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Performance of Cell-Free Massive MIMO with Rician Fading and Phase Shifts

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ABSTRACT: In this paper, we study the uplink (UL) and downlink (DL) spectral efficiency (SE) of a cell-free massive multiple-input-multiple-output (MIMO) system over Rician fading channels. The phase of the line-of-sight (LOS) path is modeled as a uniformly distributed random variable to take the phase-shifts due to mobility and phase noise into account. Considering the availability of prior information at the access points (APs), the phase-aware minimum mean square error (MMSE), non-aware linear MMSE (LMMSE), and least-square (LS) estimators are derived. The MMSE estimator requires perfectly estimated phase knowledge whereas the LMMSE and LS are derived without it. In the UL, a two-layer decoding method is investigated in order to mitigate both coherent and non-coherent interference. Closed form UL SE expressions with phase-aware MMSE, LMMSE, and LS estimators are derived for maximum-ratio (MR) combining in the first layer and optimal large-scale fading decoding (LSFD) in the second layer. In the DL, two different transmission modes are studied: coherent and non-coherent. Closed-form DL SE expressions for both transmission modes with MR Precoding are derived for the three estimators. Numerical results show that the LSFD improves the UL SE performance and coherent transmission mode performs much better than non-coherent transmission in the DL. Besides, the performance loss due to the lack of phase information depends on the pilot length and it is small when the pilot contamination is low.

KEYWORDS: Uplink, Downlink, Spectral efficiency, Multiple-Input-Multiple-Output, Minimum Mean Square Error, LSFD, LMMSE

I. INTRODUCTION

MASSIVE multiple-input multiple-output (MIMO) is the key physical layer technology in 5G [1]. Wireless technology is the most noteworthy advancement nowadays, with widespread access that has become an integral part of society—as crucial as electricity—and the connectivity itself impels developments. Wireless communication services are accessible and pervasive in all walks of life of all the people globally, thanks to a cellular wide area, local area networks, and satellite services. Currently, wireless communication techniques can differentiate in either single carrier modulations or Multi-Carrier Modulations (MCM). MIMO-OFDM with STBC and spatial multiplexing methods are still used in 4G Technology to deliver reliability and fast data speeds. Even so, the spectral efficiency depends on Multiple access techniques and Modulation schemes. The proposed large-scale-MIMO system [2] is a continuation of significant gains in popular MIMO, which can concurrently use hundreds of transmission antennas to support thousands of UEs. Furthermore, the coexistence of massive-MIMO and OFDM employs SDMA to make considerable multiplexing advantages by enabling various UEs on the same time-frequency services. To enable efficient interference suppression in the spatial domain a characteristic feature of MIMO is that the AP has more antennas than the active UEs in the cell[7]. Recently, FBMC technology surpassed all other drawbacks enumerated in conventional OFDM. So, it attracted much attention nowadays. The FBMC strengths are:

- pulse-shaping filters are employed,
- lower spectral side-lobes,
- the possibility of asynchronous transmission adjustable parameters.

II. LITERATURE SURVEY

The insufficient allocation of the RF spectrum and dynamic space-time-varying wireless environment presents more challenges to wireless device designers. The largescale MIMO network has considerable advantages for wireless communication; it brings significant changes to the data output and connecting range without increasing bandwidth or transmits power. Adhikary et al. proposed, in the proposed MIMO, several transmission antennas are placed in a single transmitter solution in 1993 and 1994 to increase the potential connection throughput. MIMO is being recognized as an indispensable technology in Fourth Generation (4G) wireless networking systems.

II.(1). MASSIVE MIMO-CHANNEL ESTIMATION:

An enormous MIMO channel prediction approach for FDD is proposed in [7] using frequency selection techniques. It is dependent on the message passing algorithm. The original AMP is now expanded to Multiple Measurement Vector (MMV) for FDD/TDD modes called M-AMP. In the Frobenius normalized squared error reduction, the group of pilots expected and the various channel sparsity standards, simulated values indicate overall improvement. According to standard traditional estimated channels used in the small-scale MIMO with the LS (Lower Squares) method, the length of the training series should equal the number of transmitter antennas. Furthermore, such strategies are inadequate for large MIMO.

