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RESEARCH ARTICLE

EFFICIENT CHANNEL ESTIMATION IN RIS-ASSISTED SYSTEMS USING DS-COSAMP ALGORITHM

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Abstract

Reconfigurable Intelligent Surfaces(RIS)can change the wireless enviro nment by adjusting the reflection coefficients of various components. However, due to the substantial number of passive components in RIS that lack signal processing capabilities, considerable pilot overhead is necessary for channel estimate in RIS-assisted wireless networks. In this second half of the invited work, we aim to reduce this complexity issue by using the dual coded stickiness of the angular domain cascaded channels used by communication consumers. We specifically observe that these channels exhibit a shared sparsity pattern in their rows (totall y mutual pathways) and a partly shared pattern in their columns (user-specific paths). Building on this rationale, we offer the Double Structur ed Compressive Sampling Matching Pursuit (DS-CoSaMP) method, consistently achieves lower Normalized Mean Squared Error (NMSE) than DS-OMP, especially as the number of users or RIS elements increases. It is more effective than DS-OMP in jointly tracking and updating these structures through its two-stage support update and signal estimation process. The simulation results demonstrate that the overheadreduction proposed by our technique for the pilot is significant compared to conventional methods.

Introduction:-

The elevated pilot overhead is a primary challenge in channel estimation, since the RIS comprises several passive components that lack signal processing The channel estimation issue may be redefined as a sparse signal recovery challenge by leveraging the sparsity of the angular cascaded channel, namely the channel cascade from the user to the RIS and from the RIS to the base station (BS). Compressive sensing (CS) techniques with reduced pilot overhead may effectively address the sparse signal recovery issue [1]. Despite advancement, significant pilot overhead continues to pose a difficulty in the majority of systems.

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The authors presented a comparison between RIS and conventional relay techniques. It contrasts the signal amplification and processing power of relays with the energy efficiency, cost, and hardware simplicity of RIS. The study comes to the conclusion that in certain low-complexity, high-efficiency scenarios—particularly in line-of-sight (LoS) environments—RIS performs better than relaying [2].

Literature Review:-

Wang et al. (2020) suggested a channel estimation technique based on compressed sensing that is specifically designed for mmWave RIS-assisted systems. To minimize training overhead, the system utilizes angular domain sparsity. It is well-suited for high-frequency RIS deployments since simulation results demonstrate that it can accomplish precise channel estimation with fewer pilots [3].Chen et al. (2023) introdced a reliable two-phase channel estimate technique for RIS-assisted multi-user MIMO systems, addressing the challenge of predicting the cascaded BS-RIS-user channels. The incorporation of MMSE estimation and structured pilot training drastically decreases pilot overhead and estimate error, making the proposed technique viable for extensive RIS networks [4].

Hu et al. (2018) proposed a hybrid precoding channel estimation method with compressive sensing and atomic norm minimisation to exploit the sparse characteristics of mmWave channels for precise estimate of angles of arrival (AoAs) and angles of departure (AoDs), hence enabling accurate channel reconstruction with little training overhead. This approach enhances system performance with a limited number of RF links [5]. Gao et al. (2019) presented a wideband beamspace channel estimate method, converts spatial channels into beamspace, using the sparsity of mmWave channels and utilising structured compressive sensing to accurately estimate the channels with little training. The results effectively enhance frequency selectivity for improved channel estimation and reduced complexity in wideband systems with lens antenna arrays [6].Wu et al. (2020) established a beamforming optimization framework with discrete transitions in phase. The system formulates a integrated optimization problem that encompasses both active and passive at the transmitter the RIS, respectively. We offer a pragmatic alternate optimization approach to optimize signal powerat the user, demonstrating that RIS may substantially enhance communication performance even when the phase shift at RIS is quantized [7].

Basar et al. (2019) introduced the notion of RIS, an innovative technology for future wireless networks. RIS use programmable passive components to modulate and refine wireless signals, enhancing coverage, energy efficiency, and spectrum efficiency. The study delineates the ideas of RIS, compares them with alternative innovations including relays and massive MIMO, and addresses difficulties with implementation. RIS is proposed as one of the enablers of 6G technology [8].Wu et al. (2019) provided the RIS system, whereby passive beamforming by the RIS is simultaneously optimized with active beamforming at the transmitter. This study focusses on minimising transmit power while adhering to user SINR constraints, demonstrating that IRS may significantly enhance signal quality and energy efficiency. Algorithms pertaining to alternating optimisation are effectively applied. The present document indicates the potential of RIS in enhancing coverage and performance in wireless networks in the future [9].

