# Constrained LS Channel Estimation for Massive MIMO Communication Systems

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***Abstract*—In recent years, the manufacturing of mobile and IoT devices has increased dramatically. For the service provider, the requirement for high throughput and extensive connectivity became a major obstacle. In B5G and 6G, different advanced technologies have been introduced to cater demands of users effectively. One of the most important technologies of next-generation networks is massive MIMO systems. In multiuser communication systems, transmission and reception of signals occur simultaneously which creates multiuser interference (MUI). The presence of MUI in the system is the major challenge for the effective operation of massive MIMO receivers. The influence of MUI must be minimized using a channel estimation technique in order to fully utilize the capabilities of a massive MIMO system. This work proposes the constrained least square (LS) channel estimate technique to improve the massive MIMO downlink system's overall performance. The Mean Square Error shows that the unconstrained LS performance is poor as compared to the constrained LS channel estimation. Additionally, the effectiveness of the proposed constraint LS channel estimate is assessed in communication systems using varying transmission antennas at the base station and number of users.**

***Index Terms*—Massive MIMO, Channel Estimation, B5G, MUI, Least Square**

## I. Introduction

In the era of globalization, contemporary networks encounter a significant upswing in traffic demand. To meet the specific demands of cellular systems, these networks are strategically deployed over short distances. Additionally, wireless Local Area Networks (WLANs) are ubiquitously employed in various locations to address connectivity needs. The growing popularity of mobile broadband services and the introduction of new concepts like machine-to-machine (M2M) and the Internet of Things (IoT) are also responsible for the rise in wireless traffic. In daily routine, consumers are more likely to rely severely on mobile data due to the widespread of cellular services. Our living standards have increased thanks to the greater potential that the 3G, 4G, and 5G have brought forth, such high data rates and minimal latency. The improved feature in new generations [1], has enabled users to do online gaming, video calls, and engagement on social media platforms such as Twitter, Instagram, and Facebook. The whole world is going to be connected by mobile devices with the evolution of networks in upcoming years. The advancement or the evolution of mobile network is evident from the increasing number of mobile devices, large connectivity, high data traffic, and increased widespread mobile applications. The massive MIMO technique is one of the important technologies for future 5G or 6G networks. The large number of antennas at BS is basically the expansion of conventional MIMO system which provide increased throughput and enhanced spectral efficiency. The essence of this technology lies in the integration of antennas, radios, and accessible spectrums to allow higher speed and capacity for the upcoming 5G era [2]. Considering its ability to boost throughput and spectral efficiency, massive MIMO is currently regarded as a technology that will be required for upcoming wireless standards [3], [4]. The crucial aspect lies in the substantial array gain achieved by massive MIMO through the utilization of a significant number of antennas [4]. One key technological advancement that makes 5G and advanced networks possible is massive MIMO. Massive MIMO and intelligent sensing systems are closely related because intelligent sensing systems mainly depend on 5G and beyond networks to operate.

Conventional multi-access methods for collecting data from multiple smart sensors are very unfeasible and result in decreased reliability, low data rates, and high latency. However, Massive MIMO is excellent at detecting data from several sensor transmissions at once, drastically cutting latency, and giving sensors higher data rates and more stable connections. This is due to its extensive beam forming and multiplexing capabilities. The real-time transmission of data gathered by smart sensors to central monitoring hubs is expected to be made possible by massive MIMO systems. This will enable a variety of applications, including intelligent highways, innovative buildings, autonomous vehicles, remote healthcare, smart grids, advanced antennas, and environmental monitoring.

Fig. 1 shows the number of connected devices and data traffic for each year from 2020 to 2030, and it is evident that both the number of devices per person and data traffic are steadily rising each year.

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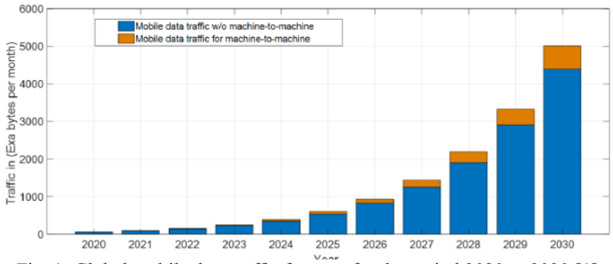


Fig. 1: Global mobile data traffic forecast for the period 2020 to 2030 [1].

