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Optimized Hybrid Precoding for Energy and Spectrum Efficiency in mmWave Massive MIMO System

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***Abstract*—**This paper presents a novel hybrid connection structure-based precoding algorithm specifically designed for large-scale MIMO millimeter-wave (mmWave) systems. The pri- mary objective of this algorithm is to enhance both energy and spectrum efficiency while managing the inherent hardware complexity associated with such systems. By utilizing a con- stant modulus constraint, the algorithm addresses continuous interference and applies gradient descent along with alternating minimization techniques to develop an optimal hybrid precoding matrix.Simulation results demonstrate that the proposed algo- rithm achieves near-optimal spectrum efficiency, particularly in cases where the number of RF links exceeds the number of data streams. As the antenna count increases, the algorithm's performance becomes even more pronounced when compared to existing techniques. Additionally, the hybrid connection archi- tecture outperforms both full and partial connection structures, offering significantly higher energy efficiency. While full con- nection structures exhibit marginally better spectrum efficiency, their practical applicability is hindered by increased hardware complexity and lower energy efficiency.Moreover, the proposed approach shows robustness against channel estimation errors, particularly in large antenna arrays, making it suitable for a wider range of deployment scenarios. The algorithm's resilience in the face of imperfect channel state information (CSI) further broadens its potential for real-world applications. This makes the method a promising and efficient solution for future mmWave massive MIMO systems, especially as the industry moves to- wards 5G and beyond. The balance achieved between spectral efficiency, energy efficiency, and hardware complexity sets the proposed method apart, ensuring its relevance in modern wireless communication networks.

Keywords: Hybrid precoding,mmWave massive MIMO,Spectrum efficiency,Energy efficiency,Constant modulus constraint,Gradient descent,Alternating minimization.

I. INTRODUCTION

Millimeter-wave (mmWave) massive MIMO systems are re- garded as one of the main accelerators for 5G and be- yond wireless communication systems, offering significant improvements in system capacity, spectral efficiency, and data transmission rates. These systems employ large antenna arrays and leverage hybrid precoding to optimize signal transmission while maintaining energy efficiency, addressing both hardware complexity and performance challenges [1][2]. Hybrid precod- ing combines analog and digital techniques, when compared to fully digital precoding, drastically lowers the number of radio frequency (RF) chains needed, making it more energy- efficient, particularly in mmWave applications [3][4].

Hybrid architectures integrate RF beamforming with baseband signal processing, making it possible to achieve high-quality data streams while operating under stringent power constraints. These architectures typically reduce the number of phase shifters required, thereby lowering hardware complexity. How- ever, the completely connected hybrid precoding structure, in which every RFchain is coupled to every antenna, results in high implementation complexity and significant energy consumption as the number of antennas ramps up[5].

Numerous precoding solutions have been developed to address these issues. For example, compared to traditional approaches, hybrid precoding based on the geometric mean decomposition (GMD) has been demonstrated to improve bit error rate (BER) performance while simplifying bit allocation [6]. Other strategies, such RF/baseband linear precoding, decrease the mean square error (MSE) by combining RF and baseband precoders to diagonalize the channel as efficiently as possible [7]. The performance of mmWave large MIMO systems can only be enhanced using these optimization methods.

Based on partially linked architectures—where each RF chain is connected to a subset of antennas—researchers have sug- gested hybrid precoding techniques that balance energy econ- omy, the complexity of the hardware and spectrum efficiency. This approach reduces hardware complexity significantly in comparison to fully integrated solutions, but at the cost of spectral efficiency [8][9]. Machine learning-based techniques for hybrid precoding, which optimize channel measurements and precoding vectors, have been presented to increase energy efficiency and preserve acceptable spectral efficiency [10].

To achieve more optimization, a new hybrid precoding method based on a hybrid connection structure has been proposed. The RF links are divided into blocks by this technique, and each block has some partial connectivity. By striking a compromise between system performance and hardware complexity, the hybrid connection topology outperforms fully and partially connected designs in terms of energy efficiency [11][12]. Large-scale mmWave massive MIMO systems could benefit greatly from this structure's significant energy efficiency gains, even though its spectral efficiency is reduced when compared to fully connected structures.