Amiri et al. (2018) investigated Extremely Large Aperture Massive MIMO (xMaMIMO) systems, focussing on the development of low-complexity receiver architectures. The substantial dimensions of xMaMIMO antenna arrays make standard centralized processing impractical. The authors provide a distributed and scalable receiver architecture that segments the array into sub-arrays for local processing. These strategies are more straightforward and maintain performance, so xMaMIMO may be used in forthcoming ultra-dense wireless networks [10].

Wei et al. (2021) addressed an overview of channel estimation issues in wireless systems aided by RIS, where passive RIS components render conventional estimation techniques insignificant, is given in this paper. It goes over the system structure and looks at three main ways to decrease the high pilot overhead: using angular domain sparsity, multi-user correlation, and two-timescale channel properties. Future research directions are also outlined in the paper, emphasizing the need for more effective and scalable 6G wireless network solutions [11]. This research also proposes an improved channel estimation methodology using double-structured sparsity, which includes shared sparsity across users and individual innovation sparsity. It employs a DS-OMP technique to reduce pilot overhead while enhancing estimate accuracy. But this structure has high pilot overhead and limited estimation accuracy, especially in multi user cases [12]. Motivated by the observation that cascaded channels exhibit a **double-**structured sparsitywith both common sparsity across users **and** individual innovation sparsity.The authors propose a DS-CoSaMPalgorithm. Byexploiting thesparse structure, this technique reduces training overhead and improves estimation accuracy.

Problem Statement:-

Estimation of channels in RIS-assisted wireless communication systems, the pilot overhead and the extensive dimensions of cascaded channels pose challenges to precise channel estimation. Traditional and alternative structured sparse recovery methods fail to fully use the inherent sparsity structures present in the channel. The examined study addresses the decrease of pilot overhead and the improvement of estimate accuracy via the execution of double-structured sparsity among numerous users in the angular domain, relying on a combination of common and inventive sparsity. This study fills a gap by introducing a new DS-CoSaMP algorithm to minimize the number of training symbols for accurate channel estimation the structure is intended to improve NMSE, reduce computing complexity. The overview of existing methods is displayed in Table 1

Table 1: Comparative analysis of existing methods

Author	**Title**	**Method**	**Limitations**
P. Wang et al [5]	Compressed Channel Estimation for RIS assisted mm Wave Systems	Conventional CS	No joint sparsity and limited scalability to multi-usersystems. Performance degradation in low SNR conditions
J. Chen et al [6]	Channel Estimation for RIS aided Multiuser MIMO Systems	Row-structured	Suffering from increased pilot overhead as user count raises. Performance is dropped with **path correlation**
W. Xiuhong et al [12]	Channel Estimation for RIS assisted Wireless Communications; An Improved Solution Based on DS Sparsity	DS-OMP (Lc=0 to 8)	It requires prior estimation of the number of common paths and slightly more complicated than standard OMP due to joint sparsity

System Model:-

The Double-structured sparsity of the angular cascaded channels are shown in Figure 1. Initially, while many users interact with the base station (BS) over the shared reconfigurable intelligent surface (RIS), the channel G from the RIS to the BS is uniform for all users.

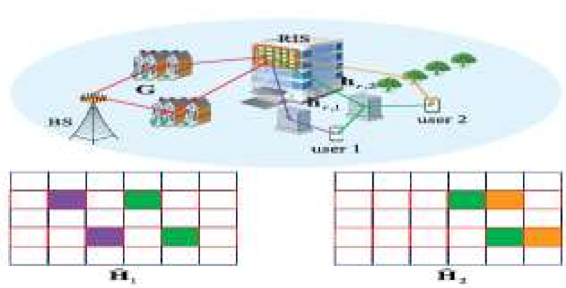

Fig.1. Double-structured sparsity of the angular cascaded channels [12].