Multiuser interference (MUI) inside the system is the main obstacle faced in the development of huge MIMO receivers. This challenge arises due to the simultaneous reception and transmission of users simultaneously, which results in severe degradation of overall system performance. A channel estimate method must reduce the MUI in order to fully utilize the massive MIMO system. A downlink massive MIMO system is taken into consideration in this study. To improve channel estimation performance, a constrained LS solution has been proposed. The outcomes demonstrate that the suggested constrained LS solutions outperform the unconstrained LS algorithm. The constrained algorithm is adopted from [5] for constrained channel estimation. Constrained least square channel estimation is a technique used to improve wireless communication system channel estimation accuracy while maintaining constraints pertaining to operational or physical characteristics of the system.

The rest of the paper is organized below. The most recent advancements in massive MIMO communication are covered in Section 2, recent trends in channel estimation of massive MIMO is discussed in Section 3, and the system model is explained in Section 4. Channel estimation is covered in Section 5, and the outcomes are covered in Section 6. Section 7 concludes the entire paper.

## II. MASSIVE MIMO SYSTEMS

MIMO techniques are a crucial component of contemporary wireless networks, and in order to achieve significant improvements in both spectral and energy efficiency, they have been used more and more in recent years [26]. SISO techniques were common before MIMO was adopted; these systems could not reliably sustain a great number of users due to their low throughput. Many MIMO technologies, including single-user MIMO (SU-MIMO), have been introduced to meet the growing demand from multiple users [6], [7], MU-MIMO [8] and network MIMO [9], [10] were created. But even with these state-of-the-art technologies, the demands are too great to meet on their own. The exponential increase in wireless users in recent years has resulted in trillions of data that need to be controlled with efficiency and dependability. Additionally, the use of billions of Internet of Things (IoT) devices for smart energy, smart healthcare, and smart homes contributes to the rise in data traffic.

The 4G/LTE networks' existing MIMO technologies are inadequate to deal with this significant surge in traffic of data with the necessary speed and dependability. Massive MIMO technology is thus being investigated by the 5G network as a potential remedy for the problems brought on by the massive data traffic and the expanding user [3], [11]. The massive MIMO system has been studied extensively for its advantages [12]. One of the most important technologies for 5G and 6G is the massive MIMO communication technology. It is an advanced version of conventional MIMO, however in massive MIMO, thousands of antennas at the base station service tens of users [13]. In mm-Wave communication, antennas can be combined in a small area as compared to the microwave due to the small wavelength. Fig. 2 depicts the uplink and downlink massive MIMO system. Numerous antennas at the base station can create a directed beam for the intended user, allowing for great throughput at the user end with little interference to nearby users. When using massive MIMO instead of traditional MIMO systems, a high spectral efficiency is possible. Improved capacity and better signal quality are accomplished via numerous antennas, leading to sophisticated wireless communication systems [14]. The effect of rain on throughput is investigated in [27] and an AI-based solution is proposed to mitigate the effect of rain on throughput. The solar panel-based 3D array antennas is investigated in [28] for MIMO applications and no negative effects on the antenna system performance.

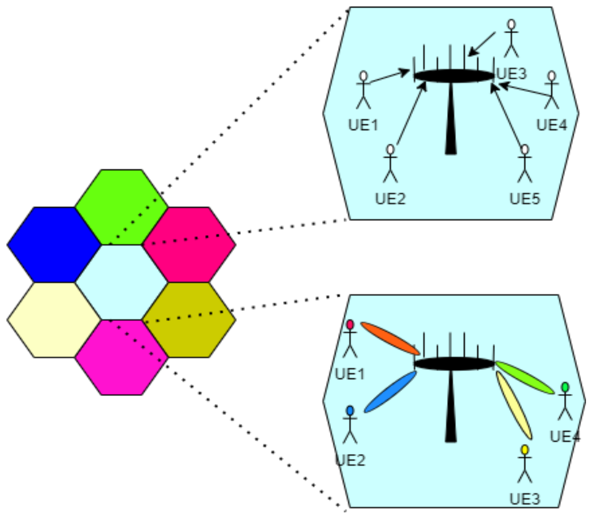


Fig.2: Massive MIMO uplink and downlink.

## III. RECENT TRENDS IN MASSIVE MIMO CHANNEL ESTIMATION

Channel estimation is a technique to estimate the condition of wireless channels such as distortion, multipath effect and signal attenuation etc., the robust wireless communication system is only possible with effective channel estimation. The massive MIMO channel estimation recent trends is shown in Table 1.

