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Enhanced resource allocation strategies to improve the spectral efficiency in massive MIMO systems

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Abstract

The accuracy of the channel state information is important for correct channel estimation. However, when conducting channel estimation, more resources are allocated to pilots for estimation compared to data transmission. Furthermore, when the number of users increases, the number of pilots for estimation increases. Subsequently, there is an increase in the transmission overhead and hence reduces the spectral efficiency. Therefore, the advantage of obtaining channel state information is significantly reduced. To improve the performance of massive MIMO systems, the study analyses the tradeoff between the number of resources required to correctly estimate the channel using pilots to avoid interference while maintaining optimum spectral efficiency in massive MIMO antennas. Therefore, this study proposes an algorithm to address the challenge of optimum resource allocation in a massive MIMO. Pilot Frequency reuse, max–min fairness algorithm, and Zadoff–Chu sequences were adopted to achieve optimal allocation of resources and reduce interference for users in different cells using the same frequencies. The results reveal improved performance in terms of spectral efficiency with the adoption of the resource optimization approach. The study contributes to the performance improvement of massive MIMO antennas for 5 G communications.

Keywords: Channel state information, Massive MIMO, Resource allocation, Spectral efficiency

Introduction

Accurate channel state information (CSI) enables the system to achieve optimal performance by using multiple antennas in a massive MIMO [1]. Achieving the correct estimation for the CSI, while utilizing the least number of pilots for estimation and more resources for transmission is essential to acquire optimal spectral efficiency [2]. Research shows that accurate CSI is essential in ensuring improved system performance [3]. Each transmitting antenna in massive multiple input multiple output (MIMO) networks sends pilot signals to analyze the channel during the channel estimation process. To determine the wireless channel status, the transmitter analyzes the CSI out of each cell. To support receiver channel estimation, each transmitting antenna is assigned a unique pilot waveform during each coherence interval, and all pilots have to be mutually orthogonal [4].

The challenge, however, is to distribute orthogonal pilot sequences to all users within the coherence interval due to resource constraints [5]. Non-orthogonal pilot training sequences are re-used in neighboring cells considering that orthogonal pilot training sequences are finite during coherence time. As a result, estimates from nearby cells contaminate the channel estimates obtained from such cells, minimizing the estimation quality and eventually leading to pilot [5, 6]. Optimal resource allocation is vital for efficient performance of the system [1, 7]

Therefore, this study addresses the challenge of optimum resource allocation in massive MIMO antenna using pilot assignment methods. According to research pilot assignment methods can improve resource allocation and reduce pilot contamination [7–12]. Moreover, the adoption of time division duplexing (TDD) minimizes the number of pilots used for channel estimation. When compared to frequency division duplexing (FDD), the adoption of TDD has a significant impact on spectral efficiency when the coherence interval is shorter [13]. TDD can be adopted for estimation to allow mobility of user terminal with limited coherence interval while reducing the impact on the spectral efficiency.

The rest of this paper is organized as follows; The Related Works section presents studies that address similar challenges of massive MIMO resource allocation. The Problem Formulation section elaborates on the parameters used, the massive MIMO channel model, and the objective function. The Methods section explains the spectral efficiency optimization techniques, pilot contamination mitigation techniques, and the proposed algorithm. The Results and Discussion section presents the spectral efficiency results against the signal-to-noise ratio, the number of base station antennas, the coherence interval, and the frequency reuse pattern. Finally, the paper provides a conclusion and recommendations for future works in massive MIMO systems.

Related works

Different authors have exploited a variety of pilot assignment approaches to combat pilot contamination. Compared to cell-centered users, cell edge users are most affected by pilot contamination, hence, scholars recommend the allocation of the right proportion of power to data and pilots [9, 14]. An efficient pilot allocation based on asynchronous scheduling which was based on the fractional pilot reuse was proposed by [15]. The different sets of pilots are allocated to the different groups of users on the cell edge and the cell center. The results indicated that the performance of the recommended scheme outperformed the conventional integer reuse approach [15]. However, a drawback of the fractional pilot reuse method is the introduction of an additional pilot overhead [14].