Algorithm1: DS-CoSaMP for RIS Channel Estimation
1. **Initialize**: $\tilde{H}_k = 0_{MxN}$ for all users
2.**Stage 1**: Estimate completely common row support $\hat{\boldsymbol{\Omega}}_{\mathbf{r}}$using **Algorithm 2**
3. **Stage 2**: Estimate partially common column supports $\{\hat{\boldsymbol{\Omega}}_{l_1}, \boldsymbol{Com_c}\}$ using Algorithm 3
4.**Stage 3**: Estimate individual column supports $\{\hat{\boldsymbol{\Omega}}_{\mathbf{l_1,k_c}}\}$ using **Algorithm 4**
for $l_1 = 1$ to L_G for each user $k = 1$ to K 7. **Stage 4**: Estimate: $\tilde{H}_k^H(\hat{\Omega}_{l_1,k_c}, l_1) = \tilde{\theta}(:, \hat{\Omega}_{l_1,k_c}) + \tilde{y}_k(:, l_1)$

8. Recover final spatial-domain channel: $\widehat{\mathrm{H}}_{\mathrm{k}} = \mathrm{U_M} \times \widetilde{\mathrm{H}}_{\mathrm{k}} \times \mathrm{U_N}$
Output: Estimated cascaded channels $\{\widehat{\mathrm{H}}_{\mathrm{k}}\}$, for all k
Algorithm2: Joint Row Support Estimation
Input: $\widetilde{\mathrm{Y}}_{\mathrm{k}}, \mathrm{L_G}$
1. Initialize: g = zeros(M, 1)
2. for each m = 1 to M: $$\mathrm{g(m)} = \sum \mathrm{k}\lVert\mathrm{R_k}(:,\mathrm{m})\rVert^2\_\mathrm{F}$$
3.Select $\widehat{\boldsymbol{\Omega}}_{\mathbf{r}}$= indices of top **LG** entries in **g**
Output: Estimated completely common row support $\widehat{\boldsymbol{\Omega}}_{\mathbf{r}}$

Algorithm 3: Joint Partially Common Column Support Estimation
Input:$\widetilde{\mathrm{Y}}_{\mathrm{k}}$,$\tilde{\theta}$,$\mathrm{L_{r,k}}$,$\mathrm{L_c}$,$\widehat{\Omega}_{\mathrm{r}}$
for each $\mathrm{l_1}$ in $\widehat{\Omega}_{\mathrm{r}}$:
1.Initialize $\mathrm{c_{l1}}$=zeros (N,1)
For each user k: $\tilde{\mathrm{r}}_{\mathrm{k}} = \tilde{\mathrm{y}}_{\mathrm{k}}$
2. $\widehat{\Omega}_{\mathrm{l_1,k_c}} = \emptyset$
for $\mathrm{l_2} = 1$ to $\mathrm{L_{r,k}}$:
3. $\mathrm{n}^* = \mathrm{argmax_n}\left\lVert\tilde{\theta}(:,\mathrm{n})^{\mathrm{H}}\tilde{\mathrm{r}}_{\mathrm{k}}\right\rVert^2$
4. $\widehat{\Omega}_{\mathrm{l_1,k_c}} = \widehat{\Omega}_{\mathrm{l_1,k_c}} \cup \mathrm{n}^*$
5. $\tilde{\mathrm{h}}_{\mathrm{k}} = \mathrm{zeros\ (N, 1)}$
6. $\tilde{\mathrm{h}}_{\mathrm{k}}(\widehat{\Omega}_{\mathrm{l_1,k_c}}) = \tilde{\theta}(:,\widehat{\Omega}_{\mathrm{l_1,k_c}}) + \tilde{\mathrm{y}}_{\mathrm{k}}$
7. $\tilde{\mathrm{r}}_{\mathrm{k}} = \tilde{\mathrm{y}}_{\mathrm{k}} - \tilde{\theta} \times \tilde{\mathrm{h}}_{\mathrm{k}}$
8. $c_{l_1}(n^*) = c_{l_1}(n^*) + 1$ 9. Select $\widehat{\Omega}_{l_1,Com\,c}$: Top L_G entries in c_{l_1}
10.**Output**: Estimated completely common row support $\{\widehat{\Omega}_{l_1,Com\,c}\}_{l_1=1}^{L_G}$
Algorithm 4: Estimate individual column supports for each user
1. for each $\mathrm{l_1}$ in $\widehat{\Omega}_{\mathrm{r}}$
2. for each user k:
3. $\tilde{\mathrm{y}}_{\mathrm{k}} = \mathrm{R_k}(:,\mathrm{l_1})$
4. $\widehat{\Omega}_{\mathrm{l_1,k_c}} = \widehat{\Omega}_{\mathrm{l_1,Com\ c}}$
5. $\tilde{\mathrm{h}}_{\mathrm{k}} = \mathrm{zeros\ (N, 1)}$
6. $\tilde{\mathrm{h}}_{\mathrm{k}}(\widehat{\Omega}_{\mathrm{l_1,k_c}}) = \tilde{\theta}(:,\widehat{\Omega}_{\mathrm{l_1,k_c}}) + \tilde{\mathrm{y}}_{\mathrm{k}}$
7. $\tilde{\mathrm{r}}_{\mathrm{k}} = \tilde{\mathrm{y}}_{\mathrm{k}} - \tilde{\theta} \times \tilde{\mathrm{h}}_{\mathrm{k}}$
8. for $\mathrm{l_2} = 1$ to $(\mathrm{L_{r,k}} - \mathrm{L_c})$:
9. $\mathrm{n}^* = \mathrm{argmax_n}\left\lVert\tilde{\theta}(:,\mathrm{n})^{\mathrm{H}}\tilde{\mathrm{r}}_{\mathrm{k}}\right\rVert^2$
10. $\widehat{\Omega}_{\mathrm{l_1,k_c}}$=$\widehat{\Omega}_{\mathrm{l_1,k_c}} \cup \{\mathrm{n}^*\}$
11. $\tilde{\mathrm{h}}_{\mathrm{k}} = \mathrm{zeros\ (N, 1)}$
12. $\tilde{h}_k(\widehat{\Omega}_{l_1,k_c}) = \tilde{\theta}(:,\widehat{\Omega}_{l_1,k_c}) + \tilde{y}_k$