III. EXISTING METHOD

Overcoming demand for 5G high-speeds involves a conventional MIMO system, which enables significant MIMO to increase the potential contribution towards spectral efficiency, reliance, and overall power in TDD/FDD cell systems. The subsequent work studied large MIMO systems, with primary reception and transmitting techniques, which render a higher yield. Thus, they are classified into ultrareliable communication systems with low latency and use reduced latency according to their capacity and potential at work, including higher mobile bandwidth.

With the massive MIMO's extensive features, the following challenges are fulfilling to reach expected wireless demands

1. Beam-forming is the major challenging issue, which entails accurate channel state information for downlink communication.
2. Another challenging issue is pilot overhead in FDD to engage cellular demands because most 5G cellular networks make FDD since TDD protocol employs in massive MIMO due to reciprocity which requires complicated calibration.
3. Conventional estimates for channels include an oversized pilot and overhead input, usually on a scale predicated on the combination of BS transmitting antennas, resulting in unworkable conditions for large FDD MIMO systems.

IV. PROPOSED METHOD

We consider a cell-free Massive MIMO system with M APs and K UEs. All APs and UEs are equipped with a single antenna. The multi-antenna AP case can be straightforwardly covered by treating each antenna as a separate AP, if it is assumed that there is no correlation between the small-scale fading coefficients (or phase-shifts) [19]. However, for a more realistic analysis, single-antenna results can be generalized to multiple antenna case by taking the spatial correlations between antennas into account. It will result in non-diagonal covariance matrices. The channels are assumed to be constant and frequency-flat in a coherence block of length τ_c samples (channel uses). The length of each coherence block is determined by the carrier frequency and external factors such as the propagation environment and UE mobility [17]. The channel $h_{m,k}$ between UE k and the AP m is modeled as

$$h_{m,k} = h_{m,k}^- e^{j\phi_{m,k}} + g_{m,k}, \quad (1)$$

where $g_{m,k} \sim \text{NC}(0, \beta_{m,k})$, the mean $h_{m,k}^- \geq 0$ represents the LOS component, and $\phi_{m,k} \sim U[-\pi, \pi]$ is the phase-shift. The small-scale fading from non-LOS (NLOS) propagation has a variance $\beta_{m,k}$ that models the large-scale fading, including geometric pathloss and shadowing. Note that (1) is a Rician fading model since $|h_{m,k}|$ is Rice distributed, but $h_{m,k}$ is not Gaussian distributed as in many prior works that neglected the phase shift. We assume that $h_{m,k}$ is an independent random variable for every $m = 1, \dots, M, k = 1, \dots, K$ and the channel realization $h_{m,k}$ in different coherence blocks are i.i.d. All APs are connected to a central processing unit (CPU) via a fronthaul network that is error free. The system operates in time division duplex (TDD) mode and the uplink (UL) and DL channels are estimated by exploiting only UL pilot transmission and channel reciprocity.

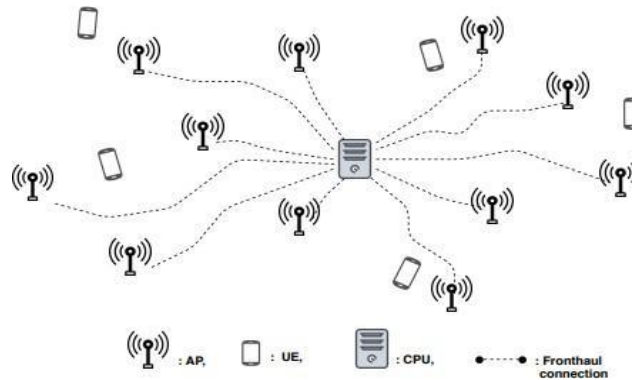


Fig. 1: Illustration of a cell-free massive MIMO network.