TABLE I
CHANNEL ESTIMATION TECHNIQUES

| Ref. | System Model | Channel Estimation Technique |
|---|---|---|
| [15] | Uplink system model with Gaussian mixture model (GMM). | Machine learning-based Channel Estimation. |
| [16] | Uplink training in flat Rayleigh fading channels. | Maximum likelihood-based MMSE channel estimator. |
| [17] | Uplink XL-MIMO OFDM communication. | Near-field XL-MIMO channel estimation schemes. |
| [18] | Massive MIMO system operating at millimeter waves using a lens array | Channel Estimation based on Deep Learning. |
| [19] | Downlink massive MIMO system | Compressive sensing-based channel estimation. |
| [20] | Down link massive MIMO | Channel estimation based on block iterative support detection. |
| [21] | Rayleigh fading Downlink channel massive MIMO system model. | There are two methods proposed: one makes use of a neural network with fully connected layers, and the other makes use of a CNN. |
| [22] | Narrowband flat block fading multiuser massive MIMO system. | Suggested a method to streamline CSI acquisition and decrease pilot overhead |
| [23] | One-bit mmWave massive MIMO | The Fisher information matrix (FIM) for these channel models. |
| [24] | millimeter-wave (mmWave) multiple-input multiple-output (MIMO) systems | Channel estimation approach using an iterative reweighting log-sum constraint. |
| [25] | Multiuser massive MIMO uplink system | Estimating Channels in Hybrid Massive MIMO Systems with Adaptive-Resolution ADCs. |

## IV. SYSTEM MODEL

In this paper, a downlink single-cell massive MIMO system with multiple base station antennas serving $K$ single-antenna users simultaneously is examined given in Fig 3.

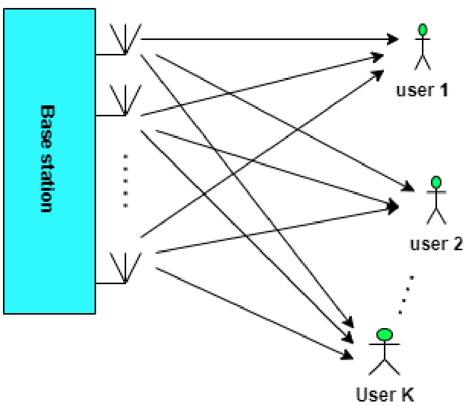


Fig. 3: System Model.

In this system model, antennas are arranged in an array linearly, which allows simplified design and implementation. The above arrangement is used to obtain enhanced beamforming. It will provide more coverage to the user available in the system in any direction.

The signal that was received at time $i$ is shown below.

$$r(i) = \sum_{k=1}^{K} \boldsymbol{u}_k(i)\boldsymbol{h} + v(i) \quad (1)$$

where $\boldsymbol{u}_k(i) = [u_k(1), u_k(2), \cdots, u_k(M)]$, $\boldsymbol{h} = \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_M \end{bmatrix}$, and $v$ is noise.

In (1), desired user, interference, and noise can be written as follows

$$r(i) = \underbrace{\boldsymbol{u}_1(i)\boldsymbol{h}}_{\text{desired}} + \underbrace{\sum_{k=2}^{K} \boldsymbol{u}_k(i)\boldsymbol{h}}_{\text{interference}} + \underbrace{v(i)}_{\text{noise}} \quad (2)$$

$N$ is the number of samples used for the channel estimation procedure, and the variables in (2) can be specified as follows.

$$\boldsymbol{y} = \begin{bmatrix} r(1) \\ r(2) \\ \vdots \\ r(N) \end{bmatrix}, \quad \boldsymbol{U}_k = \begin{bmatrix} \boldsymbol{u}_k(1) \\ \boldsymbol{u}_k(2) \\ \vdots \\ \boldsymbol{u}_k(N) \end{bmatrix}, \boldsymbol{v} = \begin{bmatrix} v(1) \\ v(2) \\ \vdots \\ v(N) \end{bmatrix}$$

Now, (2) can be written as follows

$$\boldsymbol{y} = \boldsymbol{U}_1\boldsymbol{h} + \sum_{k=2}^{K} \boldsymbol{U}_k\boldsymbol{h} + \boldsymbol{v} \quad (3)$$

Now, (3) can also be written as

$$\boldsymbol{y} = \boldsymbol{U}\boldsymbol{h} + \boldsymbol{v} \quad (4)$$

Where $\boldsymbol{U}$ is the sum of all $\boldsymbol{U}_k$

$$\boldsymbol{U} = \sum_{k=1}^{K} \boldsymbol{U}_k \quad (5)$$

## V. CHANNEL ESTIMATION

Since the estimated channel primarily determines overall system performance and error-free sent data detection, it is an essential component of wireless communication systems. It is a well-known fact that the performance of any optimization goal improves by designing proper constraints on the optimization objective. This is due to the fact that the constraints restrict the search space for the optimization task and hence improves the convergence of the constrained optimization algorithm. Therefore, the channel estimate in multiuser massive MIMO system, constrained and un-constrained least square (LS) solution is designed. In this section LS based channel estimation technique is derived by considering different constraint such as when desired user pilots are known and when all the users pilot are known and results are compared to investigate the performance of each designed algorithms.

