, radio transmitter, beamforming, convolutional neural networks, deep learning.

I. INTRODUCTION

Introduction: Utilizing the available spectrum more effectively is becoming increasingly important due to the constantly increasing need for high data rates and increased user capacity. By enabling simultaneous communication between the base station (BS) transmitter and several mobile stations (MS) receivers while utilizing the same time-frequency resources, multi-user MIMO (MU-MIMO) increases the efficiency of the spectrum. The number of BS antenna components can be in the range of tens or hundreds thanks to massive MIMO, which also mass the volume of data streams in a cell.

The number of Base Station BS antenna components can be in the range of tens or hundreds thanks to massive MIMO, which also mass the volume of data streams in a cell. Millimeter wave (mmWave) bands are utilized by 5G wireless systems to benefit from their increased bandwidth. Large-scale antenna arrays are another feature of the 5G systems which are used to reduce the mmWave band's significant propagation loss. The mmWave band has a substantially shorter wavelength than current wireless technologies. Although this increases the number of components that may fit in an array of the same physical space, it also raises the cost of providing a transmit-receive (TR) module or RF chain for every antenna element. With lesser Radio frequency (RF) chains in comparison to the number of transmit components, transceivers that are hybrid are workable solutions because they combine digital beam formers in the baseband domain and analogue beam formers in the RF domain [1].
This example demonstrates the derivation of pre-coding matrices at the transmit end. It also shows their application to an OFDM MIMO system, which builds on the system outlined in the MIMO-OFDM pre-coding with Phased Arrays example

A. Background and Related Works

When determining the beamforming coefficients, modern radio systems frequently use methods like eigen-beamforming and zero-forcing (ZF). Also developed are more sophisticated algorithms (see, for instance, [2]), however, these techniques are often computationally more taxing. Additionally, a lot of research recently examined the use of ML in beamforming. As an illustration, [3] and [4] offer ML algorithms for pre-computed beam selection. Additionally, [5], [6] describe a method in which the channel state data is fed into a CNN network to forecast important variables in conventional beamforming methods. Furthermore, [7] suggests an unsupervised learning approach to beamforming. For frequency-division duplex (FDD) systems, [8] proposes the use of ML for predicting a codebook index (an integer) which is transmitted from UE to BS for the calculation of beamforming coefficients. To acquire the channel estimations that the beamformer will employ, however, is typically treated as a separate problem by the

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majority of these techniques. For example, in 5G TDD systems, the SRS (sounding reference signal) provided by the user equipment (UEs) is frequently the source of this channel information. The SRS can be employed for the estimation of the reciprocal DL channel, and the beamformer uses this estimate to determine the precoding coefficients. However, this type of approach is accurate only for slowly fading channels or if the channel does not significantly change between the UL and DL slots. Especially if they are moving quickly, mobile UEs rarely adhere to this. It has been demonstrated that such channel ageing can dramatically worsen radio performance, especially when DL beamforming is present [9]–[10].

II. METHODOLOGY USED

Methodology Used A spatially multiplexed system can use precoding to increase the signal energy in the desired direction and channel if channel information is available at the transmitter. This is made easier by sounding the channel first, presuming a slowly fluctuating channel. Utilizing a reference transmission that the MS receiver uses to estimate the channel, the BS sounds the channel. For the purpose of calculating the precoding required for the upcoming data transmission, the MS transmits the channel estimate data back to the BS. The processing for the channel sounding model is illustrated in the following schematic.

