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Deep Learning-aided Channel Estimation Combined with Advanced Pilot Assignment Algorithm to Mitigate Pilot Contamination for Cell-Free Networks

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Abstract

Objectives: The performance of Cell-Free Massive Multiple Input Multiple Output (CFMM) is analyzed in this paper for its two bottlenecks i.e., Pilot Contamination (PC) and Channel Estimation Error (CEE). **Methods:** The CFMM network is strongly affected by PC which is one of the bottlenecks due to which quality of service and accuracy of channel estimation gets impacted. Therefore, we address this problem by presenting advanced pilot assignment algorithm to mitigate PC and deep learning aided channel estimation for reducing CEE for the CFMM systems to maximize spectral efficiency (SE). We derive achievable uplink and downlink SE expressions for the proposed system, and compare with Minimum Mean Square Error and Maximum Ratio combining techniques. As well, the performance is evaluated for different antenna configurations. The advanced pilot assignment algorithm is compared with greedy pilot assignment and random pilot assignment methods. The performance of cellular massive multiple input multiple output (MIMO) is derived for comparison. The performance of CFMM system is evaluated using MATLAB software. **Findings:** The UL and DL performance of the proposed system in terms of SE is 3.2 times higher than the conventional CFMM with MMSE and MR combining techniques. Average sum spectral efficiency of the proposed system increases with increase in number of access points (APs). Comparison with different antenna configurations reveals that, with 400 APs equipped with single antenna, only UE with good channel condition shows performance enhancement, but when each AP is equipped with 4 antennas, the UE with unfavourable channel condition also give better performance. Advanced pilot assignment scheme proves to be better than greedy and random pilot assignment techniques. For the same cellular set up, the proposed CFMM system achieves higher SE than the cellular massive MIMO. **Novelty:** Due to the advanced pilot assignment algorithm used in the proposed CFMM system, at a time, only one AP is selected and the selected AP with its full received power serves the desired UE, which suppresses interference resulting in improved SE performance. The serving AP is selected considering the distance between UE and AP, rather than using large scale fading coefficient which is the unique feature of pilot assignment algorithm. The proposed deep learning-aided channel estimation method, minimizes the mean square error (MSE) between the actual channel and the channel estimates obtained from the MMSE estimation resulting in reduction in channel estimation error. Thus, the use of the proposed advanced pilot assignment algorithm and deep learning-aided channel estimation method increase the SE performance of the CFMM system.

Keywords: CellFree Massive Multiple Input Multiple Output; Pilot Contamination; Channel Estimation Error; Minimum Mean Square Error; Maximum Ratio

1 Introduction

Unlike optical wireless communication [1–3] where light is used to transmit data, wireless communication uses radio waves to transmit data. The Cell-Free Massive Multiple Input Multiple Output (CFMM) system is the core technology for the upcoming sixth-generation (6G) networks, for deploying massive multiple-input multiple-output (MIMO) systems without the restriction of cells, which provides high data throughput, ultra-low latency, ultra-high reliability, high spectral and energy efficiency and uniform coverage [4,5]. The CFMM systems reaps the benefits of network MIMO, small cells (SC) and massive MIMO [6–8]. We know that PC and accuracy of CE are inversely proportional to each other i.e., with increase in PC, the accuracy of CE decreases. In TDD, CE is done in the UL training phase. Due to channel reciprocity property of TDD, we can use CSI obtained in UL phase for DL phase as well. Therefore, it is very important to obtain accurate CSI during the UL phase. But generally, number of UEs is greater then, the number of orthogonal pilots due to which orthogonal pilots are reused between UEs leading to PC. Herein we assume that length of the pilot sequence (τ_p) is equal to the number of orthogonal pilots. With $\tau_p < K$, other options for orthogonal pilots must be evaluated. Again, if we consider non-orthogonal pilots then it will also introduce PC thereby degrading CE accuracy. The CEE caused due to PC will deteriorate SE of the UE. So, we can formulate a method which will maximize the SE of the UE. But any maximization problem can be solved, by using optimization method which is computationally complex and whose solution will require exhaustive search. Such optimization method will be complicated with large number of allocations of UEs and pilots. Therefore, to reduce computational complexity of the network, deep learning aided CE is introduced. Further CEE is reduced by using deep learning aided CE proposed for the CFMM system. Also, to avoid PC an advanced pilot assignment algorithm is proposed for the CFMM system. Further CEE is reduced by using deep learning aided CE proposed for the CFMM system. Thus, advanced pilot assignment algorithm and deep learning aided CE will improve the SE of the UE as discussed below in different sections. Thus, two future research directions [9] and areas of concern for the CFMM networks are addressed in this paper i.e., channel estimation (CE) and pilot contamination (PC). There are different techniques in literature for CE such as least square (LS), MMSE [10]. LS CE technique is less complex because it does not require prior information of channel statistics but it does not consider the effect of noise. MMSE CE considers the effect of noise but prior CSI is mandatory for it. Due to this MMSE, CE technique is more computationally complex as compared to LS, CE technique. Considering above drawbacks of CE, a new research area is emerging which is known as Machine Learning (ML) [11,12], which will address the problem of CE effectively with incredibly fast and robust training models. In the proposed paper, we are using Deep