### *A. Unconstrained LS (Least Square) when all users' pilots are known*

We can assess it as follows by using the MSE as the cost function to be minimized

$$J = E\left[\left\|\widehat{\boldsymbol{h}} - \boldsymbol{h}\right\|^2\right] \tag{6}$$

Estimated channel can be written as

$$\widehat{\boldsymbol{h}} = \boldsymbol{W}_{LS}\boldsymbol{y} \tag{7}$$

We can solve the norm and $J$ expand as

$$J = E\left[\left(\widehat{\boldsymbol{h}} - \boldsymbol{h}\right)^H\left(\widehat{\boldsymbol{h}} - \boldsymbol{h}\right)\right] \tag{8}$$

Now substituting value of $\widehat{\boldsymbol{h}}$ from (7)

$$J = E[(\boldsymbol{W}_{LS}\boldsymbol{y} - \boldsymbol{h})^H(\boldsymbol{W}_{LS}\boldsymbol{y} - \boldsymbol{h})] \tag{9}$$

Solving transpose, we get

$$J = E\left[\left(\boldsymbol{y}^H{\boldsymbol{W}_{LS}}^H - \boldsymbol{h}^H\right)(\boldsymbol{W}_{LS}\boldsymbol{y} - \boldsymbol{h})\right] \tag{10}$$

Now substituting the value of $\boldsymbol{y}$ from equation (4)

$$J = E\left[\left\{(\boldsymbol{h}^H\boldsymbol{U}^H + \boldsymbol{v}^H){\boldsymbol{W}_{LS}}^H - \boldsymbol{h}^H\right\}\{\boldsymbol{W}_{LS}(\boldsymbol{U}\boldsymbol{h} + \boldsymbol{v}) - \boldsymbol{h}\}\right] \tag{11}$$

Solving ${\boldsymbol{W}_{LS}}^H$ and $\boldsymbol{W}_{LS}$ inside bracket we obtain

$$J = E\left[\left\{\boldsymbol{h}^H\boldsymbol{U}^H{\boldsymbol{W}_{LS}}^H + \boldsymbol{v}^H{\boldsymbol{W}_{LS}}^H - \boldsymbol{h}^H\right\}\{\boldsymbol{W}_{LS}\boldsymbol{U}\boldsymbol{h} + \boldsymbol{W}_{LS}\boldsymbol{v} - \boldsymbol{h}\}\right]$$

Applying property of trace, we get,

$$J = Tr\left(E\left[\{(\boldsymbol{W}_{LS}\boldsymbol{U} - \boldsymbol{I}_M)\boldsymbol{h} + \boldsymbol{W}_{LS}\boldsymbol{v}\}\left\{\boldsymbol{h}^H\left(\boldsymbol{U}^H{\boldsymbol{W}_{LS}}^H - \boldsymbol{I}_M\right) + \boldsymbol{v}^H{\boldsymbol{W}_{LS}}^H\right\}\right]\right) \tag{12}$$

Rearranging the above equation, we receive

$$J = Tr\left((\boldsymbol{W}_{LS}\boldsymbol{U} - \boldsymbol{I}_M)E[\boldsymbol{h}\boldsymbol{h}^H]\left(\boldsymbol{U}^H{\boldsymbol{W}_{LS}}^H - \boldsymbol{I}_M\right)\right) + Tr\left(\boldsymbol{W}_{LS}E[\boldsymbol{v}\boldsymbol{v}^H]{\boldsymbol{W}_{LS}}^H\right) \tag{13}$$

Since $E[\boldsymbol{h}\boldsymbol{h}^H] = \boldsymbol{I}_M$ and $E[\boldsymbol{v}\boldsymbol{v}^H] = \sigma_n^2\boldsymbol{I}_N$

Therefore,

$$J = Tr\left((\boldsymbol{W}_{LS}\boldsymbol{U} - \boldsymbol{I}_M)\boldsymbol{I}_M\left(\boldsymbol{U}^H{\boldsymbol{W}_{LS}}^H - \boldsymbol{I}_M\right)\right) + Tr\left(\boldsymbol{W}_{LS}\sigma_n^2\boldsymbol{I}_N{\boldsymbol{W}_{LS}}^H\right) \tag{14}$$