Figure 2 shows the system block diagram of a baseband OFDM system with MMIMO [68-69] antennas. Denote $X_l(l = 0, 1, 2, \dots, N - 1)$ as the modulated symbols on the l th transmitting subcarrier of OFDM symbol at transmitter, which are assumed independent, zero-mean random variables, with average power $\sigma^2 X$. The complex baseband OFDM signal at output of the IFFT can be written as

$$x_n = \frac{1}{\sqrt{N}} \sum_{l=0}^{N-1} X_l e^{j \frac{2\pi n l}{N}}, n = 0, \dots, N - 1 \quad (4.1)$$

where N is the total number of subcarriers in an OFDM frame and the OFDM symbol duration is of T seconds. At the receiver, the received OFDM signal is mixed with the local oscillator signal, with the frequency offset deviated from Δf compared to the carrier frequency of the received signal owing to frequency estimation error or Doppler velocity.

The received signal y_n is given by

$$y_n = (x_n \otimes h_n) e^{j \frac{2\pi n \Delta f T}{N}} + z_n \quad 4.2$$

where h_n represents the channel impulse response, $j \frac{2\pi n \Delta f T}{N}$ is the corresponding frequency offset of received signal at the sampling instants with $\Delta f T$ being the frequency offset to subcarrier frequency spacing ratio, and z_n is the AWGN respectively, while \otimes denotes the circular convolution. Assuming that a cyclic prefix is employed, the receiver has a perfect time synchronization. Note that a discrete Fourier transform (DFT) of the convolution of two signal in time domain is equivalent to the multiplication of the corresponding signals in the frequency domain signal on the k th receiving subcarrier becomes

$$= X_k H_k S(0) + \sum_{l=0, l \neq k}^{N-1} X_l H_l S(l - k) + Z_k \quad (4.3)$$

The first term of Eq. (5.3) is a desired transmitted data symbol and the second term represents the ICI from the undesired data symbols caused by other subcarriers in OFDM symbols. H_l is the frequency-domain channel impulse response and Z_k denotes the frequency domain of z_n . The sequence $(l - k)$ is defined as the ICI coefficient between k th and l th sub carriers, which can be expressed as given in Eq. (4.4).

Now, ICI mitigation scheme in MIMO systems

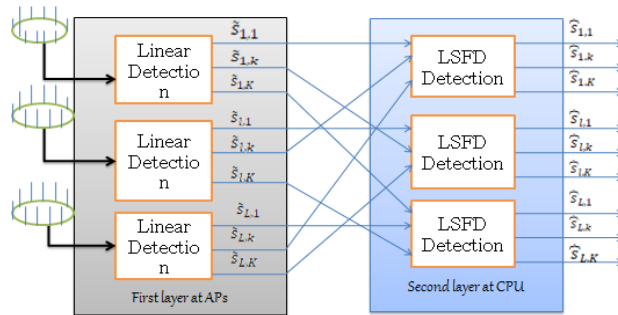


Fig 2: Massive MIMO architecture

is presented as shown in Figure 4.1. The modulated symbols ($l = 0, 1, 2, \dots, N - 1$) are encoded with the Alamouti space-time-block coding (ASTBC). The transmitted frequency domain signal on l^{th} transmitting subcarrier from an antenna one is denoted by

$A_{1,l} = (X_0, 0, X_1, 0, \dots, X_{N/2-1}, 0$ for $l = 0, \dots, N - 1$, respectively) and from antenna two is denoted by $A_{2,l} = (0, X_1, 0, X_0, \dots, 0, X_{N/2-1},$ for $l = 0, \dots, N - 1$, respectively). Assuming that CP is employed, the receiver has the perfect time synchronization. Note also that the frequency offset [61] is constant over two-path time interval. The time-domain received signal is expressed by

$$y_n = (a_{1,n} \otimes h_{1,n} + a_{2,n} \otimes h_{2,n}) e^{\frac{j2\pi n\epsilon T}{N}} + z_n \quad (4.4)$$