13. $\tilde{r}_k = \tilde{y}_k - \tilde{\theta} \times \tilde{h}_k$
Output: Estimated the individual column supports $\{\{\widehat{\Omega}_c^{l_1,k}\}_{l_1=1}^{L_G}\}_{k=1}^{K}$.

The step by step procedure of Algorithm1 can be described as follows:
1. Initially obtain an estimation of the angular-domain channel $\widetilde{\mathrm{H}}_{\mathrm{k}}$ with zero matrices of dimensions M×N for all users k=1, 2,...,K.
2. **Stage1** indicates an estimation of the completely common row support $\widehat{\boldsymbol{\Omega}}_{\mathbf{r}}$using Algorithm 2. Here we can compute the row-wise power for all users to determine the common active rows from the acquired pilot signals $\widetilde{\mathrm{Y}}_{\mathrm{k}}$.
3. **Stage2** indicates an estimation of the completely common column support $\{\widehat{\Omega}_{\mathrm{l}_1,\mathrm{Com}\ \mathrm{c}}\}$ using Algorithm 3, which suggest RIS-side angular pathways shared by groups of users. In contrast to the row support, which is uniform across all users, the column supports exhibit modest variations across different user groups. Algorithm 3 evaluates u ser signals to derive: $\widehat{\Omega}_{\mathrm{l}_1}$: Total active columns for row l_1. $\mathrm{Com}_{\mathrm{c}}$: Collections of shared supports among user groups.
4. **Stage3** estimates individual column supports $\widehat{\Omega}_{\mathrm{l}_1,\mathrm{k}_{\mathrm{c}}}$ using Algorithm 4, improves the support by predicting user-specific column supports. For each user k and each row $l1$, identify supplementary columns that are exclusive to that user's channel. Algorithm 4 presumably uses residual-based selection to ascertain the user's specific angular components.
5. **Stage4** estimates the entries of the angular domain cascaded channel matrix and is given by $\widetilde{\mathrm{H}}_{\mathrm{k}}^{\mathrm{H}}\left(\widehat{\Omega}_{\mathrm{l}_1,\mathrm{k}_{\mathrm{c}}},\mathrm{l}_1\right)$, where $\tilde{\theta}$ indicates the sensing matrix, $\tilde{y}_{\mathrm{k}}$ is the measurement vector for user k.
6. Finally recover the spatial domain channel using the equation

$$\widehat{\mathrm{H}}_{\mathrm{k}} = \mathrm{U}_{\mathrm{M}} \times \widetilde{\mathrm{H}}_{\mathrm{k}} \times \mathrm{U}_{\mathrm{N}}$$