After simplification we obtain

$$J = Tr\left((\boldsymbol{W}_{LS}\boldsymbol{U} - \boldsymbol{I}_M)\left(\boldsymbol{U}^H{\boldsymbol{W}_{LS}}^H - \boldsymbol{I}_M\right)\right) + \sigma_n^2\boldsymbol{I}_N Tr\left(\boldsymbol{W}_{LS}{\boldsymbol{W}_{LS}}^H\right) \tag{15}$$

Rearranging the above equation, we get

$$J = Tr\left(\boldsymbol{W}_{LS}\boldsymbol{U}\boldsymbol{U}^H{\boldsymbol{W}_{LS}}^H\right) - Tr(\boldsymbol{W}_{LS}\boldsymbol{U}) - Tr\left(\boldsymbol{U}^H{\boldsymbol{W}_{LS}}^H\right) + Tr(\boldsymbol{I}_M) + \sigma_n^2\boldsymbol{I}_N Tr\left(\boldsymbol{W}_{LS}{\boldsymbol{W}_{LS}}^H\right) \tag{16}$$

We determine the aforementioned cost function's gradient with respect to the weight matrix and set it to zero in order to identify the best solution.

$$\frac{\partial J}{\partial {\boldsymbol{W}_{LS}}^H} = \boldsymbol{W}_{LS}\boldsymbol{U}\boldsymbol{U}^H - \boldsymbol{0} - \boldsymbol{U}^H + \boldsymbol{0} + \sigma_n^2\boldsymbol{I}_N\boldsymbol{W}_{LS} = \boldsymbol{0}$$

Finally, we get the solution is, therefore,

$$\boldsymbol{W}_{LS} = \boldsymbol{U}^H(\boldsymbol{U}\boldsymbol{U}^H + \sigma_n^2\boldsymbol{I}_N)^{-\mathbf{1}} \tag{17}$$

### *B. Constrained LS when only desired user's pilot is known*

In this case, we assume that $\boldsymbol{u}_1$is known and all other $\boldsymbol{u}_k$'s are unknown.

We apply the following constrained optimization

$$\min J = E\left[\widetilde{\boldsymbol{h}}\widetilde{\boldsymbol{h}}^H\right] \text{ subject to } \boldsymbol{W}_{CLS1}\boldsymbol{U}_1 = \boldsymbol{I}_M$$

Where $\widetilde{\boldsymbol{h}} = \widehat{\boldsymbol{h}} - \boldsymbol{h}$

Before proceeding further, we define

$$z \triangleq \sum_{k=2}^{K} U_k h + v \tag{18}$$

Therefore, equation (3) becomes

$$\boldsymbol{y} = \boldsymbol{U}_1\boldsymbol{h} + \boldsymbol{z} \tag{19}$$

Consequently, the problem of limited optimization can be formulated as

$$\min J = E\left[(\widehat{\boldsymbol{h}} - \boldsymbol{h})(\widehat{\boldsymbol{h}} - \boldsymbol{h})^H\right] \text{ subject to } \boldsymbol{W}_{CLS1}\boldsymbol{u}_1 = I_M$$

$$\min J = E[(\boldsymbol{W}_{CLS1}\boldsymbol{y} - \boldsymbol{h})(\boldsymbol{W}_{CLS1}\boldsymbol{y} - \boldsymbol{h})^H] \tag{20}$$

Using the values of **y** and **z**, we get

$$\begin{aligned}\min J &= E[(\boldsymbol{W}_{CLS1}\boldsymbol{u}_1\boldsymbol{h} + \boldsymbol{W}_{CLS1}\boldsymbol{z} - \boldsymbol{h})(\boldsymbol{W}_{CLS1}\boldsymbol{u}_1\boldsymbol{h} + \boldsymbol{W}_{CLS1}\boldsymbol{z} - \boldsymbol{h})^H] \\ &= E[(\boldsymbol{W}_{CLS1}\boldsymbol{z})(\boldsymbol{W}_{CLS1}\boldsymbol{z})^H] \text{since } \boldsymbol{W}_{CLS1}\boldsymbol{u}_1 = I_M \\ &= E\left[\boldsymbol{W}_{CLS1}\boldsymbol{z}\boldsymbol{z}^H{\boldsymbol{W}_{CLS1}}^H\right]\end{aligned} \tag{21}$$

Rearranging above equation, we receive

$$\min J = \boldsymbol{W}_{CLS1}\, E[\boldsymbol{z}\boldsymbol{z}^H]{\boldsymbol{W}_{CLS1}}^H$$

$$\min J = \boldsymbol{W}_{CLS1}\boldsymbol{R}_z{\boldsymbol{W}_{CLS1}}^H \tag{22}$$

