



Bachelor Term Project

Phase 2

*Configuring Passive Intelligent Surfaces for
maximizing data-rates in wireless communication*

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April 17, 2021

Abstract

Wireless Communication is ever improving with the 5G based wireless communication being now being deployed in a lot many geographies. With the advent of beamforming technology and MIMO based communication, concerns over power consumption, security and logistical issues are bound to be raised. Many solutions have come forward for what is labelled as “5G and beyond” stack, one such solution is the use of reflecting surfaces which have reflecting elements which can inflict a phase and magnitude shift on the incoming wave and reflect it without the use of any active components.

Passive Intelligent Surfaces (PIS) or Intelligent Reflecting Surfaces (IRS) as they are sometimes called are an up and coming advancement to the ever improving field of wireless communication. PIS have a wide variety of applications including but not limited to unclogging dead zones, enhancing physical layer security and enhancing the power of the received signal. There are a wide variety of problems related to the development, deployment and operation of such a surface but this thesis concerns with the specific class of problems related to setting the reflection coefficients of the IRS elements such that the data rates for information users are maximised in linear time.

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1 Introduction

5G and beyond networks come with more demands than their predecessor, like improving energy efficiency, decreasing monetary costs, higher reliability and domineeringly lower latency. However, emerging solutions to 5G services (e.g. ultra-reliable and low latency communication (URLLC)) include an increasing number of active nodes, packing more antennas and migrating to higher frequencies involves increasing energy, hardware and cost requirements. Hence this need for cheaper energy-efficient smart solutions has led to the conceptualization of Passive Intelligent Surfaces(PISs) (also known as Intelligent Reflecting Surfaces (IRSs)). These are surfaces (not necessarily flat) which reflect signals from base station to the user and vice-versa. In addition to reflecting they are also capable of changing the phase and magnitude of the signal and are configurable by a controller.

Formally, PIS is a re-configurable environment for Beyond 5G wireless communication systems constituting passive elements which reflect incoming signals and additionally inflict a controllable phase and magnitude change to them [1].

PIS reflection surface is realizable using the existing programmable meta surfaces [2]. These reflection elements are tuned by the help of a controller connected to the base station, and Micro Electro Mechanical Switches (MEMS) are used to control the reflection coefficients. This thesis does not delve into the physical implementation any more than this but details can be found in [3].