Then the frequency-domain received signal model of a primary path on the k^{th} receiving subcarrier expressed is

$$Y_k = \sum_{l=0, l \neq k}^{N-1} A_{1,l} H_{1,l} S(1, l-k) + \sum_{l=0, l \neq k}^{N-1} A_{2,l} H_{2,l} S(2, l-k) + Z_k \quad (4.5)$$

An equalizer is a type of filter circuit which is connected at the front end of the wireless receiver to compensate the variations in the amplitude and time delay characteristics of the received signal. The equalizer should follow the time varying characteristics of the channel due to the nature of fading. This equalizer can be either time varying or adaptive. An adaptive equalizer has training mode and tracking mode of operations.

IV.(1). LEAST-SQUARE (LS) ALGORITHM

The Least-Square (LS) method is a mathematical procedure to identify the best fit line to the data. It is used to estimate the parameters that fit a function $f(x)$ for a set of data x_1, x_2, \dots, x_n . For a best fitting of the given data, LS method decreases the sum of squared residuals which is also described as Sum of Squared Errors (SSE). It is given by Equation (4.9)

$$SSE = \sum_{i=1}^n r_i^2$$

Where r_i is the residual. It is represented by the following equation.

This LS method can be either in linear or non-linear mode. The Linear LS method is one of the most common linear regression methods used to find the best fitting of data as straight line. The equalized function is given by Equation (4.11).

Where a, b are the constants. This method is used to minimize the sum of squared errors which are denoted by Equation (4.12).

To minimize this function, the partial derivative of with respect to a and b are considered to be zero. The block diagram of LS equalizer is shown in Fig. 4.2.

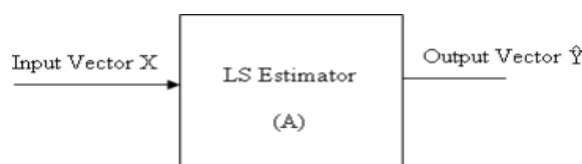


Fig. 4.2: Block Diagram of LS Equalizer

Let it be considered a linear LS equalized function which is represented in the form given in Equation (4.13)

$$y_i = a_1 \times x_1 + a_2 \times x_2 + \dots + a_m \times x_m + r$$

The above function can be described in the matrix format which is given as

$$Y = [X]A + R$$

Where X is the input matrix of the dataset, Y is the output vector, is an unknown vector, and A is a residual vector. To minimize the residual vector, the partial derivative of each coefficient of Equation (4.13) is equated to zero. Due to this, a set of normalized equations is obtained which can be represented in the matrix form of Equation (4.15).

IV(2): MINIMUM MEAN SQUARE ERROR (MMSE) ALGORITHM

The MMSE algorithm is used as a mathematical channel equalization model to find channel coefficients. This algorithm minimizes the Mean Square Error (MSE). It can be expressed as quadratic cost function mathematically. Let be the (nX1) dimension of input vector and y be the (mX1) dimension of output vector and be the equalized vector. There is an error between the original input and the equalized output. This equalization error is given by Equation(4.17). $e = x - \hat{x}$

IV.(3). LMMSE DECODING

We now assume that the channel coefficients h_1 and h_2 can be recovered perfectly at the receiver (figure 2). We use these coefficients as the CSI. The combiner combines the received signal as follows

$$x'_1 = h_1^* r_1 + h_2 r_2^* = (\alpha_1^2 + \alpha_2^2) x_1 + h_1^* n_1 + h_2 n_2^*$$

$$x'_2 = h_2^* r_1^* - h_1 r_2^* = (\alpha_1^2 + \alpha_2^2) x_2 + h_2^* n_1 - h_1 n_2^*$$

and sends them to the maximum likelihood detector, which minimizes the following decision metric,

$$|r_1 - h_1 x_1 - h_2 x_2|^2 + |r_2 + h_1 s_2^* - h_2 s_1^*|^2$$

expanding the above equation and deleting terms that are independent of the code words, the above minimization reduces to separately minimizing