The deep learning approach is used for CSI sensing and recovery based on the channel structure from training samples; thus, the CSI is recovered [16]. A novel CSI sensing and recovery approach that learns to use channel structure from training samples to determine the CSI was developed by [17]. The results show considerably improved signal reconstruction quality and reduced time complexity compared with existing compressive sensing approaches [17]. Research by MSE [18] also uses a deep learning approach whereby the pilot power allocation vector is optimized using a multi-layer fully connected deep neural network (DNN) that receives the channel large-scale fading coefficients as input and outputs the pilot power allocation vector to minimize the sum mean square error (MSE). The DNN's loss function is defined as the sum MSE, and the DNN is trained using an unsupervised learning technique. Simulation findings reveal that the suggested scheme outperforms existing schemes in terms of total MSE [18].

The Zadoff–Chu (ZC) sequences mitigate interference between neighboring cells using the same time–frequency resources. The sequences at each base station are multiplied element-wise with the base station row to make the sequence orthogonal across the network [19]. The user terminal selects randomly one of the multiplied ZC sequences from a given set for transmission on the channel at the beginning of the coherence interval. The sequence has a small variation in frequency in the advantage of channel estimation at the receiver and a low cross-correlation property hence producing a small inter-cell interference [20]. Research by Ali et al. in [19] proposed a design of orthogonal uplink pilot sequences to eliminate pilot contamination from TDD massive MIMO systems. The proposed design uses Zadoff–Chu (ZC) pilot sequences and eliminates pilot contamination during the channel estimation. The ZC sequence generates orthogonality among pilot sequences across the neighboring cells. Simulation results show that the sum-rate performance of the proposed design significantly outperforms both the pilot-assisted CE and MMSE CE.

The angle of arrival (AOA)-based methods entail the process whereby non-overlapping users reuse pilots with different AOA. The location-based PR scheme to alleviate the pilot contamination was proposed in [21] by assigning pilot sequences based on the path loss as well as the AOAs. The angle of arrival (AoA) approach has been used to acquire location information of users to estimate and monitor the distance between users in different cells [10, 12], thus facilitating to determine the possible transit power interference among users.

A joint pilot allocation and pilot sequences optimization scheme was recommended to mitigate pilot contamination and maximize spectral efficiency [10]. The approach uses location information to compute the distance between users in different cells to determine the interference among users. Furthermore, the angle of arrival (AoA) pilot assignment scheme with low complexity optimization problems was used in the research by Shahabi et al. in [12], which exploited a pilot assignment scheme with low complexity optimization problems. To address the non-convex optimization, the problem was solved iteratively and sequential convex programming was exploited. The results showed that the proposed scheme outperformed the conventional methods in terms of complexity; however, a decline in the uplink sum rate was experienced.

Problem formulation

For this study, the assumption is that the channel model is Rayleigh; thus, there is no correlation between reception and the transmission antennas. The coherence interval of τ_c was obtained from the product of the coherence time, and coherence bandwidth, B_c as follows,

$$\tau_c = T_c \times B_c \tag{1}$$

For a multi-cell massive MIMO system with K user terminals per cell and a reuse pattern of η_{reuse} in the network, the pilots occupy τ_p samples from the total τ_c samples. If the number of user terminals is small, larger cluster sizes are reasonable since the pilots occupy a small portion of the entire coherence interval as $\tau_p = \sum_{i=1}^{n_{\text{reuse}}} K_i$. Assuming that each cell has the same number of user terminals, then $\tau_p = k \times n_{\text{reuse}}$. The pilot overhead thus becomes the fraction $\frac{K \times \eta_{\text{reuse}}}{\tau_c}$. Hence, as the number of users increases per cell, the number of pilot sequences increases but the spectral efficiency decreases. However, the disadvantage comes from increasing the pilot overhead within the coherence interval. The channel coherence interval decreases as the carrier frequency and user terminal speed increase. The coherence time varies inversely with the Doppler spread. As the speed of the vehicle increases, the coherence time becomes shorter. The COST231 Hata model for the urban environment was used as the path loss model. The path loss, according to [22], is modeled as follows:

$$\beta_{lk}^{j} = \sigma_{lk}^{j} + \gamma - 10\alpha \log_{10}\left(\frac{d_{lk}^{j}}{1Km}\right) \tag{2}$$