Feed Forward (DFF) neural network for CE, which proves significant in mitigating CEE and thus enhancing the system SE performance. Furthermore, pilot sequences used in CE process for UEs may be orthogonal or non-orthogonal. The use of orthogonal pilot symbols is beneficial for high coherence interval and a smaller number of UEs. But for densely populated cell-free networks it will create pilot PC and use of non-orthogonal pilot symbol will affect spectral efficiency (SE) adversely. So, there must be a trade-off between the two methods to enhance the system performance. There are many papers [13,14] which consider different methods taking PC into consideration such as pilot reuse, maximization of SINR, partitioning of cell into rings etc. Recently various pilot decontamination [15,16], pilot contamination [17,18] mitigation techniques are also investigated. Different pilot assignment methods are studied in paper [19]. Motivated by the above-mentioned work, this paper aims to mitigate PC of the CFMM networks by proposing an advanced pilot assignment algorithm and deep learning aided CE method, thereby enhancing system performance. We examine UL and DL analysis of CFMM network using Rayleigh Fading channel between AP and UE. The advanced pilot assignment algorithm is proposed to mitigate PC by assigning pilot symbols in sequential order. The system performance is further enhanced by considering multi- user UL scheduling at the Central processing unit (CPU) end. We also propose a DFF neural network for CE at the CPU which minimizes CEE. Comprehensive results are reproduced to demonstrate the efficacy of proposed cell-free networks. The proposed CFMM network is compared with cellular massive MIMO, conventional CFMM with MMSE and MR [20] combining techniques. Simulation results prove the efficiency of proposed CFMM network against its cellular and conventional CFMM counterpart. The rest of the paper is organized as follows. Section two introduces methodology which includes explanation of the system model for CFMM network, the problem formulation, pilot assignment and transmission, local CE and learning aided CE, Multi-user UL scheduling and data transmission. Performance analysis of the proposed scheme is discussed in section three followed by conclusions drawn in section four and references in section five.

2 Methodology

We consider a cell-free network with 'M' number of APs having 'N' number of antennas and 'K' number of UEs with single antenna, that are randomly distributed over the assigned coverage area. It is assumed that for CFMM system $M \gg K$ [21], but due to the proposed scalable framework, the CFMM system goes well for any values. All APs are connected to CPU via a back-haul network [21]. The channel h_{mk} UE 'k' and AP 'M' is modelled as Rayleigh Fading channel [11] given by;

$$h_{mk} \sim NC(0, R_{mk}) \tag{1}$$

where R_{mk} [21] is spatial correlation matrix having dimension $R_{mk} \in C^{N\times N}$ with large scale fading coefficient $\beta_{mk} \triangleq \frac{t_{r(R_{mk})}}{N}$ featuring shadowing and path loss. We assume that h_{mk} is an independent random variable for every$m = 1 \ldots .M,\ APs\ and\ K = 1 \ldots \ldots K,\ UEs$ and channel realization h_{mk} in different coherence blocks are i.i.d., This paper considers UL and DL transmission of CFMM system, which is assumed to operate in TDD mode, wherein $\tau_c = \tau_p + \tau_{UL} + \tau_{DL}$. In each coherence block τ_p samples are reserved for pilot assignment, and τ_{UL} for UL data transmission and τ_{DL} for DL data transmission. The basic UL signal flow of proposed CFMM system is depicted in Figure 1. As shown in the diagram, local MMSE CE is done at the AP. Then the estimates are forwarded to CPU, where MMSE estimation error is minimized with the help of deep feed forward (DFF) neural network. Multi-user UL scheduling, data detection and data transmission are also done at the CPU.

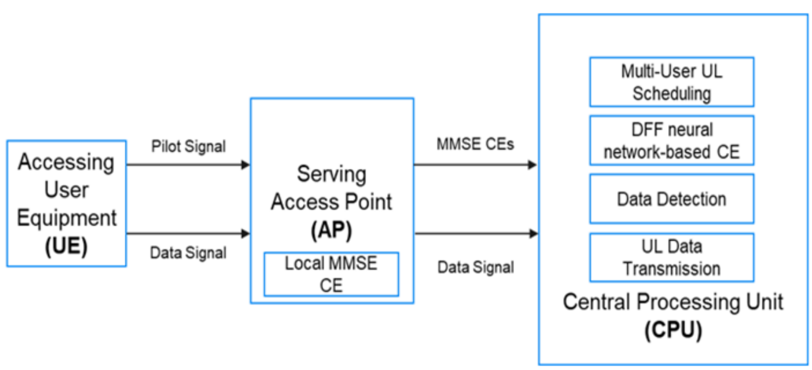

Fig 1. Block Diagram of UL CFMM system depicting signal processing flow

2.1 Pilot Assignment and Transmission

A unique pilot assignment technique, which is the modified version of the technique mentioned in paper[21] is used for mitigating PC. Due to PC, quality of CE gets affected. So, to avoid the aforementioned drawback, a unique pilot assignment algorithm is proposed in this paper. Consider τ_p mutually orthogonal pilot sequences and pilot sequence of UE 0K0 is denoted by φ_k wherein ($||\varphi_k||$)2 =τ_p and $\varphi_k \in$ C ($\tau_p \times 1$). Whenever a UE gains access into the network, a pilot is assigned to the UE depending on the distance between mobile UE and AP. The AP which is nearest to the UE, will serve that UE. If there are more than one APs near to the UE, then β large scale fading factor will decide the serving AP. In this way pilot assignment and AP selection is done through a small algorithm as follows:

- **Accessing UE selection:** Here the UE gaining access to the network is selected using a specific process through which first of all, poor channel quality UE are assigned with pilot sequence and then other UEs are considered for pilot assignment. The channel quality of UEs is determined by large scale fading coefficient i.e., beta. This fading coefficient is calculated for all accessing UEs and the values are stored in set S as per descending order. Accordingly, the accessing UE, is selected for further process.
- In 5G, accessing UE communicates[14] with its neighbouring APs using either primary or secondary synchronization signals. Depending on the nearest distance measurement d_n a serving AP AP_n is chosen by the accessing UE.

$$Serving\ (AP_n)\ =\ arg\ (min\ d_n) \tag{2}$$

- If there are more than one equidistant APs in neighbourhood of the accessing UE, then the serving AP is chosen based on the large-scale fading coefficient, β.
- The serving AP_n will serve the accessing UE with all its N number of antennas. It will assign pilot p to the accessing UE using specific algorithm.
- The serving AP_n will give information to all neighbouring APs that pilot p is being used by accessing UE. As a consequence of this, other pilot sequences will be considered for transmission apart from pilot p which will reduce PC to a significant extent. Finally, accessing UE will appoint serving AP, the one which is nearest to it and Serving AP will assign unused pilot p to the accessing UE. This will not only ensure reduced PC but also increases system performance to a greater extent as shown in the simulation results.

Consider all UEs transmit their pilot signals, then the pilot signal received by $m^{th}AP$ is given as:

$$Z_m^p = \sum_{i=1}^{k} \sqrt{\rho_i \tau_P h_{im} \phi_K} + n_m^P \tag{3}$$

where ρ_i is the UL pilot power of the i^{th} UE. $n_m^P \varepsilon C^{N\times\tau_p}$ is the received noise matrix i.e $n_m^P \sim NC(0,\sigma^2)$ and σ^2 is the noise power.

Algorithm 1 Optimal Pilot Allocation Algorithm
Require:$U_A, U_L, \tau_p, K, M, \tau, \beta, s$
Ensure:ϕ_k optimal = U_A
1. InitializeU_A = UL
2. Calculate β of all users and store in descending order in 's'
while $U_{A\neq}\phi$ **do**
3. Select U_A asper order defined in 's'
4. If $K \leq \tau_p$assign$\varphi_k$to the K^{th} user
5. If $K > \tau_p$then find out best serving AP using Equation (2) for U_A
6. Then select optimal pilot having the least impact on U_A
end while
7. Return

Now to have initial estimate of h_{mk}, project the receiving pilot signal Z_m^ponto φ_k, so that we have,

$$Z_{mk}^p =\ Z_m^p\ \phi_K^H \tag{4}$$

$$Z_{mk}^p = \sum_{i=1}^{k} \sqrt{\rho_i \tau_P h_{im} \phi_K^H} + \phi_K^H n_m^P \tag{5}$$

Here we assume that $K > \tau_p$ due to which each pilot sequence is shared by more than one UE, leading to so called PC. Also, we define subset S_K of UEs with same pilot sequence as UE K. So, we can write Equation (5) as:

$$Z_{mk}^{p} = \sum_{i \in S_K} \sqrt{\rho_i \tau_P h_{im}} + \phi_K^H n_m^P \tag{6}$$

Now if we observe Equation (6), then it is clear that mutual interference is created due to sharing of same pilot sequence by UEs leading to so called PC. Due to PC, system performance is degraded similar to cellular massive MIMO. Also, CE quality is affected and channel estimates becomes correlated. This correlation is directly proportional to number of AP antennas i.e., 'N'. Both factors will have negative impact on UE performance.

2.2 Channel Estimation (CE)

In this paper, local CE is done at the serving AP. Now according to standard theory of MMSE estimation, we can calculate channel estimate $\widehat{h}_{mk}$ for K^{th} UE at m^{th}AP which belongs to the subset S_K is given as:

$$\widehat{h}_{mk} = \sqrt{\rho_k \tau_p R_{mk} \psi_{mk}^{-1} Z_{mk}^{p}} \tag{7}$$

Where $\psi_{mk} = E\left(Z_{mk^p}\ \left(Z_{mk^p}\ \right)\right\} = \sum_{i \in S_K} \rho_i \tau_p R_{im} + I_N$ is the correlation matrix of received signal Equation (4). We can also write Equation (5) as:

$$\widehat{h}_{mk} = Y_{mk} Z_m \tag{8}$$

where $Y_{mk} = \sqrt{\rho_k \tau_p R_{mk} \psi_{mk}^{-1}}$ and depends on channel statistics. So, we can have channel estimate by multiplying Z_{mk^p} with N $\times$ N matrix Y_{mk} of each UE served by AP m. The value of Y_{mk} is known prior to AP m and is calculated at AP m. This will reduce the computational complexity at AP m, to a significant extent.

2.2.1 Proposed DFF neural network

MMSE CE often considers the impact of noise, which improves CE accuracy but at the same time, prior knowledge of channel statistics is mandatory leading to increase in computational complexity. Additionally, the performance of MMSE estimation [10] cannot always be guaranteed.