The solution is well-known [5] and is given by

$$\boldsymbol{W}_{CLS1} = (\boldsymbol{U}_1^H\boldsymbol{R}_z^{-1}\boldsymbol{U}_1)^{-1}\boldsymbol{U}_1^H\boldsymbol{R}_z^{-1} \tag{23}$$

To find $\boldsymbol{R}_z$, we can evaluate it as

$$\boldsymbol{R}_z = E[\boldsymbol{z}\boldsymbol{z}^H]$$

$$\boldsymbol{R}_z = \boldsymbol{E}\left[\left(\sum_{k=2}^{K}\boldsymbol{U}_k\boldsymbol{h} + \boldsymbol{v}\right)\left(\sum_{k=2}^{K}\boldsymbol{U}_k\boldsymbol{h} + \boldsymbol{v}\right)^H\right] \tag{24}$$

$$\boldsymbol{R}_z = E\left[\sum_{k=2}^{K}\boldsymbol{U}_k\, E[\boldsymbol{h}\boldsymbol{h}^H]\sum_{k=2}^{K}{\boldsymbol{U}^{\boldsymbol{H}}}_k\right] + E[\boldsymbol{v}\boldsymbol{v}^H] \tag{25}$$

Applying estimates, we get

$$\boldsymbol{R}_z = \boldsymbol{E}\left[\left(\sum_{k=2}^{K}\boldsymbol{U}_k\right)I_M\left(\sum_{k=2}^{K}{\boldsymbol{U}^{\boldsymbol{H}}}_k\right)\right] + \sigma_n^2 I_N$$

$$\boldsymbol{R}_z = \sum_{k=2}^{K}E[\boldsymbol{U}_k{\boldsymbol{U}^{\boldsymbol{H}}}_k] + \sigma_n^2 I_N$$

$$\boldsymbol{R}_z = \sum_{k=2}^{K}\boldsymbol{R}_{uk} + \sigma_n^2 I_N \tag{26}$$

Where

$$\begin{aligned}\boldsymbol{R}_{uk} &= E[\boldsymbol{U}_k{\boldsymbol{U}^{\boldsymbol{H}}}_k] \\ &= E\left[\begin{bmatrix}\boldsymbol{u}_k(1)\\ \boldsymbol{u}_k(2)\\ \vdots\\ \boldsymbol{u}_k(N)\end{bmatrix}[{\boldsymbol{u}^{\boldsymbol{H}}}_k(1){\boldsymbol{u}^{\boldsymbol{H}}}_k(2) \ldots {\boldsymbol{u}^{\boldsymbol{H}}}_k(N)]\right] \\ &= Tr(\boldsymbol{R}_k)I_N\end{aligned} \tag{27}$$

### C. Constrained LS when all users' pilots are known

In this section, we designed another constrained LS solution for the channel estimation by utilizing the knowledge of all the users' pilots. For this purpose, we use the combined pilot matrix $\boldsymbol{U}$ to formulate the constrained LS problem as follows

$$\min J = E\left[\left\|\widehat{\boldsymbol{h}} - \boldsymbol{h}\right\|^2\right] \text{ subject to } \boldsymbol{W}_{CLS2}\boldsymbol{U} = I_M$$

$$J = E[(\boldsymbol{W}_{CLS2}(\boldsymbol{U}\boldsymbol{h} + \boldsymbol{v}) - \boldsymbol{h})(\boldsymbol{W}_{CLS2}(\boldsymbol{U}\boldsymbol{h} + \boldsymbol{v}) - \boldsymbol{h})^H] \tag{28}$$

Simplifying we get

$$J = E[(\boldsymbol{W}_{CLS2}\boldsymbol{v})(\boldsymbol{W}_{CLS2}\boldsymbol{v})^H] \tag{29}$$

Applying estimate, we get

$$J = \boldsymbol{W}_{CLS2}\boldsymbol{R}_v{\boldsymbol{W}_{CLS2}}^H, \text{ where } \boldsymbol{R}_v = \sigma_n^2 I_N \tag{30}$$

Finally, solution of equation is

$$\boldsymbol{W}_{CLS2} = \left(\boldsymbol{U}{\boldsymbol{R}_v}^{-\boldsymbol{1}}\boldsymbol{U}\right)^{-\boldsymbol{1}}\boldsymbol{U}^H{\boldsymbol{R}_v}^{-\boldsymbol{1}} \tag{31}$$

## VI. RESULTS AND ANALYSIS

Simulation of constrained and unconstrained channel estimation is carried out to verify our three solutions. The graphs, in Fig. 3, show the results for LS for following three situations:

(i) Constrained LS when only desired user pilot is known
(ii) Unconstrained LS when all users' pilots are known
(iii) Constrained LS when all users' pilots are known

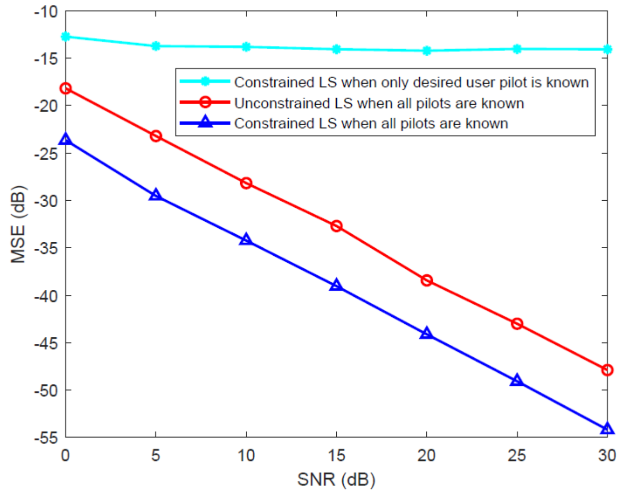


Fig. 4. Constrained LS and Unconstrained LS Algorithm.

In Fig 4, constrained LS with desired user pilot and constrained LS with all pilots are known compared with unconstrained LS when all pilots are known. The curves show that the constrained LS with all known pilots performs better than the unconstrained LS with all known pilots. Furthermore, the constrained LS with only a desired user-known pilot is poor as compared to other techniques. For example, at 30 dB SNR MSE of constrained LS, all pilots are known as -55 dB, and Constrained LS with the desired pilot is known as -13 dB. Additionally, the proposed channel estimation method is tested under various conditions, such as varying system user counts and antenna counts at the base station, and the outcomes are analyzed appropriately.

### *A. Effect of Number of Users*

Different user conditions may have an impact on accuracy estimation because different user counts in the system may result in different amounts of interference. These results help to validate the adaptability and scalability of the proposed channel estimation algorithm.

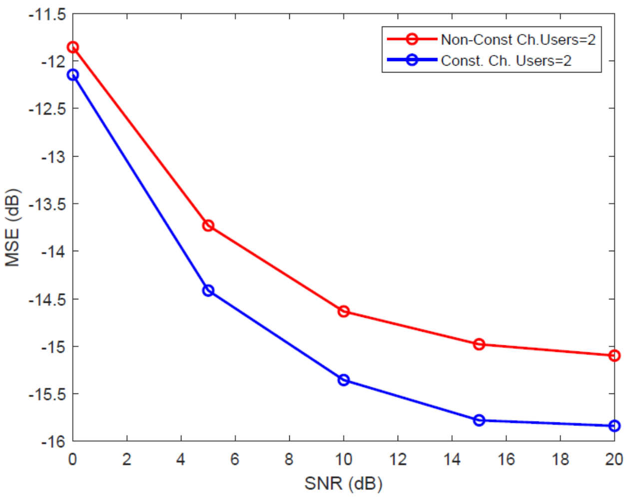


Fig.5: Constrained LS and Unconstrained LS Algorithm with 2 users.

In Fig. 5, Constrained LS and unconstrained LS are compared, and the system contains 2 users. In comparison to the unconstrained LS algorithm, the constrained LS channel estimation algorithm clearly performs better. For example, at SNR 20 dB MSE of the constrained LS algorithm is -12.7 dB, and the unconstrained LS algorithm is -11.7 dB.

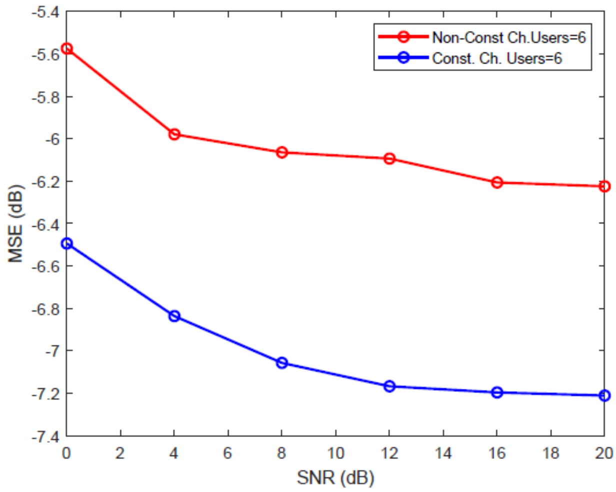


Fig. 6: Constrained LS and Unconstrained LS Algorithm with 6 users.

