

Power saving and optimal hybrid precoding in millimeter wave massive MIMO systems for 5G

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ABSTRACT

The proliferation of wireless services emerging from use cases of fifth-generation (5G) technology is posing many challenges on cellular communication infrastructure. They demand to connect a massive number of devices with enhanced data rates. The massive multiple-input multiple-output (MIMO) technology at millimeter-wave (mmWave) in combination with hybrid precoding emerges as a concrete tool to address the requirements of 5G network developments. But Massive MIMO systems consume significant power for network operations. Hence the prior role is to improve the energy efficiency by reducing the power consumption. This paper presents the power optimization models for massive MIMO systems considering perfect channel state information (CSI) and imperfect CSI. Further, this work proposes an optimal hybrid precoding solution named extended simultaneous orthogonal matching pursuit (ESOMP). Simulation results reveal that a constant sum-rate can be achieved in massive MIMO systems while significantly reducing the power consumption. The proposed extended SOMP hybrid precoder performs close to the conventional digital beamforming method. Further, modulation schemes compatible with massive MIMO systems are outlined and their bit error rate (BER) performance is investigated.

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1. INTRODUCTION

The enormous growth in smartphone usage in recent years has led to an exponential increase in the transmission of multimedia content over mobile networks. This has, in turn, led to significant growth in global mobile traffic [1]. New wireless applications are leading to a rapid increase in desire data rates and envisaged to support dense connectivity in the order of tens of thousands of connected devices in a single cell [2]. These demands have surpassed the technical capabilities of present fourth-generation long term evolution (4G LTE) cellular systems. The 5G technology promising to be so much better than the legacy 4G networks. Fifth-generation (5G) systems aim to achieve orders of magnitude increase in wireless data rates (10 Gbps in cellular networks), spectral bandwidths (1000x per unit area), coverage area (close to 100% anytime anywhere with vanishingly small probability of outage), massive device connectivity, a large reduction in round trip delay (latency as low as 1 ms) and also energy consumption (up to 10-year battery life for low power IoT devices) [3]. So, 5G puts challenges on the standardization bodies like third generation partnership project (3GPP) to

release the standards which provide dynamic, universal, user-centric, and data-rich wireless services to fulfill the aforementioned promises and importantly to meet the expectation of users [4].

The use cases of 5G are mainly, enhanced mobile broadband (eMBB), ultra-reliable low latency communications (URLLC), and massive machine type communications (mMTC). To realize these use cases and to address the challenges raised by the new services under these use cases, many researchers are devoted to proposing new technologies for 5G networks, especially in the physical layer. The physical layer technologies are, mmWave, massive multiple-input multiple-output (MIMO) [5], non-orthogonal multiple access (NOMA) [6], filter bank multicarrier (FBMC) [7] and full-duplex radio technology, beamforming, and hybrid precoding to name a few [8]. Millimeter-wave communication is a key candidate for addressing the challenge of bandwidth shortage for 5G systems [9-12]. Signals at mmWave bands (30 to 300 GHz) undergo severe path loss and are highly sensitive to blockage as compared to legendary frequency bands [13]. Thanks to smaller wavelengths of mmWave allowing more antennas to pack within the same physical area, this drives to use a large number of antennas at the transceivers, thereby forming a massive MIMO system. Massive MIMO systems enhance cellular spectral efficiency [14, 15] and provide sufficient spatial degrees of liberty for multiplexing several data streams rendering to serve multiple users simultaneously [16, 17]. They can also substantially reduce intercell interference with simple signal processing operations [18] like beamforming. Furthermore, using large-scale antenna arrays, a base station (BS) can obtain highly selective beams to focus on the desired users [19, 20]. Therefore, beamforming with large antenna arrays is key for recognizing the gains in mmWave MIMO [21, 22]. Naturally, optimal beamforming, precoder/combiner design strategies will play a critical role in the implementation of mmWave systems [23].