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Nonetheless, there are still certain restrictions with the hybrid connection arrangement. In particular, the spectral efficiency drops and the constant modulus restriction makes solving the block matrices more difficult when the data stream is smaller than the total number of RF chains [13]. An enhanced approach that minimizes the block matrix computations and Deep learning and machine learning have been added to more current techniques to optimize hybrid precoding in real-time. By dynamically modifying the precoding matrices in response to the state of the channel, these methods seek to increase en- ergy and spectrum efficiency. Furthermore, because codebook- based precoding can achieve near-optimal performance while reducing computing complexity, it has gained popularity. An ideal iterative technique for codebook-based beamforming was created by Y. Cheng and M. Pesavento[14], enabling effective downlink transmission in large-scale MIMO systems.
In terms of spectral efficiency, hybrid precoding systems can be evaluated using the formula for spectral efficiency:

$$R = \log_2 \quad \mathbf{I}_{N_r} + \frac{\rho}{\sigma_n^2 N_s} \mathbf{H}\mathbf{F}\mathbf{F}^H \mathbf{H}^H$$

maximizes spectral efficiency under constant modulus restric- tions has been created to solve these drawbacks [14]. This innovative approach is appropriate for practical uses as it improves spectrum and energy efficiency without appreciably raising hardware complexity.
This is how the rest of the paper is structured. In Section II,
relevant research on hybrid precoding methods is reviewed, with an emphasis on the advantages and drawbacks of various link topologies. The suggested hybrid connection structure- based algorithm is shown in Section III. Section IV presents the simulation results, and Section V offers the conclusions.

II. Related Work on Hybrid Precoding Techniques

Hybrid precoding combines both analog and digital tech- niques, compared to fully digital precoding, greatly lowering the number of radio frequency (RF) chains needed. This makes it more energy-efficient, particularly in mmWave ap- plications.For mmWave MIMO systems, hybrid precoding is crucial because of the limitations of large antenna arrays and the high implementation costs of entirely digital structures. Several methods have been explored to optimize the design of hybrid precoders.
Weighted sum-rate maximization was one of the first pre- coding methods, applied to MIMO broadcast channels. By creating beamforming vectors specifically for each user and allocating power in an ideal manner,Maximizing the system's overall data rate was the aim of this approach. This approach, which was put out by S. Christensen et al., improved overall system throughput by lowering interference by iteratively ad- justing the beamforming vectors using the weighted minimum mean square error (WMMSE) technique[6].
Semidefinite programming (SDP) was used in a related method to create the best downlink beamforming vectors. This tech- nique enabled multiple users to simultaneously receive high- quality signals, which was especially advantageous for sys- tems with individual SINR (Signal-to-Interference-plus-Noise Ratio) limits. To ensure that improve the system's resilience against interference, M. Bengtsson and B. Ottersten introduced a framework that uses SDP to tackle the beamforming problem for multi-user downlink scenarios[2].

where:
H is the channel matrix,
- **F** is the hybrid precoding matrix,
- N_r is the number of receive antennas,
- N_s is the number of data streams,
- ρ is the average SNR,
- $n\,\sigma^2$ is the noise power[5].

Hybrid connection structures, which divide the RF chains into sub-arrays, have also been explored as an effective strategy to balance energy efficiency and hardware complexity. In this architecture, only a portion of the RF chains are connected to each sub-array, reducing hardware costs and power consump- tion without significant performance degradation. S. Zarei et al. presented a linear precoding approach with low complexity for huge MIMO systems, which utilized a hybrid connection structure to achieve high energy efficiency[9].
However, one of the challenges of hybrid precoding systems is dealing with constant modulus constraints in analog precoders. These constraints arise from the hardware limitations of phase shifters, which can only adjust the signal's phase and not its amplitude. To address this, alternating minimization tech- niques are used to decompose the precoding matrix into analog and digital components, iteratively refining each component to meet the modulus constraint while maximizing spectral efficiency. This optimization challenge has been successfully solved by splitting the precoding matrix into smaller sub- matrices using singular value decomposition (SVD)[12].
In conclusion, hybrid precoding methods, which provide a reasonable balance between spectrum efficiency, energy ef- ficiency, and hardware complexity, are essential for the realis- tic implementation of mmWave MIMO systems. Technology developments in machine learning, codebook-based methods, and connection structure optimizations keep

pushing the en- velope of what is possible in these large-scale, high-frequency antenna systems[6][9][12][14].