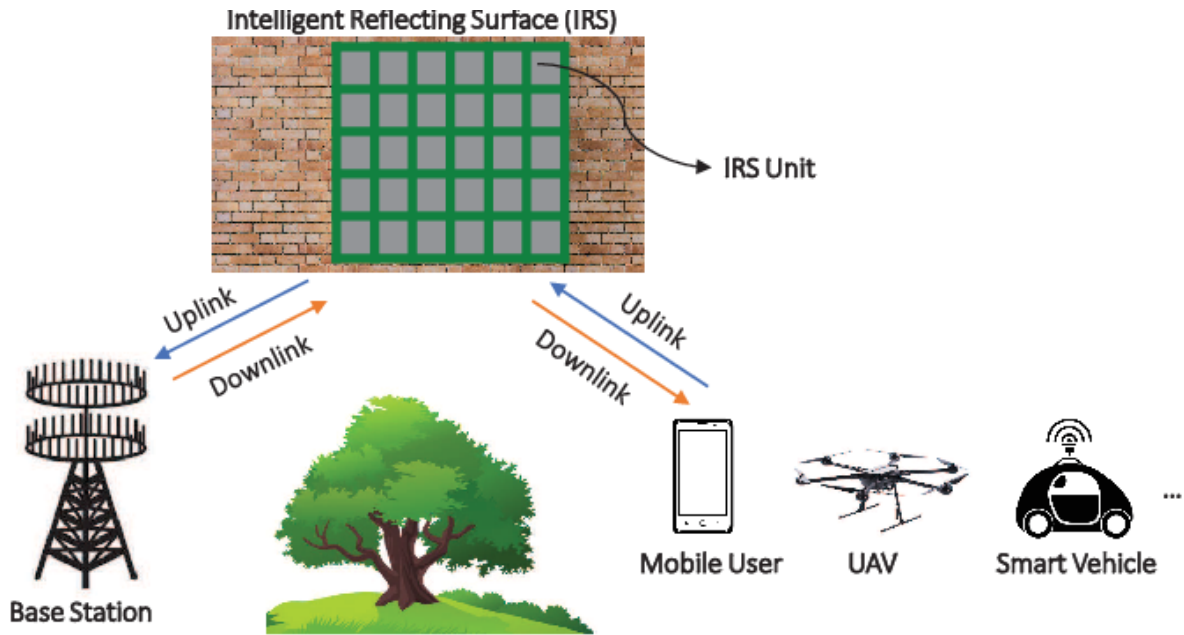


Figure 1: Basic setup of how Passive Intelligent Surfaces or Intelligent Reflecting Surfaces are deployed and work. Image Credits: Figure 1 of [4]

2 Literature Review

PIS has a variety of different use cases been explored in the areas of Wireless Communication and Energy Transfer as surveyed in [5]. Configuring a PIS to maximize energy recieved or data-rates requires information about the channel coefficients [6]. Estimation can be done in both the frequency and time domain, and using different sequences of PIS elements is required, as was studied in the previous phase of this project and also in [7].

Once estimated, the reflection coefficients need to be tuned to meet the optimization objective. This could be done as a joint beamforming optimization where both active beamforming at the Base Station and passive beamforming by setting coefficients of PIS, similar to [8]. The phase shifts of the elements need not be discrete and could be based in a practical setting as studied in [9] and [10]. [10] suggested iterative alternating optimization algorithms to optimize the SINR of the recieved signal.

Practical models involving PIS aided MIMO-OFDM based communication have been explored in [11] recently, which go on to show that solving the optimization problem of maximizing the data-rates has non-convex constraints, which makes it tough to solve. Some techniques like Successive Convex Approximation [12] and Block Coordinate Descent [11] have been used to find an approximate solutions but such approaches have non linear time complexity.

3 System Description

3.1 System Model

A single information user OFDM-based wireless setup is considered, where an PIS is deployed to improve the communication link between Base Station (BS) and User (U) where both have a single antennae. The PIS has N reflecting elements given by set \mathbb{N} . The focus is on downlink communication from BS to U and using reciprocity we could derive similar results for the uplink as well. The PIS elements are configured such that they can only induce a phase shift of 0 or π and no amplitude change. This last consideration, simplifies analysis and as will be discussed later can be removed suitably.

3.2 Signal Model

The total bandwidth B is equally divided into K orthogonal sub-carriers (SCs) given by set \mathbb{K} . It is assumed that the power is equally divided within all these sub-carriers and the total power is less than P . The training signal $\mathbf{x}_t^{N \times 1}$ has power distributed across all N sub-carriers and so the signal is instead represented by a single symbol x_t . The received symbol is given by $\mathbf{x}_r^{N \times 1}$.

3.3 Channel Model

The channel is a multi-tap channel with L taps. The direct channel between BS and User is given by $\mathbf{h}_d^{K \times 1} \in \mathbb{C}^{K \times 1}$. The channel between the BS and the i^{th} PIS element is given by $\mathbf{h}_{b_i}^{K \times 1}$ and the channel between the i^{th} PIS element and the User is given by $\mathbf{h}_{u_i}^{K \times 1}$. The reflection coefficients of the i^{th} PIS elements is given by $\beta_i e^{j\theta_i}$. For this case $\beta_i = 1$ and $\theta_i \in \{0, \pi\} \forall i \in \mathbb{N}$.