The analysis of massive MIMO mainly focused on the digital systems in which all the signal processing is performed at baseband and every antenna element needs individual radio frequency chain (RF chain). Fully-digital massive MIMO systems can serve multiple users simultaneously. The digital precoder creates multiple beams to multiplex several data streams, choosing the transmitting directions. Each RF chain is a cascade of amplifier, filter, mixers, attenuator, and detector. The huge number of RF chains in digital precoding systems consume a large amount of power become a bottleneck that limits the advancements of massive MIMO systems. Hence a mechanism that would reduce the power consumption in massive MIMO systems is essentially the need of the art. When operating at mmWave frequencies, these RF chains tend to be very costly and naturally the hardware complexity of digital massive MIMO systems is significantly large. These drawbacks of digital systems have paved a way for the development of novel architectures named hybrid mmWave massive MIMO systems. In hybrid architectures, signal processing is accomplished by a mixture of analog and digital domains, this is termed hybrid precoding. The hybrid architectures use fewer RF chains and hence hybrid precoding can potentially achieve high spectral efficiencies while requiring less cost and power consumption than fully-digital solutions.

Hybrid precoding architecture uses a small number of transceivers having N_t^{RF} RF chains at the transmitter and N_r^{RF} RF chains at the receiver such that $N_s < N_t^{RF} < N_t$ and $N_s < N_r^{RF} < N_r$ respectively. Here N_s denotes the number of streams, N_t and N_r represents the number of antennas at transmitter and receiver respectively. Hybrid precoding enables a millimeter wave (mmWave) system to take advantage of both spatial multiplexing and beamforming gain. A major challenge with hybrid precoding is its configuration. Figure 1 illustrates fully-connected hybrid architecture where all the antennas connected to each RF chain. Partially connected hybrid architecture is depicted in Figure 2, where the antenna array gets divided into subarrays, each subarray connected to its corresponding RF chain. Partially connected architecture of hybrid beamforming further reduces the hardware complexity at a cost of less flexibility. Figure 3 shows a partially connected hybrid architectures using switches to select subsets of antennas. The model in Figure 3 avoids the power consuming phase-shifters contributing for further reduction in power.

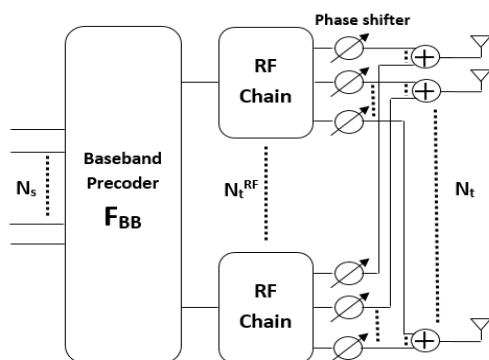


Figure 1. Fully connected

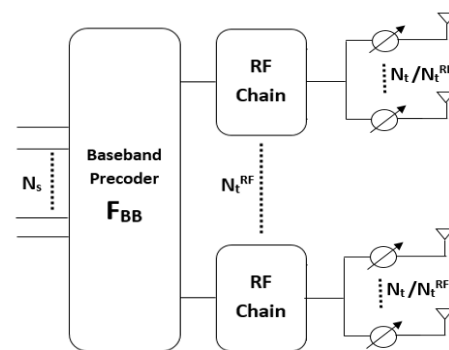


Figure 2. Partially connected

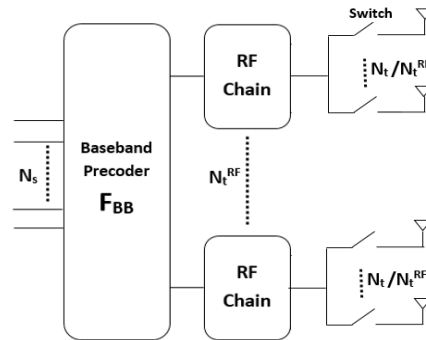


Figure 3. Partially connected using switches

Authors in [24, 25] presented, low-cost hybrid precoding schemes where a reduced number of RF chains can be used can be us to achieve the relatively same performance as that of full-digital precoding. A hybrid precoding method addressing the issues in recovering sparse signal under constant modulus constraints inflict by analog phase shifters and an orthogonal matching pursuit (OMP) an algorithmic solution is provided in [26, 27]. To reduce the computational complexity of the OMP method, [28] proposed a parallel-index-selection matrix-inversion-bypass simultaneous OMP scheme by avoiding matrix inversion operation. These methods assume perfect channel conditions and become inefficient for uncertain channel situations.