Where U_{M} and U_{N} Unitary DFT or dictionary matrices depending on system

Computational Complexity Analysis:-
The computational complexity of the recommended DS-CoSaMP algorithm is examined in terms of three stages of identifying supports. In stage 1, the computational complexity mainly comes from Step 2 in Algorithm 2, which computes the power of M columns of $\tilde{Y}_k \in \mathbb{C}^{Q\times M}$ for k = 1,2,⋯ ,K. The corresponding computational complexity is $O(KMQ)$. In Stage 2, for each non-zero row l_1 and each user k in Algorithm 3, the computational complexity $O(NQL_{r,k}^3)$ is the same as that of OMP algorithm [6]. Assuming $L_G K$ iterations, Algorithm 3 incurs a computational complexity of $O(L_G KNQL_{r,k}^3)$, While Algorithm 4 has a complexity of $(L_G KNQ(L_{r.k} - L_c)^3)$. For least squares reconstruction computational complexity is $O(L_G KNQL_{r,k}^2$ and for residual computation its complexity is $O(KQNM)$.
The complexity in spatial domain is $O(KMN\,log(MN))$.Therefore, the overall computational complexity of propose dDS CoSaMP algorithm is $O(KMG) + O\left(L_G KNQL_{r,k}^3\right) + O(L_G KNQ(L_{r.k} - L_c)^3) +$
$O(L_G KNQL_{r,k}^2\ O(KMN\,log(MN))$.

Results and Discussions :-
In our simulation configuration, we examine a system whereby the base station (BS) is outfitted with M = 64 antennas organized in an 8×8 uniform planar array, while the reconfigurable intelligent surface (RIS) has N = 256 components grouped in a 16×16 grid. The system concurrently accommodates K = 16 single-antenna users. The number of propagation pathways between the base station (BS) and the reconfigurable intelligent surface (RIS) is established as $\mathrm{L}_{\mathrm{G}} = 5$, while the number of paths from the kth user to the RIS is set as $\mathrm{L}_{\mathrm{r.k}} = 8$ for $\forall_{\mathrm{k}}$. All angular parameters are presumed to reside on established quantised grids. Each component of the RIS reflection matrix $\boldsymbol{\theta}$ is selected from the discrete set$\left\{-\frac{1}{\sqrt{\mathrm{N}}}, +\frac{1}{\sqrt{\mathrm{N}}}\right\}$, taking into account finite-resolution phase shifts as referenced in [7]. The intricate route gain between the BS and the RIS is represented as$\left|\alpha_{\mathrm{l}}^{\mathrm{G}}\right| = 10^{-3}\mathrm{d}_{\mathrm{BR}}^{-2.2}$, where the distance between the BS and RIS, d_{BR} is 10 meters. The path gain between each user and the RIS is expressed as$\left|\alpha_{\mathrm{l}}^{\mathrm{r,k}}\right| = 10^{-3}\mathrm{d}_{\mathrm{RU}}^{-2.8}$, where the RIS–user distance d_{RU} is assumed to be 100 meters for all users.

The signal-to-noise ratio(SNR) is described as:-

$$\mathrm{SNR} = \mathrm{E}\{\left\|\tilde{\theta}\widetilde{\mathrm{H}}_{\mathrm{k}}^{\mathrm{H}}\right\|_{\mathrm{F}}^{2} / \left\|\widetilde{\mathrm{W}}_{\mathrm{k}}\right\|_{\mathrm{F}}^{2}\}$$

is set as zero dB. We evaluate the performance of the proposed DS-CoSaMP-based scheme against three methods: the conventional compressive sensing (CS) approach [5] and the row-structured sparsity-based scheme [6], and DS-

OMP method [12]. In standard CS methods, OMP algorithm estimates the user specific sparse cascaded channel $\widetilde{H}_k$ independently, neglecting any shared sparsity patterns. The row-structured sparsity scheme, on the other hand, first identifies the common row support Ω_r with L_G indices shared among all users. Then, for each user and each selected row l_1, the corresponding column supports are individually estimated using the classical OMP technique. Additionally, we include an oracle least squares (LS) estimator as a performance benchmark, where it is assumed that the exact support of all sparse channels is perfectly known in advance.

Figure 2 gives the comparison between DS-CoSaMP and DS-OMP variations .In this figure, for all systems, the NMSE declines as the pilot overhead Q rises, implying that additional pilot symbols enhance estimate accuracy. The suggested DS-CoSaMP performs better than other DS-OMP variations, consistently attaining the lowest NMSE across all values of Q.Among the DS-OMP variations, performance improves with a rise in Lc, namely from Lc = 0 to Lc=8, however it continues to underperform relative to DS-CoSaMP.Theeffectiveness of DS-CoSaMP in situations with limited pilot resources is shown by the performance difference between it and DS-OMP, which is more noticeable at lower pilot overheads.