The received signal can be given by:

$$\mathbf{x}_r = \sum_{n=1}^{n=N} \mathbf{h}_{b_i} \theta_i \odot \mathbf{h}_{u_i} + \mathbf{h}_d^T x_t + \mathbf{w}$$

where $w \in \mathbb{C}^{K \times 1}$ is the noise (convoluted with the channel) where the noise power spectral density is given by N_o . The equation above could be further vectorized further to make it analytically more tractable, also the direct channel can be considered similar to a sub-channel via a PIS element with the gain as 1 and the phase shift as 0. The updated model would look like,

$$\mathbf{x}_r = (H_b \odot H_u) \Theta + w$$

where $H_b = [\mathbf{h}_d, \mathbf{h}_{b_1}, \mathbf{h}_{b_2} \dots \mathbf{h}_{b_N}]$, $H_b \in \mathbb{C}^{M \times N}$, $H_u = [1, \mathbf{h}_{u_1}, \mathbf{h}_{u_2} \dots \mathbf{h}_{u_N}]$, $H_u \in \mathbb{C}^{M \times N}$ and $\Theta = [1, e^{j\theta_1}, e^{j\theta_2} \dots e^{j\theta_N}]$, $\Theta \in \mathbb{C}^{N \times 1}$ are the The channel coefficient matrices and reflection coefficient vector. Let $G = H_b \odot H_u$, therefore since the above equation is a linear equation, G can be estimated using pilot signals, by an appropriate estimator. The challenge that this project deals is that once the estimates for the channel coefficients are obtained how should the reflection elements be set so that to optimize certain metric, specifically the data-rates for a single user.

4 Reflection Coefficient Optimization to maximize achievable rates

4.1 Optimization Problem

The data-rate for a single column can be given by,

$$R = \frac{B}{K + L - 1} \sum_{\nu=0}^{K-1} \log_2 \left(1 + \frac{P |G_\nu \Theta|^2}{B N_o} \right)$$

where G_ν is the ν^{th} row of G . It is R that we need to optimize and the optimization problem can be set up as,

$$\max_{\Theta} R \tag{1}$$

$$\text{s.t. } \theta_i \in \{0, \pi\} \forall i \in \mathbb{N} \tag{2}$$

An exhaustive search over the whole space of Θ would require 2^N computations and would prove out to be inefficient when N is in thousands. Therefore there is a need to reduce the amount of computations while almost achieving the optimal data rates. These algorithms would preferably should be of linear time complexity ¹

4.2 Ideal Optimization

Optimizing without the constraint of having discrete phase shift has already been done in [12] and [13]. The result was is that the PIS configuration that attain the optimal data-rates is one where the phase shift induced by the PIS is equal to the difference in phase shift of the direct channel and that of the cascaded channel. In other words, the PIS would be expected to compensate for the delays induced by the rest of the channel. But since deploying continous phase shifts practically is not possible, PIS elements often have discrete phase shifts. It makes sense to then try and compensate as much as possible for the phase shifts induced. But this approach becomes redundant when the number of possible phase shifts is very low, for example 2. The algorithms developed ahead still follow the same underlying philosophy but also exploiting the discrete nature of the phases.

4.3 Optimizing across Multiple Frequencies: OFDM

If we consider the frequency response for the channel to be flat across the bandwidth the Rate becomes,

$$R = \frac{BK}{K + L - 1} \log_2 \left(1 + \frac{P|G_\nu \Theta|^2}{BN_o} \right)$$

and maximizing this is equivalent to maximizing just the Channel Coefficient $L2$ Norm. Therefore our equation 1 becomes,

$$\max_{\Theta} |G_\nu \Theta|^2 \tag{3}$$

$$\text{s.t. } \theta_i \in \{0, \pi\} \forall i \in \mathbb{N} \tag{4}$$

The algorithms developed here are under this assumption and hence the vector sum of the channel coefficients are maximized by optimally and efficiently selecting the reflection phase shifts. But if the channel is not flat across the bandwidth then one of the approaches as taken by [14], would be to estimate the channel coefficients in the time domain, select some T strongest taps and then optimally selecting the delays of PIS elements using analogous algorithms. Although in [14], the algorithms developed optimally in $O(N^3)$

¹It can be shown that the minimum possible time complexity can be linear since the channel via each element of the PIS would have to be evaluated unless grouping the PIS elements is an option.