Contribution of this work can be summarized as:

- This work presents power-saving models for massive MIMO systems under perfect and imperfect channel conditions. These power scaling models cater to energy-efficient transmission.
- An extended SOMP algorithm is proposed as an optimal hybrid precoding solution for mmWave massive MIMO systems.
- The compatible modulation schemes for mmWave massive MIMO are outlined and their performance analysis is presented.

The novelty of this paper can be summarized as:

- The extended SOMP algorithm is developed by considering the transmit array vectors form a basis for the column space for the mmWave channel matrix.
- The baseband precoder is formulated as a block sparse matrix containing non zero rows equal to the number of RF chains at the transmitter. The OMP scheme is applied to solve the non-convex optimization problem in the block sparse matrix. Hence the complex operation like singular value decomposition and matrix inversions are avoided.
- The RF precoder is formed from the columns of the dictionary matrix. A large size dictionary matrix is created with many angular grids greater than the number of antennas at the transmitter.

2. RESEARCH METHOD

In this section, the power-saving models for massive MIMO systems are presented and an optimal hybrid precoding algorithm is proposed. We consider a massive MIMO system on the uplink under perfect and imperfect channel conditions. The system includes one BS quipped with an antenna array of M elements and the cell has K single-antenna users.

2.1. Power optimization model under perfect channel state information (CSI)

All K users send individual pilot symbols with average power p_u , the received vector at the BS can be represented as;

$$Y = \sqrt{p_u}GX + n \quad (1)$$

Here, G represents $M \times K$ matrix of the channel encompassing fast fading, geometric attenuation and log normal shadowing between BS and K users. The vector X contains the pilot symbols transmitted simultaneously by all users, and n additive white, zero-mean Gaussian noise vector. The noise variance is set to 1, without loss of generality, the noise samples are identically independently distributed as $n_m \text{CN}(0,1)$. Considering user k as the desired user, the matched filter receiver of maximal ratio combiner expressed in terms of desired signal and interference components as in (2).

$$r_k = \sqrt{p_u} \|g_k\| x_k + \sqrt{p_u} \sum_{i \neq k}^K \frac{g_k^H}{\|g_k\|} g_i x_i + \frac{g_k^H}{\|g_k\|} \mathbf{n} \quad (2)$$

where g_k denotes the $M \times 1$ channel vector corresponds to user k , and its elements are distributed as $g_{mk} \sim CN(0, \beta_k)$, β_k models the geometric attenuation and shadow fading. Therefore, the signal-to-interference-plus-noise ratio (SINR) can be derived as in (3).

$$SINR = \frac{p_u \|g_k\|^2}{p_u \sum_{i \neq k}^K \beta_i + 1} \quad (3)$$

The power of each user is scaling inversely with respect to number of antennas at the BS, $p_u = \frac{E_u}{M}$, further SINR can be represented as in (4).

$$SINR = \frac{E_u \frac{\|g_k\|^2}{M}}{E_u \left(\frac{1}{M} \sum_{i \neq k}^K \beta_i \right) + 1} = E_u \beta_k \quad (4)$$

Furthermore, the sum-rate scales as $\log_2(1 + SINR)$, thus constant data rate can also be achieved even with power scaling. Power of the desired signal grows M times the multi-user interference added with noise power, the channel vectors of the users become pairwise orthogonal and this suppresses the multi-user interference (MUI) as the number of antennas M becomes very large using very low complexity maximum ratio combining (MRC).

2.2. Power optimization model under imperfect CSI

In imperfect channel conditions, the channel matrix gets uncertainty (channel estimation error) added as given in (5).

$$\hat{G} = G + \frac{1}{\sqrt{p_p}} \mathbf{N} \mathbf{X}^H \quad (5)$$

Here \mathbf{N} is a noise vector. The noise coefficients are distributed such that $n_k \sim CN(0, 1)$ and therefore the elements of error of channel estimation error vector are i.i.d. Gaussian with variance $\frac{1}{K p_u}$. It follows that the channel estimate of user k i.e. $\hat{g}_k = g_k + e_k$ comprises of i.i.d Gaussian elements of power $\beta_k = \frac{1}{K p_u}$. The matched filter receiver for user k with imperfect CSI is given in (6).