III. THE PROPOSED HYBRID CONNECTION STRUCTURE-BASED ALGORITHM

we propose a hybrid connection structure-based precoding framework for mmWave massive MIMO systems that efficiently balances hardware complexity, energy efficiency, and spectral efficiency. The framework leverages the hybrid pre- coding architecture, which integrates both analog and digital precoding techniques. This minimizes energy consumption and cuts down on the number of radio frequency (RF) chains needed, which is important for millimeter-wave (mmWave) systems that use a lot of antennas on both the transmitter and receiving ends.

A. System Model and Hybrid Precoding Framework

A transmitter with N_t antennas and a receiver with N_r antennas are part of the system design. The entire RF links are split into D sub-arrays at the transmitter side, and each sub- array is connected to S RF links. This leads to DN transmit antennas and SD RF connections, i.e.,

$$N_{RF} = SD \quad \text{and} \quad N_t = DN.$$

Each sub-array connects to S RF links. To simplify perfor- mance evaluation, it is assumed that the entire transmitter has the same number of antennas, and the symbol count is denoted as N_s.

The relationship between the number of frequency links and antennas at the transmitter and receiver must satisfy:

$$N_s \leq SD \leq N_t \quad \text{and} \quad N_s \leq SD \leq N_r.$$

The received signal vector $\mathbf{y} = [y_1, y_2, \ldots, y_{N_S}]$ is given by:

$$\mathbf{y} = \rho \mathbf{H}\mathbf{F}_{RF}\mathbf{F}_{BB}\mathbf{s} + \mathbf{n} = \rho \mathbf{H}\mathbf{F}\mathbf{s} + \mathbf{n} \qquad (4.1)$$

where:

- $\mathbf{F}_{BB}$ is the digital precoding matrix of size $SD \times N_s$,
- $\mathbf{F}_{RF}$ is the analog precoding matrix of size $N_t \times SD$,
- ρ is the average received signal-to-noise ratio (SNR),
- $\mathbf{H} \in C^{N_r \times N_t}$ is the channel matrix,
- $\mathbf{s}$ is the transmitted signal vector with dimensions $N_s \times 1$, and $E[\mathbf{s}\mathbf{s}^H] = \frac{1}{N_s}\mathbf{I}_{N_s}$,
- $\mathbf{F} = \mathbf{F}_{RF}\mathbf{F}_{BB}$ represents the hybrid precoding matrix,
- $\mathbf{n} \sim \mathcal{CN}(0, \sigma_n^2)$ is the noise vector.

The hybrid precoding framework must satisfy the total trans- mission power constraint:

$$\|\mathbf{F}_{RF}\mathbf{F}_{BB}\|_F^2 \leq N_s.$$

B. Channel Model

To capture the sparse nature of the mmWave channel, we adopt the Saleh-Valenzula (S-V) model [1]. The S-V channel model is a parameterized multi-path channel model, which is particularly effective in mmWave environments where the number of transmission paths is limited due to high path loss.

The spectral efficiency R of the hybrid precoding framework is given by:

$$R = \log_2 \left| \mathbf{I}_{N_r} + \frac{\rho}{\sigma_n^2 N_s}\mathbf{H}\mathbf{F}\mathbf{F}^H\mathbf{H}^H \right| \qquad (4.2)$$

where:

- $\mathbf{I}_{Nr}$ is the identity matrix of size $N_r \times N_r$,
- ρ is the average received signal-to-noise ratio (SNR),
- σ_n^2 is the noise power,
- N_s is the number of data streams,
- $\mathbf{H} \in C^{Nr \times Nt}$ is the channel matrix,
- $\mathbf{F}$ is the hybrid precoding matrix, which can be decom- posed as $\mathbf{F} = \mathbf{F}_{RF}\mathbf{F}_{BB}$.