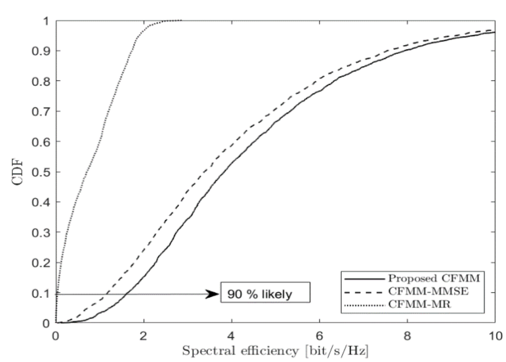

Fig 2. UL Comparison of the proposed CFMM with MMSE and MR combining techniques with M=400 and N=1 antenna configuration

To overcome the aforementioned drawbacks of MMSE estimation, Deep Feed Forward (DFF) neural network as shown in Figures 2 and 3, also known as multi-layered network of neurons wherein information travels only in forward direction is being proposed in this paper for CE. It minimizes the mean square error (MSE) between the actual channel and the channel estimate obtained from the MMSE estimation. DFF neural network-based CE is performed at the CPU and is divided into input layer, hidden layer, and output layer with different number of neurons per each layer. This neural network will map input vector x onto the output vector y. Here fully connected neural network is chosen due to its simplicity and low computational complexity. So, for fully connected L no of layers we have:

$$y_j = f\left(\sum_{j=1}^{x} w_j x_j + b\right) \tag{9}$$

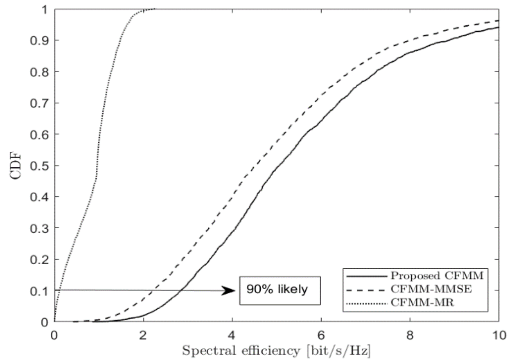

Fig 3. UL Comparison of the proposed CFMM with MMSE and MR combining techniques with M=400 and N=1 antenna configuration

Where y_j is the output, x_j is the input, $w_j$is the weight, b is the bias of j^{th} layer. The activation function f(.) used here is tanh which characterizes non-linearity of data is given by:

$$f(x) = \frac{e^{+x} - e^{-x}}{e^{+x} + e^{-x}} \tag{10}$$

The input given to the proposed DFF neural network is the channel estimates obtained from MMSE technique. So, the input $\left(\widehat{h}_{m1} \ldots\ldots\ldots.\widehat{h}_{mk}\right)_{MMSE}$ obtained from MMSE estimate for m^{th} AP is given to the neural network. The proposed neural network will minimize the MSE by learning actual channel information. Then these inputs are multiplied by weights. Then tanh activation function is applied to the product of input and weights. The output of these is given to hidden layers. It goes on through all layers and finally we get output from output layer. We will not get desired output in one epoch. This deviation of output from actual value is known as gradient or loss. Now this gradient is optimized by using Adam optimizer by adjusting weights till we get minimum gradient. Thus, the neural network will minimize MSE gradient to give desired DFF channel output i.e., $\left(\widehat{h}_{m1} \ldots\ldots\ldots.\widehat{h}_{mk}\right)_{DFF}$. The loss function used for training is mean squared error (MSE) given by:

$$L(\textstyle\sum_{j=1}^{L} Wb) = \frac{1}{RT}\sum_{R=1}^{R}\sum_{t=1}^{T}\left\|\widehat{h}_{DFF} - \widehat{h}_{actual}\right\|^2 \tag{11}$$

where T is the training size, and R is the number of realizations used for training, $\widehat{h}_{DFF}$ is the output of neural network, $\widehat{h}_{actual}$ is the actual channel, w and b are weights and biases respectively. These weights and biases are regularly updated by minimizing the loss function[22] in Equation (11). The data set for the proposed network is gathered from[22]. Out of 250880[22] realizations we have used 200000 only. For training data 140,000 realizations are used, and 30,000 for validation and data testing each respectively. The DFF neural network is trained for 900 iterations, with a learning rate of 0.001. For each iteration, mini batch size of 20 is considered. After training, performance is evaluated for test data set which gives us desired output. There are 3 hidden layers each with 1.6K,1.2K and 800 neurons respectively. All simulation parameters of DFF neural network are mentioned in Table 1. The proposed network is designed considering supervised learning approach but one can consider unsupervised approach as a future work.