From Eq. (2), β_{lk}^{j} represents the average channel gain per antenna of the channel between the user terminal i in cell l and the base station j, σ_{lk}^{j} is the shadow fading, γ represents the median channel gain at a reference distance of 1 km in the large-scale fading model, α is the path loss exponent in the large-scale fading model and d_{lk}^{j} is the distance between the transmitter and the receiver. To ensure effective channel estimation, it is necessary to use as few resources as possible that are adequate for piloting. In general, resources are divided among uplink pilots, downlink pilots, uplink data, and downlink data. Therefore, the equation is as follows:

$$\tau_{ul} + \tau_{dl} + \tau_{ul,p} + \tau_{dl,p} = \tau, \tag{3}$$

such that τ_{ul} is the uplink data, τ_{dl} is the downlink data, $\tau_{ul,p}$ is the uplink pilots, and $\tau_{dl,p}$ is the downlink pilots.

In TDD, only uplink pilots are required to estimate the channel, and only the base station obtains the CSI [23]. The amount of time and frequency resources required for pilot transmission in TDD is determined by the number of concurrent user terminals served. As a result, adopting the reciprocity principle in TDD such that if the uplink channel is H_u then the downlink becomes H_u^H. TDD makes massive MIMO scalable as the number of base station antennas increases. As a result, we have,

$$\tau_{ul} + \tau_{dl} + \tau_{ul,p} = \tau. \tag{4}$$

The aim was to maximize resource usage while increasing spectral efficiency. As a result, the approach was to reduce the resources assigned to pilots for estimation to improve the resources assigned to transmission while minimizing the pilot contamination and enhancing the spectral efficiency. As a result, the objective was to determine τ_p that enhances spectral efficiency, and hence the equation can be:

$$\begin{array}{c}\text{argmax} \\ \tau_c \\ \text{s.t. } 0 \leq K \leq \tau_p \\ \tau_p \leq \tau_c\end{array} \quad r_{u,d}\left(1 - \frac{\tau_p}{\tau_c}\right)\sum_{k=1}^{K} C_{\text{inst},k} \tag{5}$$

However, $C_{\text{inst},k} \geq \log_2 (1 + \text{SINR}_k)$, where SINR is the Signal to Interference plus Noise Ratio. Assuming that the number of users K is similar in all cells, then

$$\text{SIN R}_{kj} = \frac{\left|E\left[\mathbf{h}_{jk}^{l}\right]\right|^2}{1 + \text{Var}\{\mathbf{h}_{jkl}\}} \tag{6}$$

As the number of base station antennas rises, M approaches infinity, then $h_{jk}^{l} = \sqrt{\beta_{jk}^{l}}$. Accordingly,

$$\text{SIN R}_{lk} = \frac{\left(\beta_{jk}^{l}\right)^2}{\sum_{j\neq l}^{L}\left(\beta_{jk}^{l}\right)^2} \tag{7}$$

$$\underset{\substack{\tau_c \\ \text{s.t.}\, 0 \leq K \leq \tau_p \\ \tau_p \leq \tau_c}}{\text{argmax}} \quad r_{u,d}\left(1 - \frac{\tau_p}{\tau_c}\right)\sum_{k=1}^{K}\log_2\left(1 + \frac{\left(\beta_{jk}^{l}\right)^2}{\sum\limits_{j\neq l}^{L}\left(\beta_{jk}^{l}\right)^2}\right) \tag{8}$$

Methods

The objective of the study was to improve resource allocation in massive MIMO antennas to ensure efficient channel estimation. However, since there is a tradeoff when allocating the time–frequency resources for pilots and data transmission, an optimum method for the distribution of resources was required. For this study, the use of Zadoff–Chu sequences, combined with pilot frequency reuse, was used to ensure optimal allocation. Pilot frequency reuse enabled efficient resource allocation for pilots while ensuring neighboring cells avoid using the same pilot signals and therefore mitigate interference. The primary data were generated using a stochastic process based on random channel generation and software was used for simulation of mathematical models. Since the model involves stochastic processes with repeated experiments, the Monte Carlo simulation was used.