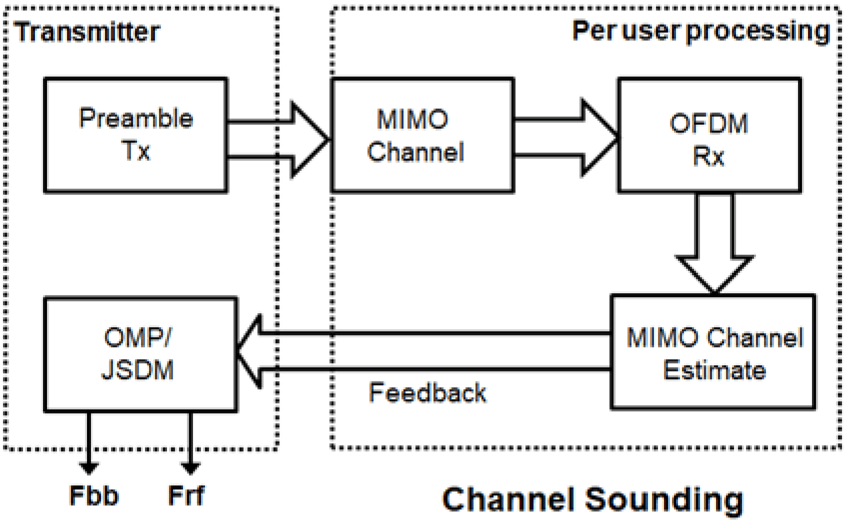

Fig. 1: MIMO-OFDM Channel estimation method block diagram

A preamble signal is delivered over all transmitting antenna elements for the specific MIMO system, and it is analyzed at the reception while taking the channel into consideration. For each link, the receiver antenna components carry out pre-amplification, OFDM demodulation, and frequency domain channel estimation. For a multi-user system, the channel estimate is fed back from each MS, and used by the BS to determine the pre-coding weights. The example assumes perfect feedback with no quantization or implementation delays.

A. *Hybrid Beamforming:*

The example utilizes the JSDM (Joint Spatial Division Multiplexing) technique [2, 4] for a system serving multi-users and the OMP (Orthogonal Matching Pursuit) algorithm [3] for a single-user system to estimate the Fbb - the digital baseband Fbb and the RF analogue Frf-precoding weights for the chosen system configuration. The array response vector - At heavily influences the OMP partitioning technique in the case of the single-user system. Random rays' collections inside a 3-dimensional space are utilized to cover the maximum possible scatterers because, in theory, all the scatterers should account for these response vectors detected by the channel. However, these vectors remain unknown for the channel realization and the actual system. The number of rays is specified by the prm.nRays function.
An analogue block dialognialisd method-based precoder diminishes the intergroup interference in the case of a multi-user system JSDM, which groups users with comparable covariance of the transmit channel with each together [5]. There is no decrease in the overhead feedback or in the sounding overhead because each user is given their own group in this situation.

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The weights which are averaged over the various subcarriers are what make up the analogue weights, or mFrf, for the wideband OFDM system that was modeled. The stronger lobes in the response pattern of the array indicate independent data streams. These lobes represent the beamforming-achieved spread or separability. In the Introduction to Hybrid Beamforming example, patterns for systems intended to serve single-user systems are compared between those realized by the best, totally digital approach and those released from the chosen hybrid approach.

B. Data Transmission

The example models an architecture where each data stream maps to an individual RF chain and each antenna element is connected to each RF chain. This is illustrated in the following diagram.

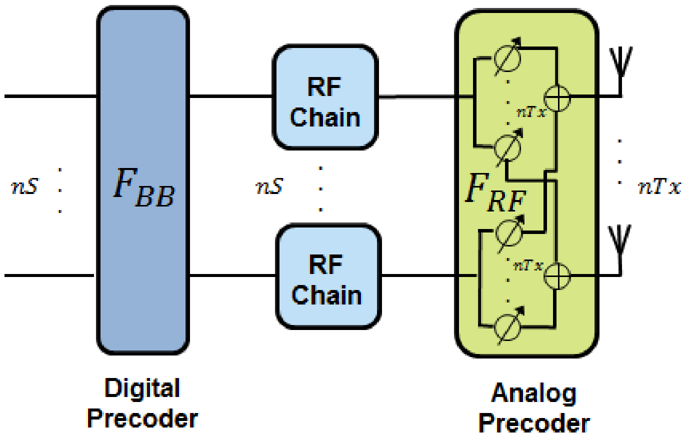

Fig. 2: Model transmitter architecture

Next, we configure the system's data transmitter. This processing entails OFDM modulation along with pilot mapping, transmit streams - baseband precoding, channel-coding, bit mapping to complex symbols, splitting of the individual data stream into numerous transmit streams, and RF analogue beamforming for all of the transmit antennas used. Each antenna element employs prm.numSTS phase shifters, as specified by the various columns of the mFrf matrix, for the chosen, fully linked RF design. The step-wis working flow diagram is shown in fig. 3.