Table 1. Simulation Specifications for DFF neural network

Parameter	Ranging values
Input Layer neurons	1248
Output Layer neurons	1248
Hidden Layer1neurons	1.6K
Hidden Layer2 neurons	1.2K
Hidden Layer neurons	800
Learning Rate	0.001
Optimizer	Adam
Batch Size	20
Gradient Descent Accuracy	10−8

Continued on next page

Table 1 continued

Activation Function	tanh
Loss Function	MSE

2.3 Multi-User UL Scheduling and Data Transmission

Every UE determines its transmission rate and conveyed the same information to the CPU through APs. Then, CPU schedules the UE with the highest transmission rate. Scheduled UE will transfer data during assigned transmission slot. If there is more than one user with the same transmission rate, then the user will be selected randomly with equal probability. Thus, multi-User UL scheduling will ensure good channel condition leading to enhanced performance of the proposed system. Now let us derive achievable UL SE equation for the proposed CFMM system. If $S_k$is the UL signal transmitted, then the received signal is given as:

$$y_m^{UL} = \sum_{k=1}^{K} h_{mk} S_k + n_m^{UL} \tag{12}$$

where $S_k \sim NC(0, \rho_k)$ with power $\rho_k = E\left\{|S_k|^2\right\}$ and $n_m^{UL} \sim NC(0, \sigma_{UL}^2)$ is additive receiver noise. The CPU will select receiver combining scalar as $V_{mk} = \left(\widehat{h}_{mk}\right)_{DFF}$ obtained from DFF neural network-based CE, then the combined received signal [6] can be decomposed as:

$$\widetilde{S_{mk}} = V_{mk} y_m^{UL} = \underbrace{V_{mk} h_{mk} S_k}_{Desired\ Signal} + \underbrace{\sum_{i=1, i\neq k}^{k} V_{mi} h_{mi} S_i}_{Inter-User\ Interference} + \underbrace{V_{mk} n_m^{UL}}_{Noise} \tag{13}$$

The above equation represents first level of receiver combining at the CPU. For second level of receiver combining, we are considering Large Scale Fading Decoding (LSFD) [23]. After second level of LSFD combining, Equation (12) will be modified as:

$$\widehat{S}_k = \sum_{m=1}^{M} a_{mk} \widetilde{S_{mk}} = \underbrace{\sum_{m=1}^{M} a_{mk} V_{mk} h_{mk} S_k}_{Desired\ Signal} + \underbrace{\sum_{m=1}^{M} \sum_{i=1, i\neq k}^{K} a_{mk} V_{mi} h_{mi} S_i}_{Inter-User\ Interference} + \underbrace{\sum_{m=1}^{M} a_{mk} V_{mk} n_m^{UL}}_{Noise} \tag{14}$$

Where a_{mk} is the LSFD weight computed by the CPU in such a way to reduce inter-user interference. The LSFD weight calculation depends on the distance between the UE and the AP. Then we can find out the UL ergodic channel capacity of UE K, using use and then forget (UatF) lower bound. Then the UL ergodic SE of UE k is given as:

$$SE_k^{UL} = \frac{\tau_{UL}}{\tau_c} log_2(1 + SINR_k^{UL}) \tag{15}$$

where the effective signal to interference and noise ratio (SINR) $SINR_k^{UL}$ is given as:

$$SINR_k^{UL} = \frac{\rho_k \left|E\{a_k\, V_k^H\, h_k\, \}\right|^2}{\sum_{i=1}^{k} \rho_i E\{|a_k\, V_k^H\, h_k|^2\} - \rho_k \left|E\{V_k^H\, h_k\}\right|^2 + \sigma_{UL}^2 E\{\|a_k\, V_k\|^2\}} \tag{16}$$

Similarly, we can find SE for MR receiver combining scheme. From Equation (16) we can calculate system throughput [20] which is given as:

$$R = \sum_{k=1}^{k} 1 - \frac{\tau_p}{\tau_c} log_2(1 + SINR_k^{UL}) \tag{17}$$

We can use Equation (17) as a performance measure to calculate UL system throughput wherein pilot symbols are considered instead of transmission data. So, with proposed advanced pilot assignment algorithm, we assign least interfering pilot sequence to the accessing UE which in turn will maximize the system throughput of the CFMM networks. Similar to UL signal processing methodology, we derive achievable DL SE equation for the proposed CFMM system. For, DL data transmission there are τ_{DL} symbols. During UL data transmission, UEs are dependent, on their own combining vectors, but in DL data transmission UEs are dependent, on normalized precoding vectors of all UEs. Therefore, during DL transmission precoding vectors are optimized jointly for all UEs. Herein we assumed to have same data signal to be transmitted from all APs to all UEs. Thus, the transmitted signal from AP m is given as;

$$T_m = \sum_{k=1}^{k} W_{mk} X_k \tag{18}$$

where $X_k \sim NC(0,1)$ is the DL transmitted signal for UE K and W_{mk} is the coherent precoding beamforming vector, chosen to satisfy DL power constraint. The signal received at the UE k is given as;

$$Y_k^{DL} = \underbrace{W_k h_k^H X_k}_{Desired\ Signal} + \underbrace{\sum_{i=1, i\neq k}^{k} W_i h_k^H X_i}_{Inter-User\ Interference} + \underbrace{n_k^{DL}}_{Noise} \tag{19}$$

Where n_k^{DL} is the receiver noise given by $\underbrace{n_k^{DL}}$ $\sim NC(0, \sigma_{DL}^2)$. Then we can find out DL ergodic capacity of UE k using UatF lower bound given as;

$$SE_k^{DL} = \frac{\tau_{DL}}{\tau_c} log_2(1 + SINR_k^{DL}) \tag{20}$$

Where SINR is given as;

$$SINR_k^{DL} = \frac{\left| E\left\{ W_k^H h_k \right\} \right|^2}{\sum_{i=1}^{k} E\left\{ \left| W_k^H h_i \right|^2 \right\} - \left| E\left\{ W_k^H h_k \right\} \right|^2 + \sigma_{DL}^2} \tag{21}$$