C. Optimization Framework

1) Stage 1: Matrix Decomposition Without Constraints: In the first stage, we optimize the hybrid precoding matrix without considering the constant modulus constraint on The optimiza- tion problem for designing the hybrid precoding matrix can be formulated as:
[ruled,vlined]algorithm2e

Algorithm 1 Matrix Decomposition for Hybrid Pre-Coding Design (Unconstrained Case)

Optimal hybrid pre-coding matrix F^{opt}, antenna array dimensions N_t, N_s, error constant ϵ Digital pre-coding matrix A_{BB}, analog pre-coding matrix A_{RF} Randomly initialize A_{RF} and compute A_{BB}:

$$A_{BB} = (A_{RF}^H A_{RF})^{-1} A_{RF}^H F^{opt}$$

while $\|F^{opt} - A_{RF} A_{BB}\|_F^2 \geq \epsilon$ **do** Update A_{BB}:

$$A_{BB} \leftarrow A_{BB} - c_1 A_{RF}^H (A_{RF} A_{BB} - F^{opt})$$

Compute c_1:

$$c_1 = \frac{\mathrm{tr}\{A_{RF} A_{RF}^H (F^{opt} - A_{RF} A_{BB})(F^{opt} - A_{RF} A_{BB})^H\}}{\mathrm{tr}\{A_{RF} A_{RF}^H (F^{opt} - A_{RF} A_{BB})(F^{opt} - A_{RF} A_{BB})^H A_{RF} A_{RF}^H\}}$$

Update A_{RF}:

$$A_{RF} \leftarrow A_{RF} - c_2 (A_{RF} A_{BB} - F^{opt}) A_{BB}^H$$

Compute c_2:

$$c_2 = \frac{\mathrm{tr}\{(F^{opt} - A_{RF} A_{BB})^H (F^{opt} - A_{RF} A_{BB}) A_{BB}^H A_{BB}\}}{\mathrm{tr}\{(F^{opt} - A_{RF} A_{BB}) A_{BB}^H A_{BB} A_{BB}^H A_{RF} (F^{opt} - A_{RF} A_{BB})^H\}}$$

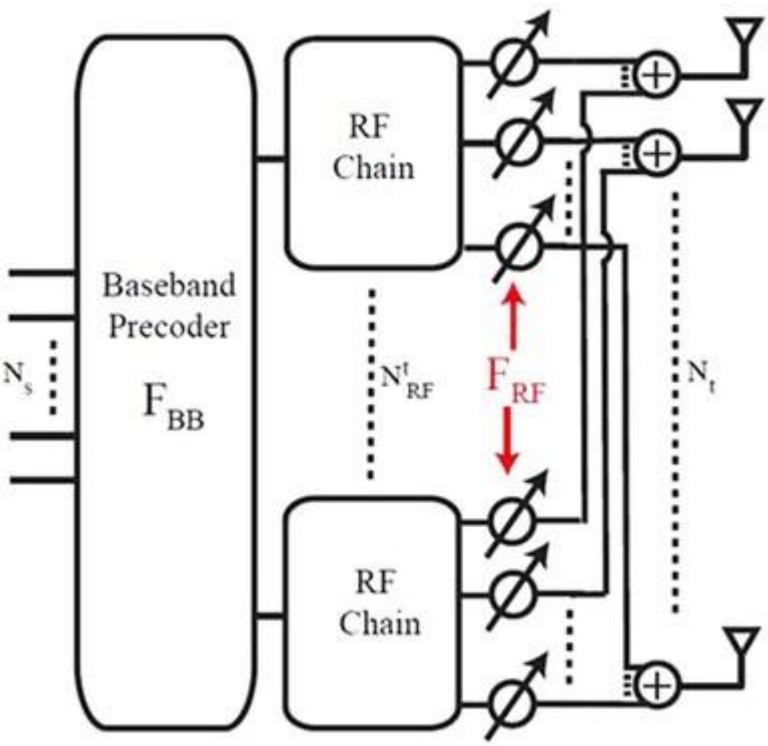

Fig. 1: A framework for hybrid precoding in MM-MIMO systems

2) Matrix Decomposition with Constant Modulus Constraints: In the second stage, we incorporate the constant modulus constraint into the design of the analog precoding matrix $\mathbf{F}_{RF}$ The optimization problem becomes:

$$\min_{\mathbf{F}_{RF},\mathbf{F}_{BB}} \|\mathbf{F}_{opt} - \mathbf{F}_{RF}\mathbf{F}_{BB}\|^2_F$$

subject to:

$$\|\mathbf{F}_{RF}\mathbf{F}_{BB}\|^2_F = N_s \quad \text{and} \quad |\mathbf{F}_{RF}(i,j)| = \sqrt{\frac{1}{N_t}}$$