4.4 Constraints and Considerations while devising the algorithm

While designing such an algorithm to figure out the optimal phase shift angles, certain considerations are needed to be considered. First of them, as already discussed would be to keep the time complexity to a minimum, preferably linear time, i.e. $O(N)$. The second would be restricting to only two phase shift values, 0 and π . As seen in the section on ideal optimization the expression for continuous phase shifts turn out to be easier than a discrete case, esp. the case where the phase shifts are only two values. Lastly, while designing it would be better to assume at first that the channels across different frequencies and PIS elements are almost of the same order. This is an unreasonable assumption, but helps develop the basic structure of the algorithm, on top of which can be developed more complex algorithms which do not assume this.

5 Descriptions of Proposed Algorithms

The first two algorithms developed ahead are optimal, assuming that the channel response does not change substantially across different frequencies and along different sub-channels via the IRS elements. The 3rd algorithm mitigates the problem of different sub-channels having varied channel response.

5.1 Heuristic Vector Addition

The first algorithm developed is based on intuition for maximizing the sum of a set of vectors where each of the vectors could either be kept in their original direction or can be flipped. Here flipping of vectors is simply the reflectors tuning channel coefficients to be multiplied by 1 or -1 . For each sub-channel the subcarrier channel coefficients are summed up to get the net coefficient for that sub-channel. Now every channel coefficient is mapped from the complex space to a vector space. Each of them are sequentially aligned with the direct channel vector. The major problem is of selecting the vectors along which to align the reflection coefficients. If the direct channel is orders greater than the other channels than it makes sense to do so but if the direct channel is itself weak than aligning might not be the optimal choice.

Algorithm 1 Heuristic Vector Addition

```
1: procedure VECTOR OPTIMIZATION( $\hat{G}$ )  ▷ Vector based optimization to configure
   the IRS
2:    $\Theta \leftarrow [\theta_1, \theta_2 \dots \theta_N]$ 
3:    $h_{\text{opt}} \leftarrow \sum_{k=0}^{K-1} \hat{g}_{0k}$   ▷ Setting initial value to direct channel
4:   for  $i \leftarrow 1, N$  do  ▷ Looping over all N IRS Elements
5:      $g_i \leftarrow \sum_{k=0}^{K-1} \hat{g}_{ik}$ 
6:     if  $\text{angle}(g_i, h_{\text{opt}}) > \frac{\pi}{2}$  and  $\text{angle}(g_i, h_{\text{opt}}) < \frac{3\pi}{2}$  then
7:        $\theta_{\text{opt},i} \leftarrow -1$ 
8:     else
9:        $\theta_{\text{opt},i} \leftarrow 1$ 
10:    end if
11:     $h_{\text{opt}} \leftarrow h_{\text{opt}} + g_i \theta_{\text{opt},i}$ 
12:  end for
13:  return  $\Theta$   ▷ The optimal angles are stored in  $\Theta$ 
14: end procedure
```

5.2 Greedy Quadrant Memoization

This algorithm is computationally a little slower than the previous algorithm but does not suffer the problem of initialization from the previous algorithm. Here we maintain two matrices of dimensions $(4, N)$. The columns denote the N different PIS elements and the rows denote the 4 quadrants of the complex plane. The 4 quadrants signify the maximum possible resultant being in that quadrant. Hence we iterate through the different PIS elements, to see what should be the configuration of the element, for the case when each of 4 quadrants contain the maximum resultant. Then these resultants and optimal configurations are stored, which are used in the next stage and so on.

The main issue with this and the previous algorithm is that if some of the sub-channels are significantly stronger than the other channels. In this case the result obtained via this procedure would be sub-optimal, since if the weaker channels were to be not considered or the weaker channels were aligned along the stronger ones, better results would be obtained than the other way around, it is with this intuition that the next algorithm is developed.