3 Result and Discussion

We consider a scenario in which the total coverage area for cell-free setting is 1×1Km area, with K single antenna UEs and M APs with N number of antennas. The UEs are independently and uniformly distributed within the specified area. For cellular setting [24], 4 square cells are deployed in 1×1Km area with a centrally located base station (BS) with 100 number of co-located antennas. The channel model, MMSE CE method used is similar to CFMM system previously. Doing similar analysis, we can calculate achievable SE of UE K, for cellular massive MIMO system, which is given as:

$$SE_k = (1 - \frac{\tau_{UL}}{\tau_c}) E\left\{ log_2(1 + SINR_k^{DL}) \right\} \tag{22}$$

Both the network configurations will have same number of antennas. The propagation model used for both networks is also same which will ensure performance differences due to difference in technology only. Apart from this location of UEs and pilot assignment technique is also same for both networks. The large-scale fading coefficient is calculated which is given by:

$$\beta_{mk} = 10^{\frac{PL_{mk} + Z_{mk\sigma_{sh}}}{10}} \tag{23}$$

Where Z_{mk} is a random variable with gaussian distribution, with σ_{sh} equal to 8db. PL_{mk} is the path loss for m^{th} AP and k^{th}UE, which is represented by three slope path loss model given by:

$$PL_{mk} = \begin{cases} -P - 35 log_{10} d_{mk} \ldots\ldots (if\ d_{mk} < 50m) \\ -P - 15 log_{10} 50 - 20 log_{10} d_{mk} \ldots\ldots (if\ 10m < \ d_{mk} \leq 50m) \\ -P - 15 log_{10} 50 - 20 log_{10} 10 \ldots\ldots (if\ \ d_{mk} \leq 10m) \end{cases} \tag{24}$$

where P is 140.7db, which is a constant and depends on carrier frequency f_c, UE height h_{UE} and AP height h_{AP} and d_{mk} is the distance between m^{th} AP and k^{th} UE. The proposed CFMM system is compared with conventional CFMM with MMSE and MR combining techniques from previous literature. In Figure 2, the UL comparison of the proposed CFMM system with conventional CFMM is done with MMSE and MR combining techniques. It shows cumulative distribution function (CDF) of the SE in UL, for M=400 and N=1 i.e., 400 APs equipped with single antenna. The abscissa value on the CDF curve represents 90 percentage of UEs. The 90 percent likely SE for the proposed scheme, CFMMMMSE scheme, and CFMM-MR scheme is 1.8