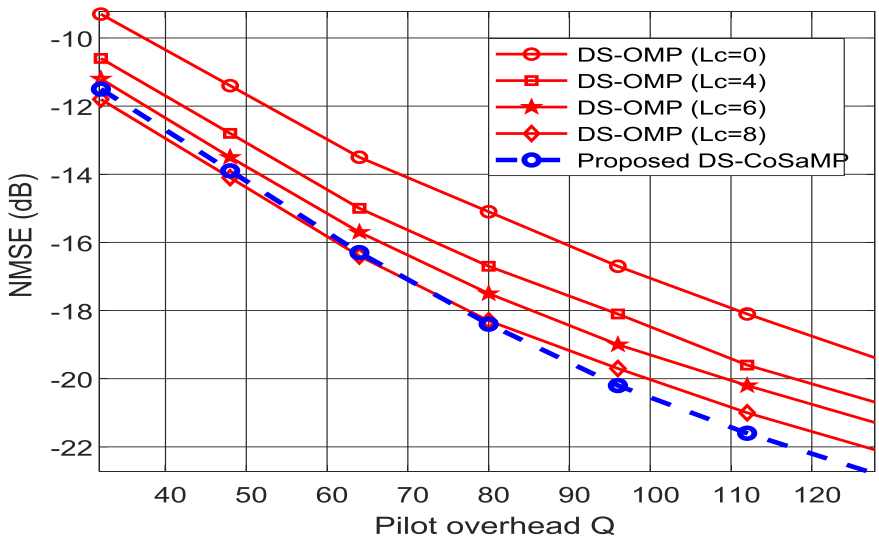

Fig. 2. Comparison between DS-CoSaMP and DS-OMP variants

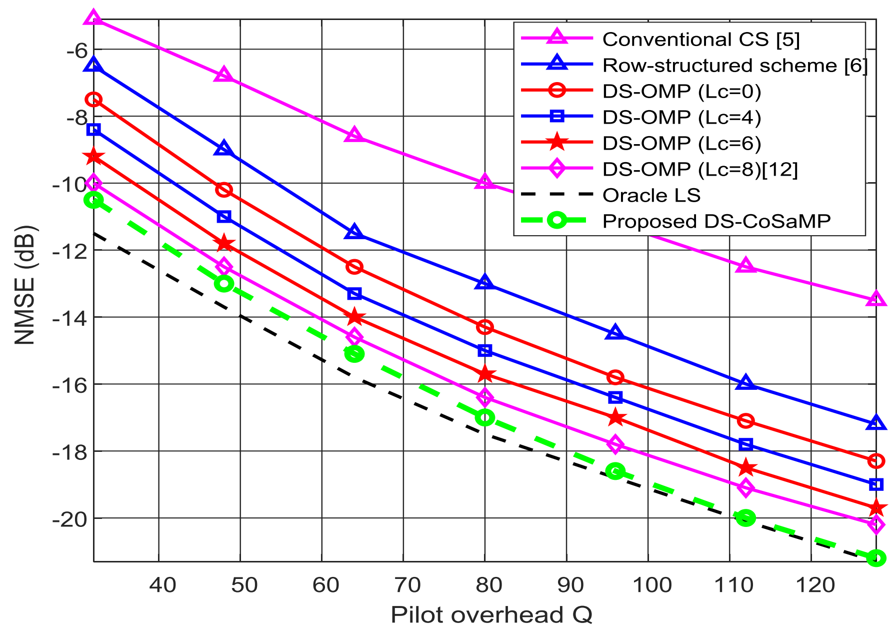

Fig. 3. Comparison between Co-SaMP and Existing Methods

In Figure 3, NMSE is plotted against pilot overhead, which is governed by the total number of time slots assigned for pilot transmission (Q) and it demonstrates that the suggested DS-OMP-based system needs less pilot resources to achieve equivalent estimate accuracy compared to the current approaches [5],[6],[12]. In situations when there are no shared propagation channels between the RIS and all users (i.e., $Lc = 0$), the double-structured sparsity simplifies to a row-structured sparsity model [6]. The NMSE performance of the DS-CoSaMP-based method corresponds with that of the row-structured sparsity scheme. As the quantity of common pathways Lc rises, the recommended method depends on the augmented structure, resulting in increased NMSE performance that approximates that of the optimal scenario with complete channel support knowledge.

Conclusion:-

The conclusions are a key component of the paper. It should complement the abstract and is normally used by experts to value the paper's engineering content. A conclusion is not merely a summary of the main topics covered or a re-statement of your research problem, but a synthesis of key points and, if applicable, where you recommend new areas for future research.

Conflict of Interest:
The authors declare no conflict of interest.

Author Contributions:
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