Algorithm 2 Greedy Quadrant Memoization

```
1: function OPTTHETASFORQUADRANTS( $g_i$ )
2:    $optThetas \leftarrow [0 \ 0 \ 0 \ 0]$ 
3:    $init \leftarrow [e^{j\frac{\pi}{4}} \ e^{j\frac{3\pi}{4}} \ e^{j\frac{5\pi}{4}} \ e^{j\frac{7\pi}{4}}]$ 
4:   for  $j \leftarrow 1..4$  do
5:     if  $\text{angle}(g_i, init[j]) > \frac{\pi}{2}$  and  $\text{angle}(g_i, init[j]) < \frac{3\pi}{2}$  then
6:        $optTheta[j] \leftarrow \pi$ 
7:     else
8:        $optTheta[j] \leftarrow 0$ 
9:     end if
10:  end for
11:  return  $optThetas$ 
12: end function
13: procedure THETA OPTIMIZATION( $\hat{G}$ )  $\triangleright$  DP Greedy optimization to configure the
    IRS
14:    $\Theta \leftarrow \begin{bmatrix} \theta_{01} & \theta_{11} & \theta_{21} \dots \theta_{N1} \\ \theta_{02} & \theta_{12} & \theta_{22} \dots \theta_{N2} \\ \theta_{03} & \theta_{13} & \theta_{23} \dots \theta_{N3} \\ \theta_{04} & \theta_{14} & \theta_{24} \dots \theta_{N4} \end{bmatrix}$   $\triangleright 0$  index for direct channel.
15:    $G_{opt} \leftarrow \begin{bmatrix} g_{opt,01} & g_{opt,11} & g_{opt,31} \dots g_{opt,N1} \\ g_{opt,02} & g_{opt,12} & g_{opt,32} \dots g_{opt,N2} \\ g_{opt,03} & g_{opt,13} & g_{opt,33} \dots g_{opt,N3} \\ g_{opt,04} & g_{opt,14} & g_{opt,34} \dots g_{opt,N4} \end{bmatrix}$   $\triangleright \theta_i$  and  $\mathbf{g}_{opt,i}$  denotes the  $i$ th column
16:    $\hat{g}_0 \leftarrow \sum_{k=0}^{K-1} \hat{g}_{0k}$ 
17:    $\theta_0 \leftarrow OptThetasForQuadrants(\hat{g}_0)$ 
18:    $\mathbf{g}_{opt,0} \leftarrow \hat{g}_0 \times \theta_0$   $\triangleright$  Setting initial value to direct channel
19:   for  $i \leftarrow 1..N$  do  $\triangleright$  Looping over all N IRS Elements
20:      $\hat{g}_i \leftarrow \sum_{k=0}^{K-1} \hat{g}_{ik}$ 
21:      $\theta_i \leftarrow OptThetasForQuadrants(\hat{g}_i)$ 
22:      $\mathbf{g}_{opt,i} \leftarrow \mathbf{g}_{opt,i-1} + \hat{g}_i \times \theta_i$ 
23:   end for
24:    $optQuad \leftarrow \text{indexOf}(\text{Max}(\mathbf{g}_{opt,N}))$   $\triangleright$  Maximum across the absolute of the 4
    values.
25:    $OptTheta \leftarrow optQuad^{th}$  row of  $\Theta$ 
26:   return  $optTheta$   $\triangleright$  The optimal angles are stored in  $optTheta$ 
27: end procedure
```

5.3 Select N Best Sub-channels

For selecting the top N best sub-channels we develop an [4] approximately linear algorithm. A straightforward approach would have been to sort the the sub-channels summed over the sub-carriers according to their absolute gain. But this operation takes at best $O(N \log N)$ and also in the practice about 10% are good enough and so sorting the rest would be not of any use. Instead we simply iteratively find out the i^{th} maximum until the

difference is not above a certain threshold, signifying that the channel gain have indeed decreased abysmally.

Algorithm 3 Select N Best Sub-channels

```

1: procedure FINDNBESTSUBCHANNELS( $\hat{G}$ )
2:   for  $i \leftarrow 1, N$  do
3:      $g_i \leftarrow \sum_{k=0}^{K-1} \hat{g}_{ik}$  ▷ Summing over sub-carriers
4:   end for
5:    $\mathbf{g} \leftarrow [g_1, g_2 \dots g_N]$ 
6:   prevBest, indexPrev  $\leftarrow$  Top( $\mathbf{g}, 1$ ) ▷ Top(x,i) returns the  $i^{th}$  best element and its
   index of x based on ranking absolute values of x's elements.
7:   Best, indexBest  $\leftarrow$  Top( $\mathbf{g}, 2$ )
8:   indexSelect  $\leftarrow [ ]$ 
9:   APPEND indexPrev to indexSelect
10:   $j \leftarrow 3$ 
11:  while prevBest - Best < Threshold do
12:    prevBest, indexPrev  $\leftarrow$  Best
13:    Best, indexBest  $\leftarrow$  Top( $\mathbf{g}, j$ )
14:    APPEND indexPrev to indexSelect
15:     $j++$ 
16:  end while
17:  return indexSelect
18: end procedure