bits/s/Hz, 1.5 bits/s/Hz and 0.1 bits/s/Hz respectively. It is observed that the proposed CFMM system performs well as compared to CFMM-MMSE and CFMM-MR systems. The average SE of the proposed CFMM system is approximately 3.2 times higher as compared to other two systems. Due to the advanced pilot assignment algorithm used in the proposed CFMM system, at a time only one AP is selected and the selected AP with its full received power will serve the desired UE, which is more than enough to suppress interference, resulting in improved performance of the proposed CFMM system depicted by the graph. If we observe the CDF curve, it is seen that performance of UEs is significantly increased for those having favourable channel condition. So, with 400 APs equipped with single antenna, only UE with good channel condition will show performance enhancement. Thus, the proposed scheme enhances performance of every UE as compared to MMSE and MR combining schemes. Figure 3 presents the UL comparison of the proposed CFMM system with conventional CFMM with MMSE and MR combining techniques. It shows cumulative distribution function (CDF) of the SE in UL, for M=100 and N=4 i. e 100 APs equipped each with 4 antennas. The 90 percent likely SE for the proposed scheme, CFMM-MMSE scheme, and CFMM-MR scheme is 3 bits/s/Hz, 2.1 bits/s/Hz and 0.1 bits/s/Hz respectively. It is observed that the proposed CFMM system performs well as compared to CFMM-MMSE and CFMM-MR systems. The average SE of the proposed CFMM system is approximately 3.2 times higher as compared to other two systems. Due to the advanced pilot assignment algorithm used in the proposed CFMM system, at a time only one AP is selected and the selected AP with its full received power will serve the desired UE, which is more than enough to suppress interference, resulting in improved performance of the proposed CFMM system depicted by the graph. Here the distance between UE and AP is increased thereby decreasing macro diversity. With each AP equipped with 4 antennas, interference is locally suppressed to a greater extent. So, the UE with unfavourable channel condition will also give better performance. As shown in Figure 4, the DL comparison of the proposed CFMM system is done with conventional CFMM with MMSE and MR combining techniques. It shows cumulative distribution function (CDF) of the SE in DL, for M=400 and N=1 i.e., 400 APs equipped with single antenna. The 90 percent likely SE for the proposed scheme, CFMM-MMSE scheme, and CFMM-MR scheme is 0.7 bits/s/Hz, 0.5 bits/s/Hz and 0.4 bits/s/Hz respectively. It is observed that the proposed CFMM system performs well as compared to CFMM-MMSE and CFMM-MR systems. The same, UL analysis holds true for DL analysis also. It is evident that APs with single antenna configuration performs well with an advantage of improving performance of UEs having lower SEs. Similarly, Figure 5 will consider the performance measures in DL. It shows the DL comparison of the proposed CFMM system with conventional CFMM with MMSE and MR combining techniques. It shows cumulative distribution function (CDF) of the SE in DL, for M=100 and N=4 i.e., 100 APs equipped with 4 antennas. The 90 percent likely SE for the proposed scheme, CFMM-MMSE scheme, and CFMM-MR scheme is 2 bits/s/Hz, 1.2 bits/s/Hz and 1 bits/s/Hz respectively. It is observed that the proposed CFMM system performs well as compared to CFMM-MMSE and CFMM-MR systems. The same, UL analysis holds true for DL analysis also. It is seen from the graph that, with multiple antennas per APs, local interference mitigation is improved. In Figure 6 the performance is evaluated by considering the average sum SE of the proposed system with increasing number of APs, during UL. From the figure, it is obvious that the proposed system outperforms the one with MMSE combining system. Also, average sum SE increases with increase in number of APs. Different UE locations and channel realizations are considered while taking average of sum SE. Again, the improved performance of the proposed system emphasizes the importance of advanced pilot assignment technique. Figure 7 measures the performance of the average sum SE of the proposed system with increasing number of APs, considering DL analysis. From the figure, it is obvious that the proposed system outperforms the one with MMSE combining system. Also, average sum SE increases with increase in number of APs. Different UE locations and channel realizations are considered while taking average of sum SE. From UL and DL analysis curve, it is clear that average DL sum SE is higher then, UL one. Again, the improved performance of the proposed system emphasizes the importance of advanced pilot assignment technique. As shown in Figure 8 the cellular massive MIMO system, is compared with the proposed CFMM system and the conventional CFMM-MMSE system. It indicates CDF as a function of SE, considering randomly located UEs. From comparing all CDF curves, it is evident that the proposed CFMM system performs well then cellular MM system and CFMM-MMSE system. The 90 percent likely SE for the proposed scheme, CFMM-MMSE scheme, and Cellular massive MIMO scheme is 6.4 bits/s/Hz, 4.2 bits/s/Hz and 2 bits/s/Hz respectively. Improved performance of the proposed CFMM system emphasizes the importance of using advanced pilot assignment and DFF neural network for CE. Comparison of advanced pilot assignment algorithm of the proposed scheme with random pilot assignment and greedy pilot assignment algorithm is shown in Figure 9. CFMM system provides uniform service to all UEs in spite of different UE location. Therefore, system throughput is considered as the performance metric in evaluating different pilot assignment algorithm. From the 90 percent likely values of the throughput, it is evident that the proposed advanced pilot assignment algorithm performs better as compared to random and greedy pilot assignment techniques.

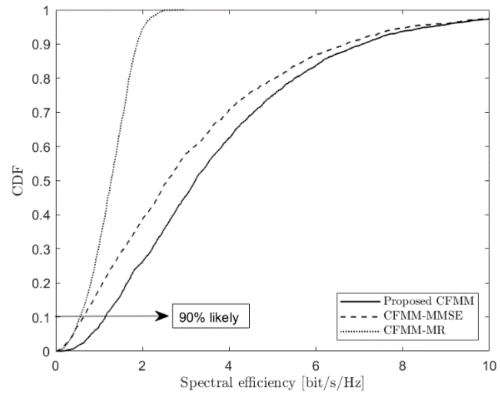

Fig 4. DL Comparison of the proposed CFMM with MMSE and MR combining techniques with M=400 and N=1 antenna configuration

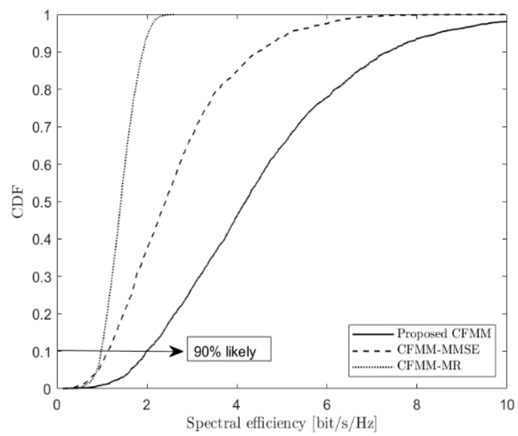

Fig 5. DL Comparison of the proposed CFMM with MMSE and MR combining techniques with M=100 and N=4 antenna configuration

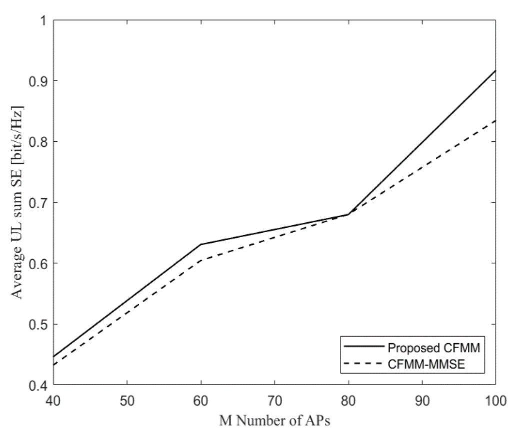

Fig 6. Average Sum SE of the proposed system compared with MMSE technique during UL analysis