$$r_k = \sqrt{p_u} \|g_k\|^2 x_k + \sqrt{p_u} e_k^H g_k x_k + \sqrt{p_u} \sum_{i \neq k}^K \hat{g}_i x_i + \hat{g}_k^H \mathbf{n} \quad (6)$$

It follows that $e_k^H \frac{g_k}{\|g_k\|} \sim CN(0, \frac{1}{K p_u})$, and also $\frac{\|g_k\|^2}{M} = \left(\beta_k + \frac{1}{K p_u} \right)$. The SINR of matched filter output with uncertain CSI can be simplified as in (7).

$$SINR = \frac{p_u \|g_k\|^2}{p_u \times \frac{1}{K p_u} + p_u \sum_{i \neq k}^K \frac{(X) \beta_i + (X)}{\beta_k + \beta_k}} \quad (7)$$

Here, $X = \beta_k + \frac{1}{K p_u}$, it is observed that, unlike in perfect CSI, we cannot scale the power as $\frac{1}{M}$ with uncertain CSI. This is because as transmit power decreases as $\frac{E_u}{M}$ CSI estimation error increases as $\frac{M}{K E_u}$. Further it is also noted that by scaling the transmit power as $p_u = \frac{E_u}{\sqrt{M}}$ the SINR can be maintained constant and is simplified as given in (8).

$$SINR = \frac{\frac{E_u}{\sqrt{M}} \|g_k\|^2}{\frac{1}{K} + \sum_{i \neq k}^K \frac{1}{K \beta_k} + 1 + \frac{\sqrt{M}}{K \beta_k E_u}} = K \beta_k^2 E_u^2 \quad (8)$$

2.3. Millimeter wave massive MIMO channel

In comparison to sub 6 GHz models, mmWave offers lower diffraction due to the reduced Fresnel zone, higher penetration losses, this leads to fewer multipath components. As mmWave inherently adopt massive MIMO leading to more sparsity in the channel. The mmWave channel model is described as in (9).

$$H = \sum_{l=1}^L \alpha_l a_R(\theta_l^r) a_T^H(\theta_l^t) = A_R H_b A_T^H \quad (9)$$

where L is number of multipath components or scatters, a_T and a_R is the array steering vectors at the transmitter and receiver respectively. The term, α_l refers to the complex gain of l^{th} path. The angles, θ_l^r and θ_l^t are angle arrival (AoA) and angle of departure (AoD) respectively. Let G is the number of basis directional cosine vectors, A_T and A_R are transmit and receive array response dictionary matrices. Also, $\theta_{i...G} \in \varphi$, where φ denotes the angular grid. The sparse combination of the basis directional vectors at the transmitter and receiver is represented by H the mmWave channel matrix. The beam space channel matrix H_b formed by stacks of coefficients which are zeros in majority forming h_b sparse vector. The channel estimation problem can be formulated as $\min_0 \|h_b\|$ which is termed as compressive sensing which is non-convex and difficult to solve using direct methods. Orthogonal matching pursuit (OMP) is one promising candidate for sparse signal estimation and solves optimization problem.

2.4. Proposed hybrid precoding scheme

Hybrid precoding is a vital task to reduce the cost and hardware complexity while delivering sufficient sum-rate [28]. To achieve better system capacity, an extended SOMP algorithm is proposed for hybrid precoding in mmWave MIMO system shown in Figure 4. A fully connected hybrid architecture is considered for multiuser communication in a downlink scenario. The optimal hybrid precoder ideally desired to design RF precoder (F_{RF}) and the baseband precoder (F_{BB}) in such a fashion that $\arg \min_F \|\bar{V} - F_{RF} F_{BB}\|^2$, where \bar{V} is the ideal precoder. From the mmWave channel given in (9), it can be analyzed that the transmit array response vectors in \bar{A}_T form a basis for the column space of H^H , therefore \bar{V} can be expressed as a linear combination of columns of \bar{A}_T in the mmWave MIMO channel as given below;

$$\bar{V} = \bar{A}_T \bar{F} \quad (10)$$

Furthermore, it is interesting to notice that the RF precoder can be formed from columns of \bar{A}_T and the coefficients of linear combination of \bar{F} can be used as the baseband precoder. However, there are two constraints to be addressed to implement this solution. Firstly, \bar{A}_T is not known in general and secondly, the above solution will only be satisfied if the number of multi-path components is less than N_{RF} . To address the first constraint, a large dictionary matrix with an angular grid φ_T of size G with $\theta_i \in \varphi_T, 1 \leq i \leq G, G \geq N_T$. The dictionary matrix A_T is constructed as in (11).