$$|r_1 h_2^* - r_2^* h_1 - x_2|^2 + (\alpha_1^2 + \alpha_2^2 - 1) |x_1|^2$$

for detecting x_1 ,

$$|r_1 h_2^* - r_2^* h_1 - x_2|^2 + (\alpha_1^2 + \alpha_2^2 - 1) |x_2|^2$$

The transmissions in the Alamouti scheme are orthogonal. This implies that the receiver antenna “sees” two completely orthogonal streams. Hence, we obtain a transmit diversity of two. Consider two distinct code sequences (x, x') and S' generated by the inputs (x_1, x_2) and (x_1, x_2) respectively, where (x_1, x_2) \neq (x_1, x_2)

The code word difference matrix is given by

$$G(x, x') = \begin{bmatrix} x_1 - x_1' & -x_2 - x_2' \\ x_2 - x_2' & x_1 - x_1' \end{bmatrix}$$

Since, the rows of the code matrix are orthogonal, the rows of the code word difference matrix are orthogonal as well.

The code word distance matrix is given by,

$$A(x, x') = B(x, x') B^H(x, x')$$

$$= \begin{bmatrix} |x_1 - x_1'|^2 + |x_2 - x_2'|^2 & 0 \\ 0 & |x_1 - x_1'|^2 + |x_2 - x_2'|^2 \end{bmatrix}$$

$$e_k = d_k - y_k$$

Since y_k depends on the weight function w_k , MSE is also related to the weight function w_k .

SIMULATION RESULTS

S In this section, the closed-form SE expressions are validated and evaluated by simulating a cell-free massive MIMO network. We have M APs and K = 40 UEs that are independently and uniformly distributed within a square of size 1x1 km² with a wrap-around setup. Maximum ratio precoding/combining is used at UL/DL in all simulations. The pathloss is computed based on the COST 321 Walfish-Ikegami model for microcells in[27] with AP height 12.5 m and UE height 1.5 m. All AP-UE pairs have a LoS path and the path-loss (PL) is modeled (in dB) as

$$PL_{m,k} = -30.18 - 26 \log_{10} \left(\frac{d_{m,k}}{1 \text{ m}} \right) + F_{m,k},$$

where d_{m,n} is the distance between AP m and UE k and F_{m,k} is the shadow fading coefficient. The Rician κ-factor is calculated as κ_{m,k} = 101.3 - 0.003d_{m,k} [27]. We assume correlated shadow fading as in [3] with F_{m,k} = √δa_m + √1 - δb_k, where a_m ~ N(0, σ₂ sf) and b_k ~ N(0, σ₂ sf) are

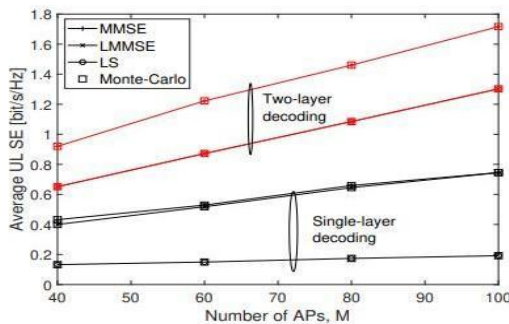


Fig. 3: Average UL SE for different number of APs. K = 40, τ_p = 5.

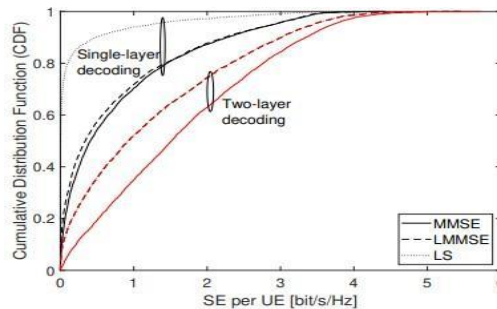


Fig. 4: CDF of UL SE for M = 100, K = 40 and τ_p = 5.