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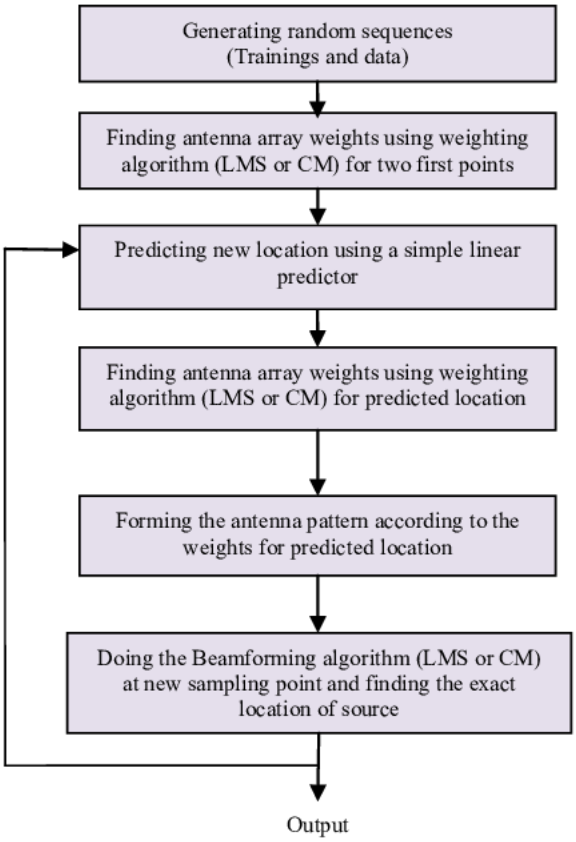

Fig. 3: Working flow diagram of beamforming

III. RESULTS AND DISCUSSIONS

After successful implementation of the MIMO-OFDM beamforming design, we have simulated it for performance. 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 utilizes the proposed approach in [1]. In this approach, the optimizations for the precoding and the combining weights are decoupled. The orthogonal pursuit algorithm is used to derive the precoding weights. The resulting number is employed to compute the appropriate combining weights after calculating the precoding weights.

If the channel is known then it is possible to determine the precoding weights which are unconstrained and optimal by channel matrices diagonalization and the removal of the first NtFR dominant modes. As seen in fig. 4, the transmit beam pattern can be plotted:

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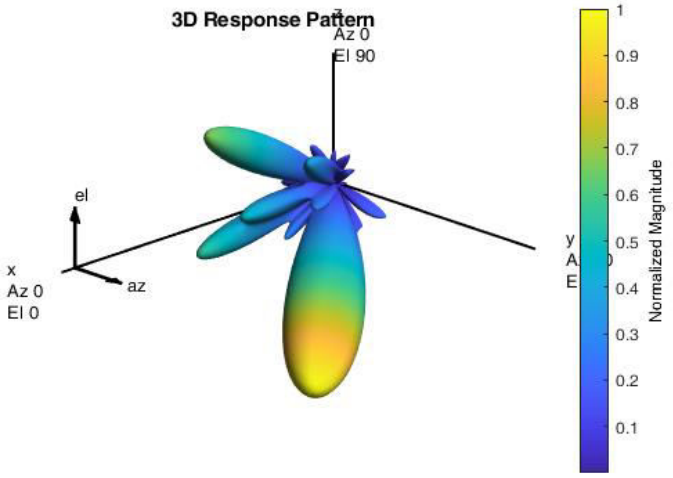