$$A_T = [a_T(\theta_1) \ a_T(\theta_2) \ \dots \ a_T(\theta_G)] \quad (11)$$

The second constraint can be addressed by minimizing the least square error as $\arg \min_F \|\bar{V} - A_T \hat{F}_{BB}\|^2$ since \hat{F}_{BB} is a block sparse matrix which contains only N_{RF} non zero rows, hence the optimization problem for the optimal precoder approximation can be derived as in (12).

$$\|\text{diag}(\hat{F}_{BB} \hat{F}_{BB}^H)\| = N_t^{RF} \quad (12)$$

Thus the baseband precoder can be designed by extracting non-zero rows from \hat{F}_{BB} and corresponding columns from matrix A_T form the RF precoder F_{RF} one promising method for estimating \hat{F}_{BB} is extended simultaneous orthogonal matching pursuit (ESOMP), as defined in algorithm 1.

Algorithm 1. ESOMP precoder optimization

Result: $F_{res}^{(k)}$
 $F_{RF}^{(0)} = [], F_{res}^{(0)} = \bar{V}$
for $1 \leq k \leq N_t^{RF}$ do
 $\psi = A_T^H F_{res}^{(k-1)}$
 $i(k) = \text{agr max} [\psi \psi^H]_{l,l}$
 $F_{RF}^{(k)} = \{F_{RF}^{(k-1)} | a_T(\theta_{i(k)})\}$
 $F_{BB}^{(k)} = \left((F_{RF}^{(k)})^H F_{RF}^{(k)} \right)^{-1} (F_{RF}^{(k)})^H \bar{V}$
 $F_{res}^{(k)} = \frac{\bar{V} - F_{RF}^{(k)} F_{BB}^{(k)}}{\|\bar{V} - F_{RF}^{(k)} F_{BB}^{(k)}\|_F}$
end

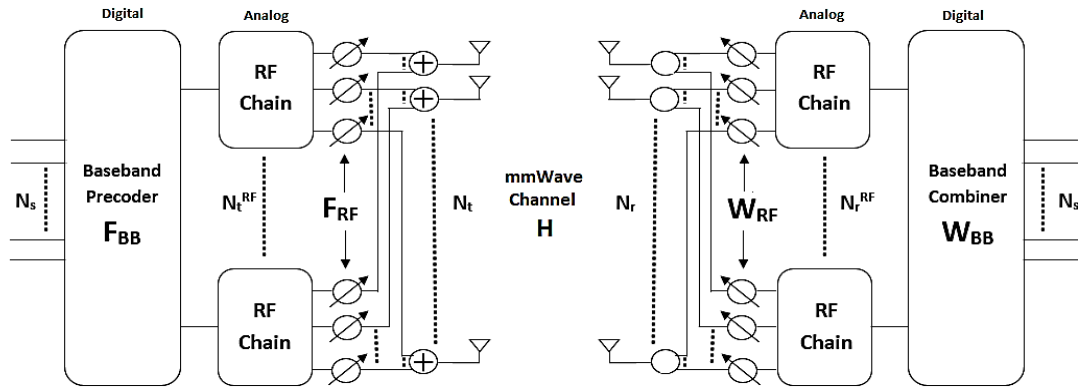


Figure 4. Millimeter wave massive MIMO hybrid precoder/combiner

3. MODULATION SCHEMES FOR MASSIVE MIMO

Millimeter-wave massive MIMO systems use hybrid beamforming architectures which include fewer transmit RF chains as compared to the number of transmit antennas. Antenna elements are connected to these RF chains. Massive MIMO hybrid beamforming systems rely on space index modulation techniques that play a significant role in achieving the desired throughput and reliable communication in 5G developments [29]. The modulation schemes use indices of antennas which represent spatial constellation points that are sending extra information bits and hence significantly improve the achievable rates.