independent and δ is the shadow fading parameter, 0 ≤ δ ≤ 1. The random variables a_m and b_k model the shadow fading effect from blocking objects in the vicinity of the AP m and UE k, respectively. The covariance functions for arbitrary AP and UE pairs are given as E {a_ma_n} = 2^{-d_{m,n}/d_{dc}}, and E {b_kb_l} = 2^{-d_{k,l}/d_{dc}}, where d_{m,n} denote the distance between AP m and AP n and d_{k,l} is the distance between UE k and UE l. The d_{dc} is decorrelation distance which depends on the environment. We set the parameters d_{dc} = 100 m, σ_{sf} = 8 and δ = 0.5 in the simulation. With this model, the large scale coefficient of h_{m,k} are

$$\bar{h}_{m,k} = \sqrt{\frac{\kappa_{m,k}}{\kappa_{m,k} + 1}} \sqrt{PL_{m,k}}, \quad \beta_{m,k} = \frac{1}{\kappa_{m,k} + 1} PL_{m,k}.$$

We consider communication over a 20 MHz channel and the total receiver noise power is -94 dBm. Each coherence block consists of τ_c = 200 samples and τ_p pilots. The pilots of first τ_p UEs are allocated randomly. The rest of UEs sequentially pick their pilots that give least interference to UEs in the current pilot set. In UL transmission, we set τ_u = τ_c - τ_p and τ_d = τ_c - τ_p in DL transmission, which means that each coherence block is either used for only UL data or only DL data. In the UL, all UEs transmit with the same power 200 mW. In the twolayer decoding scheme, we utilized the maximizing LSFD vectors for each estimator that is computed by only using large-scale fading coefficients. In single-layer decoding, the LSFD vectors are a_k = [1, . . . , 1], ∀k which simply correspond to conventional MR combining. The same DL power is assigned to UE k for both coherent and non-coherent transmission. The power is allocated proportional to the channel quality of UE by using the matrices for the coherent and non-coherent case respectively.

If the power fraction parameter ($0 \leq$

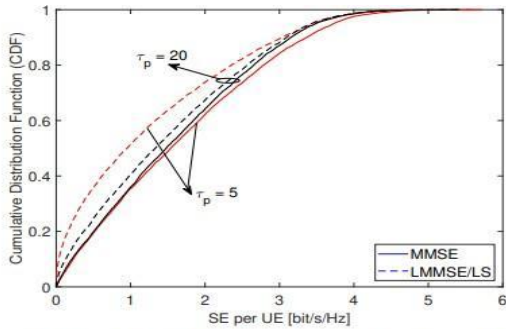


Fig. 5: CDF of UL SE for $M = 100, K = 40$ and $\tau_p = [5, 20]$. Two-layer decoding.

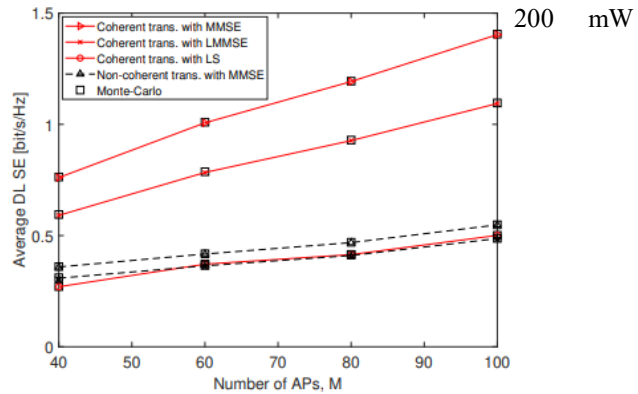


Fig. 7: Average DL SE versus different number of APs for coherent and non-coherent transmission. $K = 40, \tau_p = 5$.

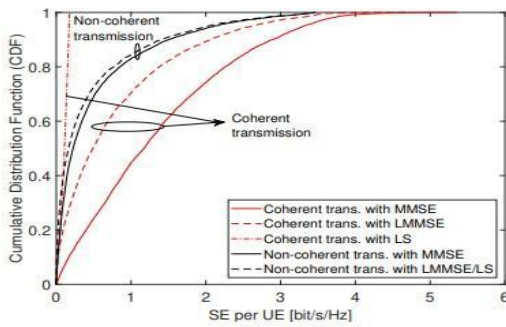


Fig. 8: CDF of DL SE for coherent and non-coherent transmission with $M = 100, K = 40$ and $\tau_p = 5$.