Zadoff–Chu sequences

The use of Zadoff–Chu (ZC) sequences, together with pilot frequency reuse for the pilot assignment was adopted for this research. Pilot frequency reuse allowed efficient allocation of resources for pilots while ensuring neighboring cells do not use the same pilot signals, and hence do not interfere. However, ZC sequences are adopted to further reduce interference between neighboring cells by enhancing orthogonality among cells using the same frequencies. The preamble sequences are created by cyclically shifting the root ZC sequences. The sequences' cross-correlation characteristic across various preambles

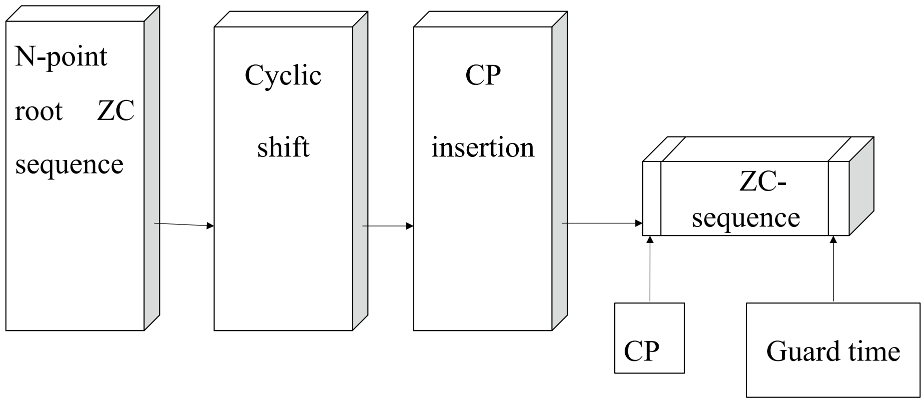

Fig. 1 Zadoff Chu sequence

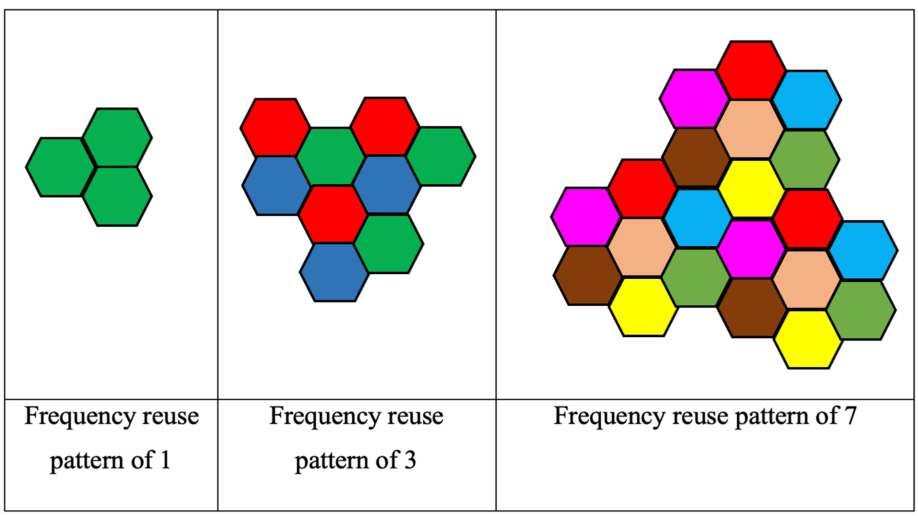

Fig. 2 Frequency reuse pattern

based on cyclic shifts reduces intra-cell interference from successive random access attempts utilizing preambles generated from the same ZC root sequence. Figure 1 shows the block diagram of a Zadoff Chu sequence [24]. The Zadoff–Chu sequences were used to minimize interference between adjacent cells by increasing orthogonality among cells that use the same frequencies as explained in [19]. The Zadoff–Chu sequence is represented by $Z_q(n) = e^{-j\left(\frac{\pi q n(n+1)}{N}\right)}$ where N is the sequence length such that q is the root of the sequence and $j = \sqrt{-1}$ and $n = 0, 1, \ldots N - 1$ [24].