Using the alternating minimization method, the optimization is divided into sub-problems that iteratively refine the ma-trices $\mathbf{F}_{RF}$ and $\mathbf{F}_{BB}$ while satisfying the constant modulus constraint. By decomposing the problem into D sub-blocks, each corresponding to a sub-array of antennas, the hybrid connection structure is optimized separately for each block. Matrix factorization and phase correction are used to find the best solution for each subproblem.

The overall hybrid precoding algorithm is summarized in Al- gorithm 2. The algorithm first initializes the analog precoding matrix $\mathbf{F}_{RF}$, and iteratively optimizes $\mathbf{F}_{RF}$ and $\mathbf{F}_{BB}$ using the alternating minimization method. The algorithm ensures convergence to a locally optimal solution by progressively minimizing the objective function in each iteration.

Algorithm 2 Alternating Optimization with Constant Modulus Constraints

Input: Optimal hybrid pre-coding matrix F^{opt}, digital pre-coding matrix A_{BB}, analog pre-coding matrix A_{RF} , number of sub-arrays D, RF links S, antennas N , error constant ϵ

Output: Optimized hybrid pre-coding matrices F_{RF}, F_{BB}

Initialization: Set $F_{R,1}$ with amplitude $1/\sqrt{N}$ and random phase values.

for $d = 1$ to D **do**

  Extract sub-matrix $F^{opt}(d) = F^{opt}((l - 1)N + 1 : dN$, ins : ins $+ S - 1)$.

  Perform singular value decomposition (SVD) on $F^H_{R,d}A_{RF} = USV^H$.

  Update the transformation matrix:

$$\phi = VU^H, \quad F_{B,d} = \phi^H A_{BB}$$

  while $\|F_{R,d} - A_{RF}\phi\|_F \geq \epsilon$ **do**

    Update $F_{R,d}$ as:

$$F_{R,d} = \frac{1}{\sqrt{N}} e^{j\langle A_{RF}\phi\rangle}$$

  end while

end for

Output the final hybrid pre-coding matrices:

$$F_{RF} = \operatorname{diag}(F_{R,1}, \ldots, F_{R,D}), \qquad F_{BB} = [F^T_{B,1}, \ldots, F^T_{B,D}]^T$$

=0

IV. Simulation Results

We used the Saleh-Valenzula (S-V) channel model from [5] in MATLAB simulations to assess the efficacy of the suggested hybrid connection structure-based hybrid precoding technique. There were $N_{cl} = 5$ scattering clusters in the simulation setup, and each cluster had $N_{ray} = 10$ transmission routes. With a 10° angular spread, the angles of arrival and departure were distributed uniformly between [π, π] and [$\pi/3, \pi/3$]. In the simulations, a uniform linear array was employed.

A. Spectrum Efficiency Analysis

The spectral efficiency of the suggested hybrid precoding technique is compared to that of current algorithms, namely those from [5] and [9], under various signal-to-noise ratio (SNR) circumstances, as shown in Figure 2. The following parameters were used in the simulation: the number of RF chains ($N_{RF} = 4$), the number of data streams ($N_s = 4$), the number of users ($S = 2$), the number of transmit antennas ($N_t = 64$), the number of receive antennas ($N_r = 16$), the number of data streams ($D = 2$), and the convergence threshold ($\epsilon = 10^{-4}$). As observed in the figure, the spectral efficiency of all al- gorithms increases with higher SNR values. However, the proposed hybrid precoding algorithm demonstrates superior performance, especially in scenarios with higher SNR. It closely approaches the optimal spectral efficiency at higher SNR values, outperforming other algorithms like those in [9] and the hybrid connection structure.

When $N_s = N_{RF}$ (the number of data streams equals the number of RF chains), the suggested technique performs exceptionally well. It provides significant gains in spectral efficiency and outperforms the technique from [9] in certain cases. The suggested approach also demonstrates a significant improvement in efficiency at lower SNR levels when compared to the hybrid connection structure method, indicating better use of available RF chains and data streams.