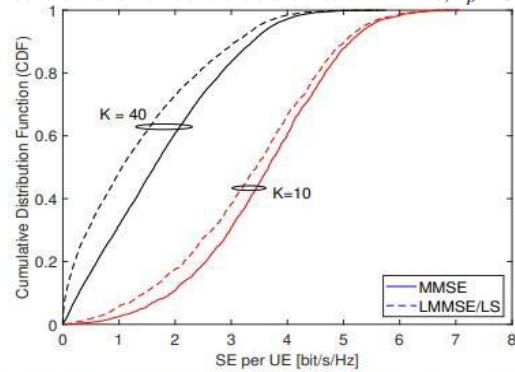


Fig. 6: CDF of UL SE for $M = 100, \tau_p = 5$ and $K = [10, 40]$. Two-layer decoding.

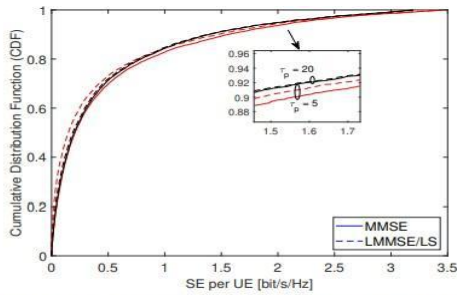


Fig. 10: CDF of DL SE with non-coherent transmission for pilot lengths where $M = 100, K = 40, \tau_p = [5, 20]$.

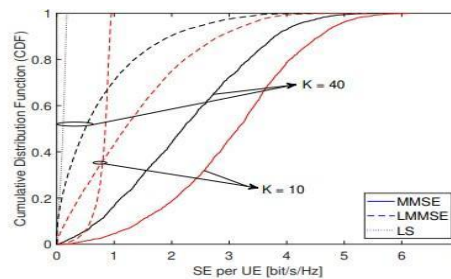


Fig. 11: CDF of DL SE with coherent transmission for different number of UEs where $M = 100, K = [10, 40], \tau_p = 5$.

V. FUTURE SCOPE

This work described the effectiveness of Massive MIMO system with the enhancement of SE and UE in presence of AWGN and frequency selective Rayleigh fading channel. A combined scheme of Doubly EM based equalizer-with ICI mitigation approach is employed for enhancing the performance of Massive MIMO system. In addition, this algorithm reduced the complexity and processing delay by improving BER performance of Massive MIMO system. However, the weights utilized in SE and UE expression are not optimal and further there is a lack of translation invariance. Thus, it is required to address these issues to maximize the performance of Massive MIMO system for 5G wireless networks.

V. CONCLUSION

This work studied the SE of a cell-free massive MIMO system over Rician fading channels. The phase of the LoS path is modeled as a uniformly distributed random variable to take phase-shifts due to mobility and phase noise into account. To determine the importance of knowing the phase, the phase-aware MMSE, non-aware LMMSE, and LS estimators were derived. In the UL, a two-layer decoding method was studied in order to mitigate the both coherent and



non-coherent interference. We observed that the LSF method provides a substantial gain in UL SE for all estimators, and should therefore always be used in cell-free massive MIMO.

Furthermore, the performance losses as a result of unavailable phase knowledge depends on the pilot length. If there is no strongly interfering user, the LoS and NLoS paths can be jointly estimated without having to know the phase. Therefore, the pilot length should be adjusted by taking the phase shifts into account in high mobility or low-quality hardware scenarios. In order to deal with the cases where there is not enough pilots, methods to explicitly estimate the phases could be considered in future work. Besides, the coherent transmission performs much better than the non-coherent one, which is the reason of its wide use in the cell-free literature.

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