Frequency reuse

The frequency reuse factor establishes the basis for the creation of clusters, whereby, the cells within a cluster cannot use the same frequencies for transmission in a communication network. Frequency reuse was implemented to minimize interference.

Cells in close vicinity using the same frequency resource have an increased probability of interference. However, spectral efficiency can be maximized, at the expense of increased interference. Figure 2 shows the frequency reuse pattern. As a result, the pilot reuse must be formulated such that interference is reduced; while, spectral efficiency is increased. The design is made by distributing the network into clusters based on the frequency reuse pattern, η_{reuse}, while the network resources represented by (τ_c), were assigned to the cluster for the number of users per cell of K. Therefore, the resource allocation for pilots is $\tau_p = \eta_{\text{reuse}} \times K$. The proportion to the total resources becomes $\frac{K \times \eta_{\text{reuse}}}{\tau_c}$ while for data becomes $\frac{\tau_c - (K \times \eta_{\text{reuse}})}{\tau_c}$. Examining the pre-log factor $\left(1 - \frac{\tau_p}{\tau_c}\right)$ in the Eq. 5 such that $\tau_p = \eta_{\text{reuse}} \times K$; so when $\left(\frac{\eta_{\text{reuse}} \times K}{\tau_c}\right)$ is minimized, the spectral efficiency approaches increases. The number of users in the system and the size of the frequency reuse pattern must be constrained to a minimum to maximize spectral efficiency.

Duplexing mode

Both frequency division duplexing (FDD) and time division duplexing (TDD) facilitate the acquisition of the channel state information (CSI) from the channel. After the analysis of both TDD and FDD, the TDD operation was adopted, since in TDD, only the base station performs channel estimation and thus maximizes the spectral efficiency. Furthermore, TDD exhibits uplink and downlink duality as the TDD offers reciprocity and eliminates the need for feedback. With TDD, only the uplink transmission uses pilots as shown in Fig. 3, and the results can be transposed to obtain the downlink channel matrix. The user terminal transmits pilots and the base station performs uplink channel estimation. Therefore, adopting the principle of reciprocity in TDD such that if the uplink channel is H_u then the downlink channel is H_u^H.

Max–Min fairness algorithm

The pilot assignment scheme was implemented to improve the efficient use of resources while reducing pilot contamination. As previously stated, with an increased number of antennas and users, more resources are required for channel estimation to ensure effective transmission. The need for optimization of resources necessitates the use of efficient pilot assignment methods. The channel estimation error, as demonstrated in [25], is equal to $(\gamma_k \ \beta_k)$, where γ_k is the predicted channel and β_k is the actual channel. The following equations illustrate the relationship between the channel errors and time–frequency resources,

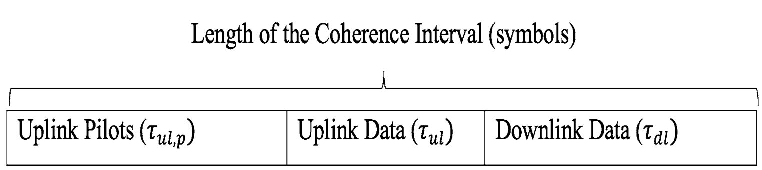

Fig. 3 TDD duplexing mode

$$\gamma_k = \{E\left[|\widehat{h_k^m}|^2\right] \quad (9)$$

$$\gamma_k = \frac{\rho_{ul}\tau_p\beta_k^2}{1 + \rho_{ul}\tau_p\beta_k} \quad (10)$$

Therefore, for correct channel estimation, $\rho_{ul}\tau_p$ is large such that

$$\rho_{ul}\tau_p \approx 1 + \rho_{ul}\tau_p. \quad (11)$$

$$\gamma_k = \frac{\beta_k^2}{\beta_k} = \beta_k \quad (12)$$

However, for practical applications, it is difficult to achieve absolute perfection in estimation; thus, τ_p should also be considered since the increase in $\rho_{ul}\tau_p$ surges the use of network resources. Since there is a tradeoff when allocating the time–frequency resources for both pilots and data transmission, an optimal method for the distribution of resources between the two is required. Therefore, the allocation of time–frequency resources was done using a max–min fairness algorithm. The max–min fairness algorithm has been used in [26]. The max–min fairness was selected due to its fairly low computational complexity and can be used for maximizing other metrics iteratively. The algorithm has shown the optimal distribution of resources in studies such as [13]. The time–frequency resources are allocated optimally to the pilots based on the number of users in the system, the rest of the bandwidth is shared between uplink and downlink for data transmission and reception.