The suggested technique offers a more effective hybrid precod- ing solution, greatly enhancing spectral efficiency, especially in situations where the quantity of data streams corresponds with the RF links and the SNR is larger. For energy and spectral efficiency in mmWave huge MIMO systems, this makes it a good option.

B. Energy Efficiency Analysis

A comparison of the energy efficiency of several precoding systems, such as the hybrid connection structure presented here and those from [1], [5], and [9], under varying RF link numbers, is shown in Figure 3. The RF link number can be anywhere from 5 to 40, and the energy efficiency is expressed in bits per second per hertz per watt (bit/s/Hz/W). The figure shows that the suggested algorithm performs much better than alternative methods in terms of energy efficiency as the number of RF lines grows.

In particular, as the number of RF links increases, the sug- gested algorithm, which is based on a hybrid connection struc- ture, keeps an energy efficiency that is constantly high—nearly 0.9 bit/s/Hz/W. Other algorithms do not exhibit this stability. For instance, the OMP method from [1], which makes use of a full connection, exhibits a significantly worse energy efficiency and stays comparatively flat as the number of RF links increases. On the other hand, the energy efficiency of the algorithm from [5] (partial connection) decreases sharply with an increase in the number of RF links, indicating that this approach is less effective when dealing with longer RF chains.

On the other hand, the suggested algorithm makes use of the hybrid connection structure to guarantee that energy efficiency is not adversely affected by an increase in the number of RF links. In terms of maintaining superior energy efficiency throughout a range of RF links, it outperforms both the best hybrid connection structure and the hybrid connection method described in the literature [9].

The suggested hybrid connection structure-based precoding strategy is the best option for energy-efficient designs in mmWave massive MIMO systems because it provides better energy efficiency, particularly as the number of RF links rises. Its practical use in real-world systems that need both high performance and energy conservation is highlighted by its ability to reliably maintain high energy efficiency throughout RF connection numbers.

C. Channel Estimation Sensitivity

Using a non-ideal Channel State Information (CSI) model, as suggested in [15], Figure 4 shows how channel estimation errors affect spectrum efficiency. The findings of the simu- lation indicate that while channel estimate mistakes have a detrimental impact on spectrum efficiency, the impact of these errors decreases with an increase in antenna count.

Plotting the spectrum efficiency against different antenna configurations, this figure shows that systems with fewer antennas are more prone to inaccurate channel estimates. Because precise CSI is necessary for precoding and detecting procedures to maximize signal transmission, these errors result in decreased performance. Nonetheless, the system gets more degrees of freedom and spatial variety as the number of antennas increases. Even in cases where the CSI is not ideal, the greater diversity makes it possible to handle estimation errors more robustly, which leads to a comparatively lesser loss in spectrum efficiency.

For huge MIMO systems, which use hundreds or thousands of antennas, this trend is essential. Even with the unavoid- able faults in channel estimation, these systems are able to retain high levels of spectrum efficiency since the degradation brought on by faulty CSI becomes less pronounced. One of the main benefits of large-scale antenna arrays in mmWave com-munications is their durability, as the high-frequency bands can make channel estimate more difficult.

In Figure 4 underscores the importance of employing large antenna arrays in mitigating the adverse effects of channel estimation errors on spectrum efficiency. As the number of antennas increases, the system becomes more tolerant of these errors, making massive MIMO systems highly effective in scenarios where perfect CSI is not available.

D. Complexity Analysis

The computational complexity of the proposed algorithm is analyzed in two stages. For Stage 1, the update complexity for c_1 and c_2 is $O(S^2N)$, while updating $\mathbf{A}_{BB}$ and $\mathbf{A}_{RF}$ has a complexity of $O(SN^2)$. For Stage 2, the complexity is $O(TSN^2)$, where T represents the number of iterations.