Fig. 4: Radiation pattern for $N_t = 16$, $N_r = 4$

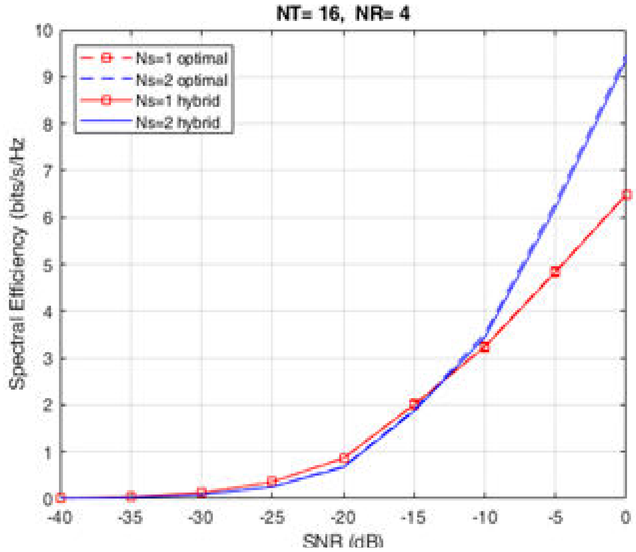

Fig. 5: Spectral efficiency vs SNR(dB) for $N_t = 16$, $N_r = 4$

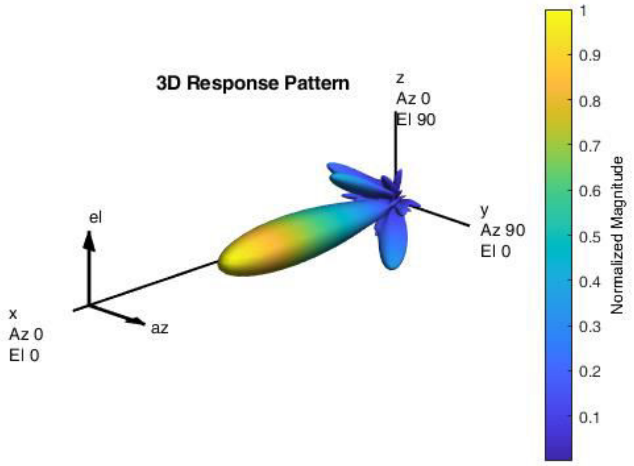

Fig. 6: Radiation pattern for $N_t = 16$, $N_r = 16$

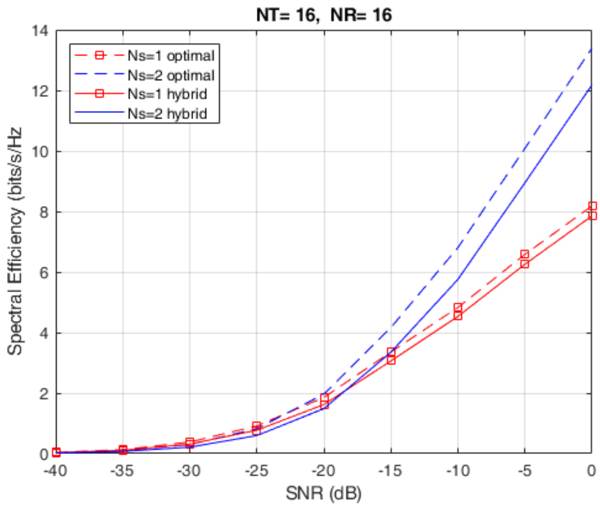

Fig. 7: Sepectral efficiency Vs SNR(dB) for $N_t = 16$, $N_r = 16$

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The above response pattern shows that in spite of the multipath environment there are limited numbers of dominant directions. From figures, 4 and 6 it is seen that with an increase in the number of transmitting and receiving antenna pairs, the beam 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 an increase in the number of transmitting and receive antennas.

IV. CONCLUSION

In this paper we considered deep learning-based radio transmit beamforming in a time division duplexing MIMO-OFDM system. We combined a CNN (Convolutional Neural Network) with zero-forcing beamforming to create a mapping between a UL channel estimate and precoding coefficients in DL. The main work of DNN is a prediction of the evolution of the channel between UL slots and DL slots. In contrast to many previous works, it is trained in a supervised manner by optimizing a loss function that is based on the performance of the UE receiver. The training requires simulating both beamforming transmitter and UE receivers, and also on the channel between them, in a differentiable manner. The proposed scheme shows a better spectral efficiency and a well-focused beam in the direction of the user.

REFERENCES

[1] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, “Artificial neural networks-based machine learning for wireless networks: A tutorial,” IEEE Communications Surveys Tutorials, vol. 21, no. 4, pp. 3039–3071, 2019.
[2] D. G¨und¨uz, P. de Kerret, N. D. Sidiropoulos, D. Gesbert, C. R. Murthy, and M. van der Schaar, “Machine learning in the air,” IEEE Journal on Selected Areas in Communications, vol. 37, no. 10, pp. 2184–2199, 2019.
[3] M. Honkala, D. Korpi, and J. M. J. Huttunen, “DeepRx: Fully convolutional deep learning receiver,” IEEE Transactions on Wireless Communications, vol. 20, no. 6, pp. 3925–3940, 2021.
[4] 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.
[5] 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.
[6] 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.
[7] M. Goutay, F. A. Aoudia, J. Hoydis, and J.-M. Gorce, “Learning OFDM waveforms with PAPR and ACLR constraints,” 2021.
[8] F. A. Aoudia and J. Hoydis, “End-to-end waveform learning through joint optimization of pulse and constellation shaping,” 2021.
[9] O. Shental and J. Hoydis, “Machine LLRning: Learning to softly demodulate,” 2019.
[10] E. Bj¨ornson, M. Bengtsson, and B. , “Optimal multiuser transmit beamforming: A difficult problem with a simple solution structure,” IEEE Signal Processing Magazine, vol. 31, no. 4, pp. 142–148, 2014.