The resource allocation algorithm

Based on the principle, the allocation is such that, to increase the bandwidth allocated to one source in the network, the bandwidth allocated to other sources which already receives lower allocation, is decreased. The time–frequency resources are allocated optimally to the pilots based on the number of user terminals, the rest of the bandwidth is shared between uplink and downlink for data transmission and reception. The proposed system was tested with various frequency reuse patterns to identify the impact of frequency allocation on the system capacity in a multicellular system. The pilot sequences are designed such that if pilot sequences from neighboring cells are ϕ_l and $\phi_{\acute{l}}$, should be orthogonal. During uplink transmission, all the user terminals communicate (synchronized transmissions and reception) to the base station by sending pilots and data. The size of the frequency reuse pattern is denoted by η_{reuse} and the pilot sequence is denoted by (ϕ), which was distributed among all cells. The pilot sequence within a cluster was $\phi = \left[\phi_1, \phi_2, \ldots \phi_{\eta_{\text{reuse}}}\right] \epsilon\, \phi^{\eta_{\text{reuse}}K \times \eta_{\text{reuse}}K}\phi_{\eta_{\text{reuse}}}$.

The pilot reuse factor, η_{reuse} is the number of cells per cluster that were assigned to the orthogonal pilots. $\phi_{\text{entire network}} = \left[\phi_{\text{cell}_1}, \phi_{\text{cell}_2}, \ldots \phi_{\text{cell}_l}\right] = \left[\phi_{\text{cell}_1}, \phi_{\text{cell}_2}, \ldots \phi_{\text{cell}_l}\right]$.

Since the entire network has L cells these cells were split into q clusters. Within a cluster, the number of cells was based upon the value of η_{reuse} decided; hence, the number of cells per cluster is equal to η_{reuse}; while, the number of clusters is,$q = \frac{L}{\eta_{\text{reuse}}}$. The distribution of pilots within a cell is given by, $\phi_{\text{cell}_l} = \left[\phi_{\text{cell}_n,\ \text{user}_1},\ \phi_{\text{cell}_l,\text{user}_2}, \cdots \phi_{\text{cell}_l,\text{user}_k}\right]$. Algorithm 1 shows the Proposed Algorithm for Optimum Resource Allocation.

Algorithm 1 Proposed Algorithm for Optimum Resource Allocation

Require: $M, K, K_{act}, N, (C_{inst,k}), H, \rho, reuse_{f}actor$
Ensure: $\max SpectralEfficiency$
Initialize parameters
Generate the Zadoff-Chu sequence
while $K_{act} \leq K$ **do**
  Determine the user with the lowest achievable rate
  for $K = 1$ to K **do**
    Calculate the achievable rate for each subcarrier $(C_{inst,k})$
    for $N = 1$ to N **do**
      Calculate the interference power
      Determine the subcarrier with the lowest achievable rate
      Allocate resources to the selected user
      Allocate subcarriers to the selected user based on frequency reuse
    end for
  end for
  return R
end while
for $K = 1$ to K_{act} **do**
  Compute the Spectral Efficiency using equation (8)
end for

Results and discussion

With pilot contamination, to correctly estimate the channel and avoid interference, the channel frequent estimation. However, estimating the channel using pilots drains the time–frequency resources for the transmission of data. As a result, the benefit of acquiring CSI is compromised by the inefficient use of the available spectral. An increase in the resources for channel estimation (using pilots), to mitigate pilot contamination reduces the spectral efficiency. Therefore, in mitigating pilot contamination, a compromise exists between the availability of time–frequency resources for estimating the channel and the reduction of pilot contamination. Therefore, the resource optimization techniques were deployed to improve spectral efficiency while reducing the pilot contamination by adopting TDD, pilot reuse, and Zadoff Chu sequencing. Since the proposed optimization is based on the distribution of time–frequency resources between the uplink transmission, downlink transmission, and pilots (uplink pilots) used for estimation by TDD approach, the total amount of transmission resources is distributed as follows:$\tau_c = \tau_p + \tau_{ul} + \tau_{dl}$. Channel parameters, including the number of user terminals, the number of base station antennas, the size of the coherence interval and the signal-to-noise ratio, influence the performance of the system. Therefore, the analysis of the spectral efficiency against the parameters is essential.