There are 6 users in the system, and Fig. 6 compares constrained and unconstrained LS. The findings demonstrate that system interference escalated with the number of users, resulting in a decrease in the performance of both methods. Results also show that the constrained LS algorithm performance is better than the unconstrained LS algorithm.

### *B. Effect of number of Antennas*

This section varies the system's base station (BS) antenna size. In order to assess channel estimate performance, it is essential to simulate different numbers of transmission antennas because the number of antennas has a direct impact on spatial diversity, signal quality, and interference patterns. The proposed algorithm's scalability and efficiency to various massive MIMO scenarios may be assessed by evaluating multiple antenna designs. Results of constrained LS and unconstrained LS are compared and discussed accordingly.

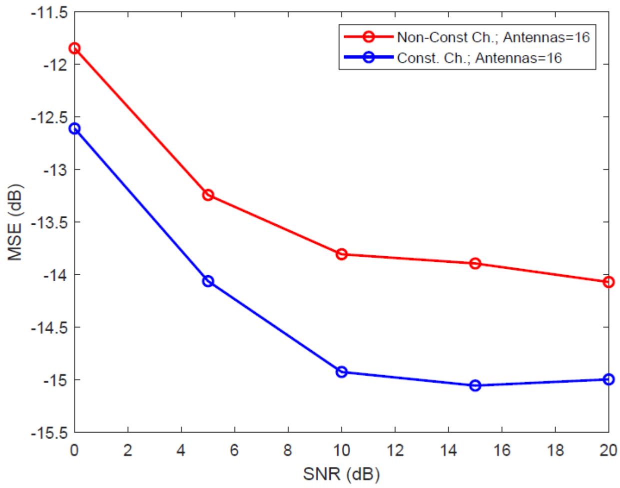


Fig. 7: Constrained LS and Unconstrained LS Algorithm BS antennas 16.

In Fig. 7, constrained LS and unconstrained LS algorithms are compared with BS having 16 antennas. Across all SNR values, the constrained LS algorithm continued to perform better than the unconstrained LS method. For example, at SNR 20 dB MSE of the constrained LS algorithm is -13.7 dB, and the unconstrained LS algorithm is -12.5 dB.

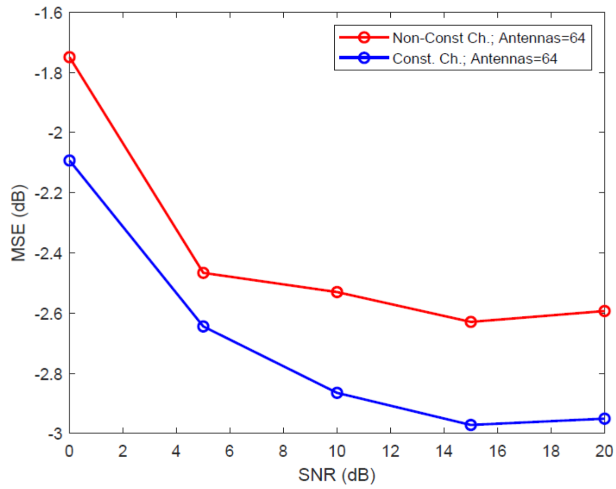


Fig. 8: Constrained LS and Unconstrained LS Algorithm BS antennas 64.

In Fig. 8, the performance of constrained LS and unconstrained LS algorithms are compared with 64 BS antennas. The results clearly show that the constrained LS algorithm gave much better performance. The findings also indicate that a base station's increased antenna count lowers channel estimation performance because it lengthens the channel path.

## VII. Conclusion

A key component of 5G and beyond 5G communication networks is the large MIMO communication technology. The system's ability to efficiently detect user-transmitted data is primarily dependent on the base station's assessment of the channel. Channel estimation is always a challenging task and it became more difficult for large antenna systems. In order to improve the accuracy of the channel estimation, the constraint channel estimation technique is presented in this study. In the proposed channel estimation technique, two scenarios are considered, LS algorithm when only the desired user pilot is known, unconstrained LS when all users' pilots are known, and constrained LS when all users' pilots are known. Results show that the performance of constrained LS when all user pilots are known is better than the other two cases. Additionally, different numbers of users in the system and varied numbers of antennas at the base station are used to compare constrained versus unconstrained algorithms. The results show that the interference level of the system grows with the number of users, which degrades the channel estimation performance of both techniques. The advanced constraint modelling can be implemented as a future work along with the integration with machine learning to optimize the selection of constraints in real-time scenarios.

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