Each type of space modulation scheme adopt their own conceptual procedure in utilizing the MIMO antennas for transmission and reception. In spatial modulation (SM) technique, the selection of antennas is made based on a group on m data bits, where $m = \log_2 N_t$ [30]. On the chosen antennas M -ary modulation alphabet is sent, and the remaining $N_t - 1$ antennas remain silent [31]. Therefore the number of bits communicated per channel in SM is $m + \log_2 M$, and its constellation $h_{N_t, M} = \{X_j, l | j = 0, \dots, N_t - 1, l = 1, \dots, M\}$. At the receiver, signal coding with SM involves determining the index of the transmitting antenna and also the M -ary symbol transmitted on it. The maximum likelihood (ML) detection method [32] can be used with the decision rule $\hat{x} = \arg \min \|y - Hx\|^2$ where y the received is signal vector and H is the channel matrix.

Space shift keying (SSK) scheme is a special case of SM in which a fixed symbol 1 is sent to the chosen antenna and the remaining $N_t - 1$ transmit antennas remains silent, the achievable rate of SSK is m [33]. Signal detection at the receiver reduces to just decoding the index of the active transmitting antenna, hence SSK has lower detection complexity than SM. The SSK constellation is expressed as $h_{N_t} = \{X_j, l | j = 0, \dots, N_t - 1\}$. The ML decision rule for finding the antenna index is represented as $\hat{j} = \arg \min \|y - Hx\|^2$.

In SM, the number of transmitting RF chains is restricted to 1 because of which only one antenna can be active at a time, this is relaxed in generalized spatial modulation (GSM) allowing multiple transmit antennas to be active simultaneously leading to higher spectral efficiency compared to SM and SSK. Out of N_t transmit antennas, N_t^{RF} elements are used to send M -ary information symbols, while remaining $N_t - N_t^{RF}$ antennas remain inactive [34]. The transmit vector for each channel will have the antenna activation pattern selection bits $\log_2 N_t C_{N_t^{RF}}$ and M -ary modulation bits $N_t^{RF} \log_2 M$. Hence the achievable rate in GSM is determined as in (13).

$$R = \left[\log_2 \left(N_t C_{N_t^{RF}} \right) + N_t^{RF} \log_2 M \right] \tag{13}$$

4. RESULTS AND DISCUSSION

This section presents the sum-rate achieved through power-saving models described in this paper. Performance of OMP method in reducing the mean square error (MSE) while estimating the mmWave channel characteristics is evaluated in comparison with the reference ORACLE model and finally, the investigations on extended SOMP method are carried out to measure mmWave hybrid precoding system capacity in comparison with conventional MIMO model. Figure 5 describes the sum-rate performance of the massive MIMO system with perfect CSI when 10 users being served simultaneously in the uplink with pilots transmit power 10 dB each. It is hinted that massive MIMO technology significantly improves the sum-rate with simple signal processing techniques. Figure 6 illustrates the energy-efficient property of massive MIMO systems; a constant rate can be maintained even when the transmit power is scaled as $\frac{1}{M}$ where M is the number of antennas at the BS. Hence, the power of each user can decrease inversely proportional to the number of antennas, this is another benefit of massive MIMO technology. Furthermore, the power of the desired signal rises M times the multi-user interference added with noise, as M

becomes very large the channel vectors of the users become pairwise orthogonal and this completely defeats the multi-user interference using simple low complexity matched filter. Figure 7 shows the achievable sum-rate with CSI uncertainty is less as compared to the perfect CSI scenario; this is because of the existence of channel estimation error. It is noticed that the power scaling in imperfect CSI cannot be $\frac{1}{M}$ because, the transmit power decreases and CSI estimation error increases as $\frac{1}{KE_u}$, thus it is further examined and observed that the consistency in sum-rate can be achieved if the power scaling is done as $\frac{1}{\sqrt{M}}$ as depicted in Figure 8.