```

6 Numerical and Simulation Results

The dataset for simulating and testing the algorithms was taken from the Signal Processing Cup, the competition which provided the main problem statement and motivation behind this phase of the project. This dataset has 51 unique setups, with 4096 IRS elements, 500 sub-carriers and 20 taps. The information regarding Noise Power Spectral Density was not made public. However the bandwidth is 20 Mhz. So the data rates are calculated taking N_0 as 10^{-20} W/hz. But the exact data rate don't matter as we are comparing performance between algorithms.

The results have been restricted to the dataset itself as it was varied enough to test on it. Figures 2 and 3 show how the channel coefficients are distributed across different sub channels and sub-carriers. Clearly the distribution across the sub channels is more varied and provides a challenge, to which Select-N algorithm is a plausible solution. 4 clearly shows the advantage of using the linear time vector based method to optimize over other conventional approaches.

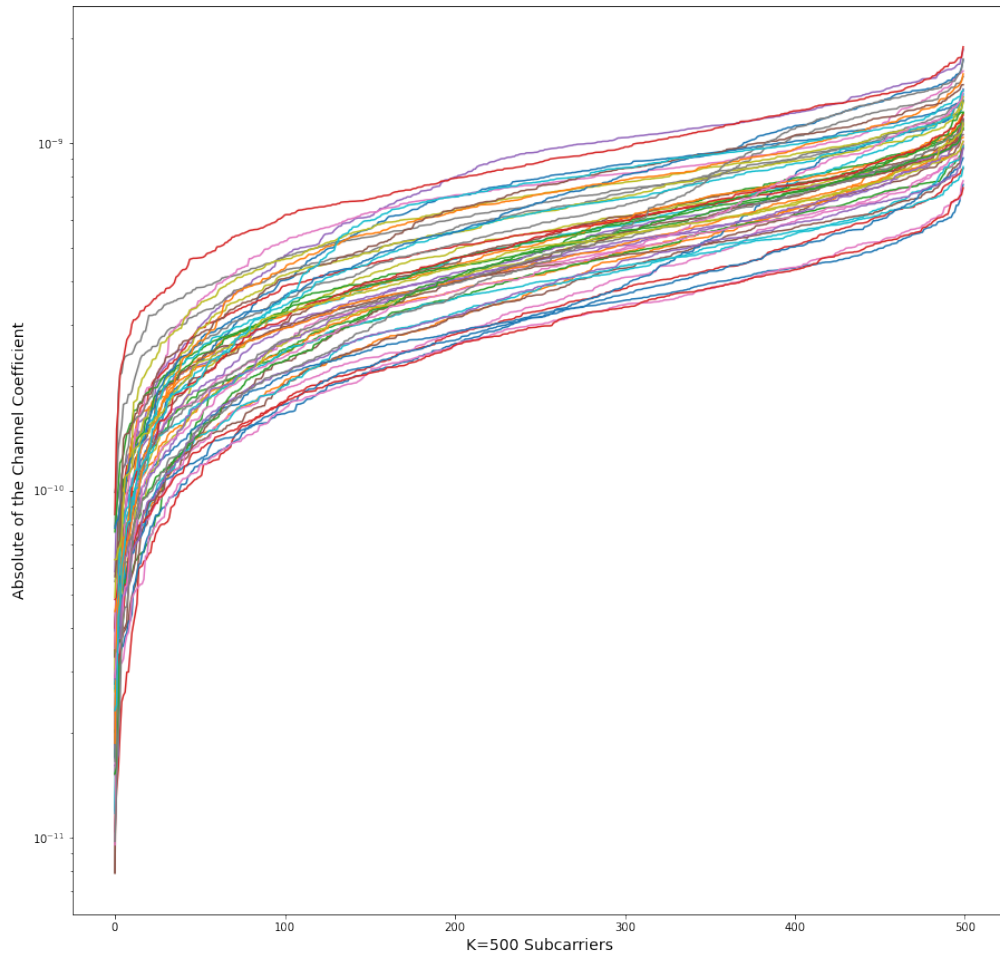


Figure 2: How the distribution of channel coefficients gain for different sub-carriers look like for users in the given dataset

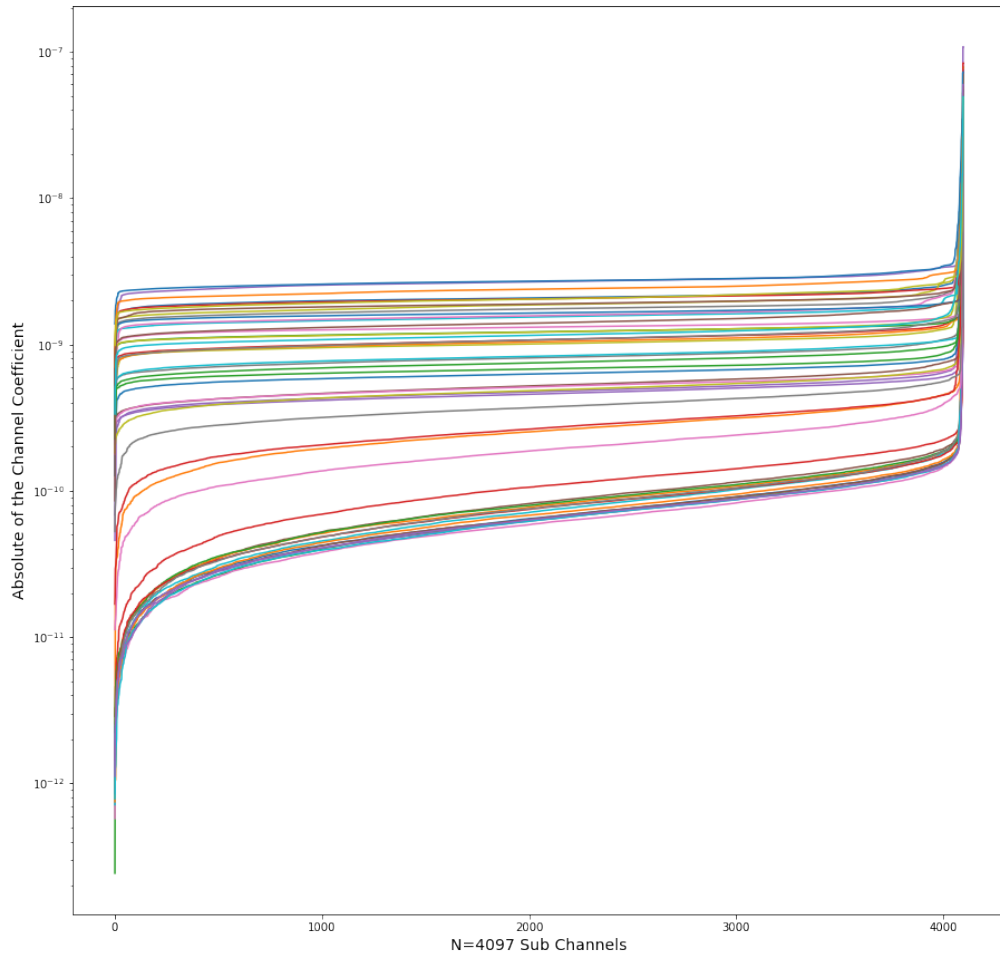


Figure 3: How the distribution of channel coefficients gain for different sub-channels look like for users in the given dataset