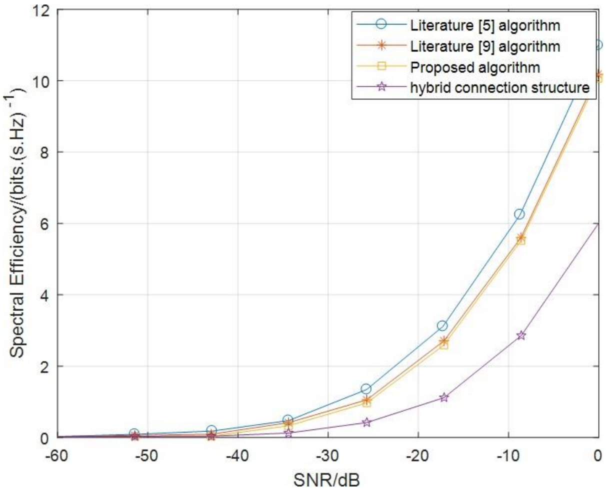

Fig. 2: Comparison of Proposed Algorithm Spectrum effi- ciency under different SNR/dB

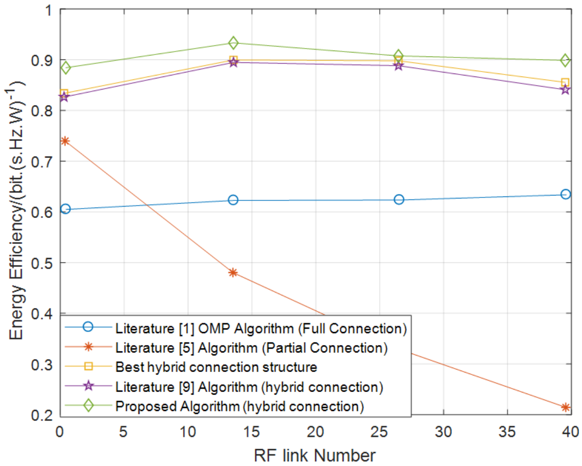

Fig. 3: Energy Efficiency comparison.

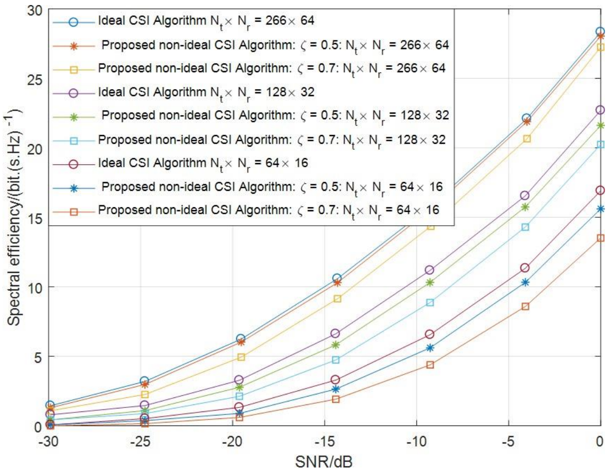

Fig. 4: Impact of Channel Estimation Errors on Spectrum Efficiency.

V. CONCLUSIONS

The proposed hybrid connection structure-based precoding algorithm offers a balanced and effective solution for mmWave massive MIMO systems, achieving notable improvements in both spectrum and energy efficiency. By eliminating continu- ous interference and optimizing the hybrid precoding matrix through gradient descent and alternating minimization meth- ods, the algorithm approaches the optimal performance even under constant modulus constraints. The simulation results show that the algorithm's performance advantage grows with the number of antennas when the number of RF links exceeds the number of data streams. The suggested strategy, especially in situations with a high antenna count, yields spectrum efficiency values substantially closer to the optimal solution than algorithms in the literature. Furthermore, compared to both complete and partial connection structures, the hybrid connection structure offers far higher energy efficiency, mak- ing it a better choice for real-world applications.

The hybrid connection structure employed in this technique has a higher overall energy and spectrum efficiency than any connection structure, even though some connection structures (such those from the literature already in existence) might have less hardware complexity. Full connection architectures have a marginally greater spectrum efficiency, but they are less practical for real-world applications due to their high hardware complexity and low energy efficiency. The approach presented in this research performs better in terms of ro- bustness to channel estimate errors, especially in large-scale antenna systems, while maintaining the same computational cost as previous state-of-the-art algorithms. Because of its robustness, the suggested method may be applied to a greater variety of settings, which makes it a more useful and effective solution for wireless communication systems that will be used in future 5G and beyond.

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