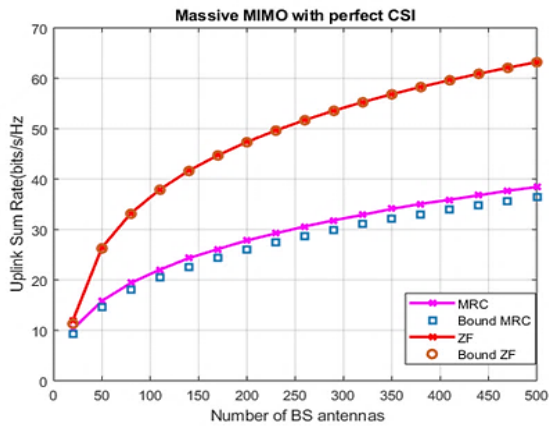


Figure 5. Sum-rate for massive MIMO perfect channel

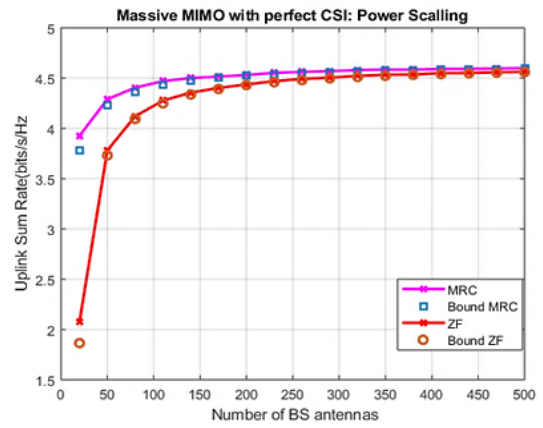


Figure 6. Sum-rate for massive MIMO perfect channel with power scaling

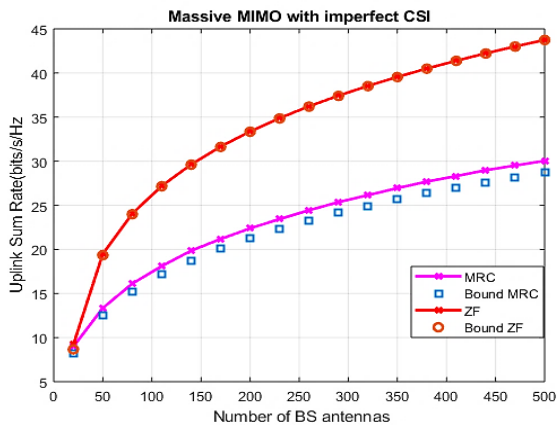


Figure 7. Sum-rate for massive MIMO imperfect channel

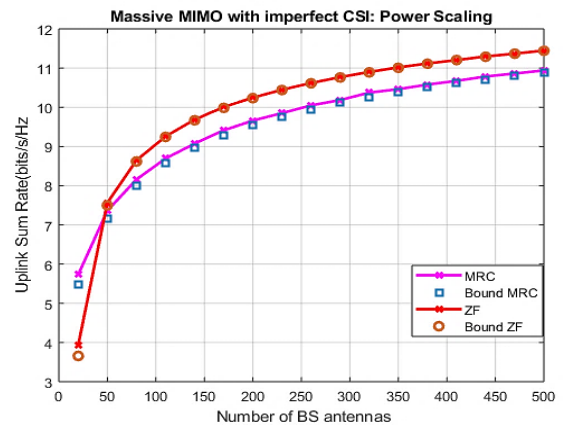


Figure 8. Sum-rate for massive MIMO imperfect channel with power scaling

In Figure 9 we present the performance of mmWave MIMO channel estimation using the OMP method. The model assumed with 32 antennas each at the transmitter and receiver, with 8 RF chains at the BS. The angles of departure in the range 0 to 180 are computed by creating a dictionary matrices with grid size 32. OMP is initialized with the threshold value of 1. The channel is considered to be sparse with sparsity level 5. In Figure 10, the investigation on capacity versus SNR is presented for mmWave system model equipped with 32 Tx/Rx and 8 RF chains, a mmWave sparse channel having the sparsity level of 8 and with 6 data streams being simultaneously transmitted.

The extended SOMP hybrid precoding algorithm is presented as an optimal solution for capacity analysis. It is noticed that the performance of the proposed scheme is very close to the conventional digital precoder which has RF chains equal to the number of antennas. It is also noticed that the system performance is maximum when number of data streams less than or equal to the sparsity level of the channel. Figure 11 and Figure 12 depict BER

analysis of SM and SSK modulation schemes on which massive MIMO technology relies. It is observed that the SM technique offers a higher data rate at the cost of complex decoder design and higher BER, on the other hand, the SSK scheme works with simple decoder and less BER as compared to SM but offers low data rate.