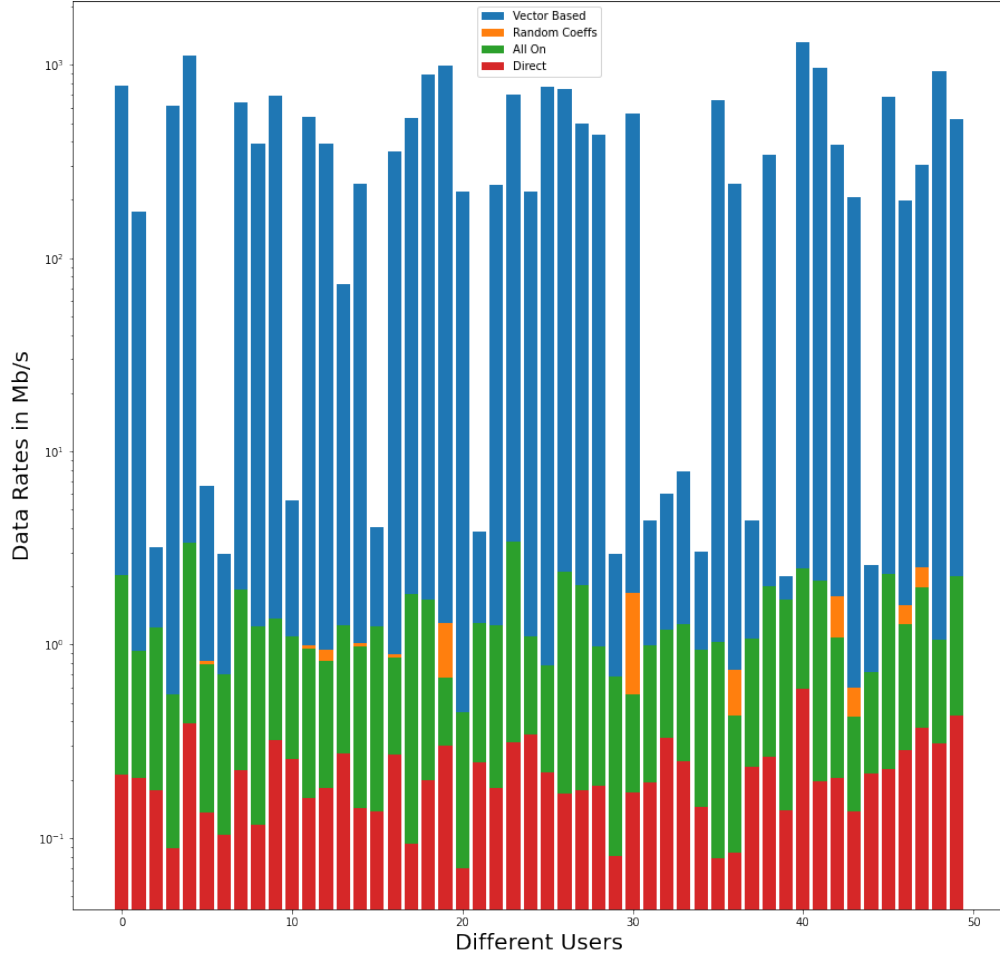


Figure 4: Datarates obtained for different methods

7 Discussions and Future Work

Results show that this algorithms can in linear time offer high data rates compared to a) the direct channel case and b) when the coefficients are all ON/randomly chosen. The Greedy Quadrant Memoization is more space savvy than the simple vector sum maximization but ensures that the initial vector does not impact the outcomes much. The results go on to show that the vector sum of the channel coefficient can indeed be maximized to maximize the datarates, given that the frequency response is flat.

This is one of the shortcomings of this method, which makes it unsuitable to be used in a practical setting. It can still be used in the case when OFDM is not being used, but that will hardly be the case with beyond 5G networks. Nevertheless the basic structure

of the algorithm can be still extended to a case where the frequency response is not constant.

One of the ways could be, to see if the channel coefficients could be estimated in the Time Domain to obtain the L different taps and then from these L taps, the strongest tap could be selected whose coefficient and index could be used to calculate the delay induced. Once the delay is known, the coefficients of each subchannel could be set to match nullify the net delay difference. It would also be interesting to see how such a setup could be extended to a multi-user setup.

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