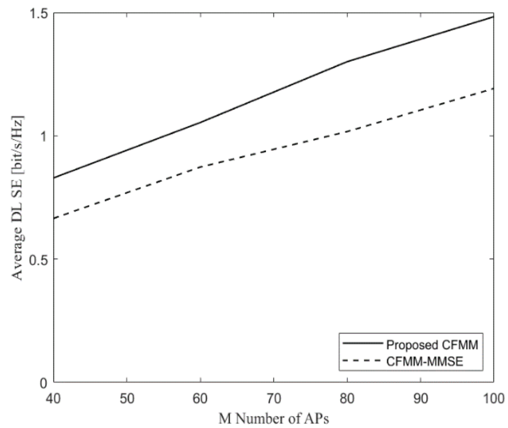

Fig 7. Average Sum SE of the proposed system compared with MMSE technique during DL analysis

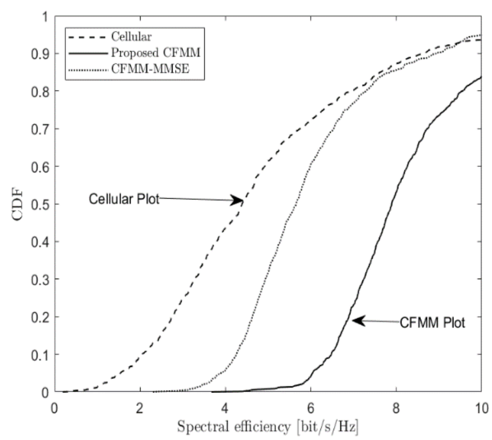

Fig 8. Comparison of Cellular massive MIMO system with the proposed CFMM system and the conventional CFMM-MMSE system

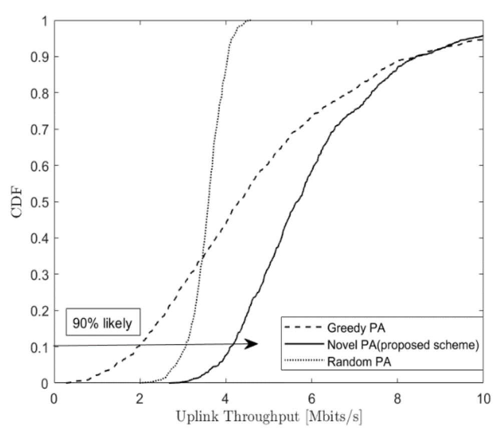

Fig 9. Comparison of advanced pilot assignment scheme with greedy and random pilot assignment schemes

4 Conclusion

This research considered a taxonomy for UL and DL CFMM system with an advanced pilot assignment algorithm and machine learning aided CE method, for Rayleigh Fading channel model. The proposed system is analysed considering pilot contamination, channel estimation error and compared with conventional cell-free networks with minimum mean square error and maximum ratio combining techniques. In this paper closed-form UL and DL SE expressions are calculated for large scale fading decoding, minimum mean square error, maximum ratio combining techniques. An advanced pilot assignment algorithm is developed, due to which the interference suppression capability of the proposed system increases thereby mitigating pilot contamination to a greater extent. Machine Learning aided channel estimation is designed, which minimizes gradient loss to zero, enabling the proposed CFMM with accurate channel prediction with faster calculations as compared to the conventional CFMM system. The simulation result shows that:

1. The 90 percent likely SE for the proposed scheme, CFMMMMSE scheme, and CFMM-MR scheme in uplink for M = 400 and N = 1, is 1.8 bits/s/Hz, 1.5 bits/s/Hz and 0.1 bits/s/Hz respectively.
2. Similarly, for M=100 and N=4, the 90 percent likely SE for the proposed scheme, CFMM-MMSE scheme, and CFMM-MR scheme is 3 bits/s/Hz, 2.1 bits/s/Hz and 0.1 bits/s/Hz respectively.
3. The SE in DL, for M=400 and N=1, for the proposed scheme, CFMM-MMSE scheme, and CFMM-MR scheme is 0.7 bits/s/Hz, 0.5 bits/s/Hz and 0.4 bits/s/Hz respectively.
4. The SE in DL, for M=100 and N=4, for the proposed scheme, CFMM-MMSE scheme, and CFMM-MR scheme is 2 bits/s/Hz, 1.2 bits/s/Hz and 1 bits/s/Hz respectively. From simulation results, it is evident that, the SE performance of the proposed system is three times better than the conventional system.
5. The 90 percent likely SE for the proposed scheme, CFMM-MMSE scheme, and cellular massive MIMO scheme is 6.4 bits/s/Hz, 4.2 bits/s/Hz and 2 bits/s/Hz respectively, which clearly indicates performance enhancement of the proposed system against its cellular counterpart.
6. Also, the system throughput obtained by using advanced pilot assignment algorithm outperforms greedy and random pilot assignment methods.

Thus, it has been demonstrated that the proposed CFMM system outperformed cellular MM, CFMM-MMSE and CFMM-MR systems. For, future research direction, one can consider the power allocation problem for the proposed CFMM system. A supervised learning approach is used for channel estimation herein, but one may go for unsupervised approach as another future research direction as well.

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