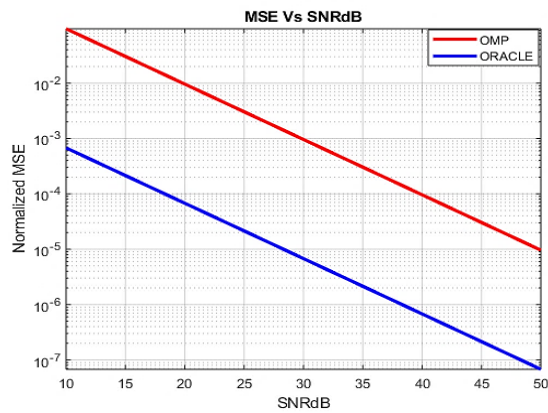


Figure 9. Millimeter Wave channel estimation error for $N_t=N_r=32$, $N_{RF}=8$, $G=32$

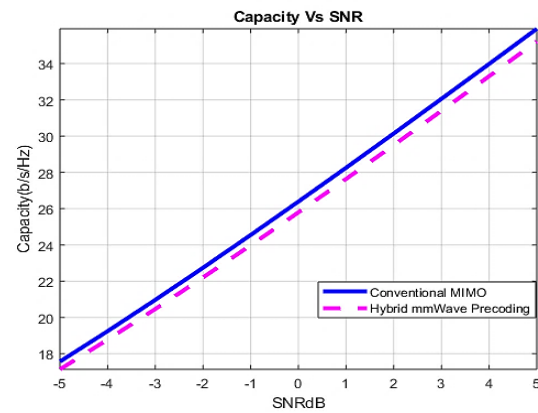


Figure 10. Capacity analysis of proposed scheme for $N_t=N_r=32$, $N_{RF}=8$, $G=32$, $N_s=6$

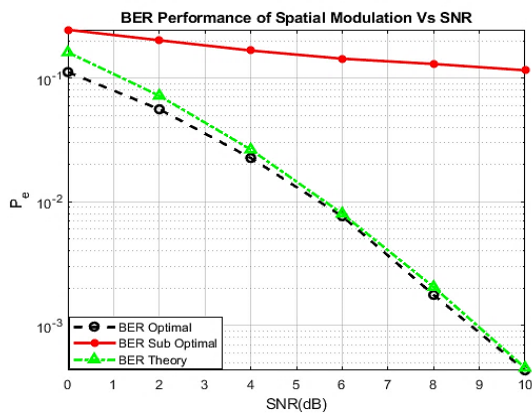


Figure 11. Error probability in spatial modulation

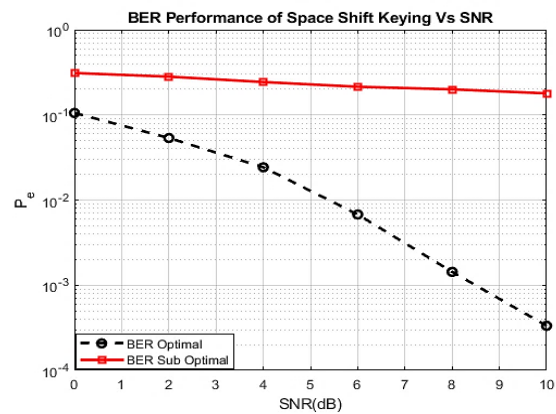


Figure 12. Error probability in space shift keying

5. CONCLUSION AND FUTURE WORK

In this paper, we evaluate the achievable sum-rate and highlight the energy efficiency properties of mmWave massive MIMO systems. The performance concerning sum-rate (system capacity) and power reduction (energy efficiency) characteristics are compared with the conventional digital precoding methods which assume separate RF chain per antenna (conventional MIMO) and simplified beamforming algorithms (ZF, MRC). The extended SOMP algorithm is proposed as an effective method for hybrid precoding optimization problem and it is proved that the proposed precoding scheme provides near-optimal system capacity as compared with conventional MIMO. It is noticed that massive MIMO technology enhances the system throughput significantly with simple signal processing approaches. The BER performance of SM and SSK schemes is described and noted that SM method offers high data rate but requires complex decoder and is more prone to error, on the other hand SSK scheme require simple decoder and has less BER but offers low data rate. In the future, this work can be extended for multi-cell, multi-user scenarios and consequently the challenges in mitigating the multi-cell interference can be addressed.

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