Spectral efficiency against the SNR

Figure 4 shows the variation of spectral efficiency with the SNR. The figure shows a plot of spectral efficiency per cell against the SNR. The figure was plotted for 18 user

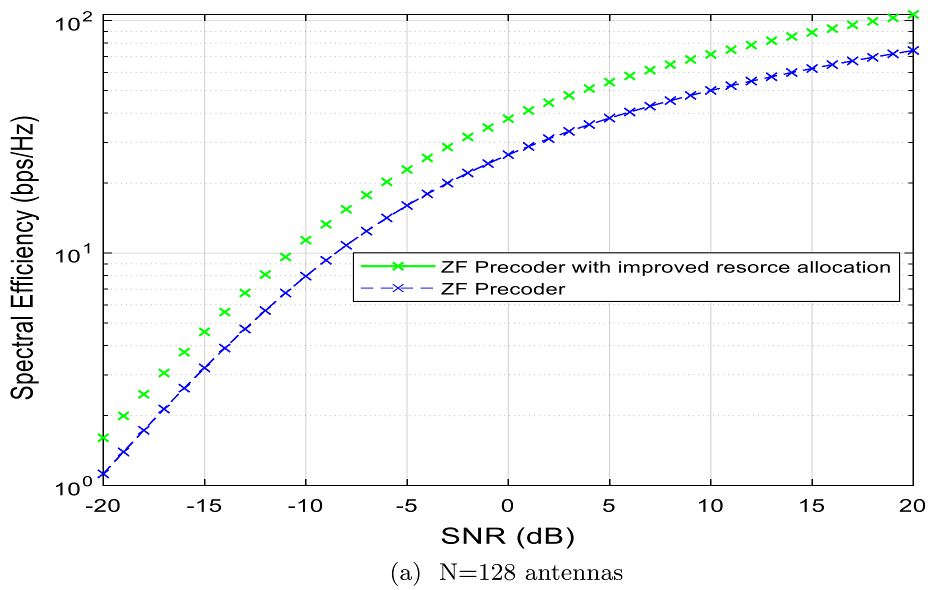

Fig. 4 Variation of spectral efficiency with the SNR

terminals, a power of 0dB, and 128 base station antennas. The results show that, as the signal-to-noise ratio (SNR) increases, the ZF precoder with improved resource allocation performs better than the conventional ZF precoder. The improved performance is a result of enhanced capabilities for inter-user interference and noise elimination. The increase in uplink SNR influences the quality of channel estimation obtained in the uplink and hence improves both uplink and downlink spectral efficiency [25]. However, the increase in spectral efficiency causes saturation, as SNR further increases. The results show that at SNR $=$ 20 dB, the ZF precoder with improved resource allocation achieves a spectral efficiency of 106.36 bps/Hz per cell; while, the conventional ZF precoder achieves a spectral efficiency of 74.45 bps/Hz per cell. Similar approaches for resource optimization and efficient pilot assignment are shown in recent studies [10–12].

Spectral efficiency against the number of base station antennas

Figure 5 shows a plot of spectral efficiency against the number of base station antennas per cell. As the number of base station antennas increases, the ZF precoder with improved resource allocation performs better than the conventional ZF precoder. As the number of base station antennas reaches 500, the ZF precoder with improved resource allocation reaches a spectral efficiency of 115.2 bps/Hz per cell while that of the conventional ZF reaches 95.98 bps/Hz per cell. The results show an improvement compared to related works in ZF precoding as presented in [27]. According to theory, with massive MIMO, an increase in the number of antennas increases throughput but reaches the saturation point with pilot contamination. As the number of base station antennas increases, the spectral efficiency increases logarithmically to saturation. The increase in the number of base station antennas increases the system's ability to focus the beam on intended user terminals and mitigate interference. The channel estimation eventually

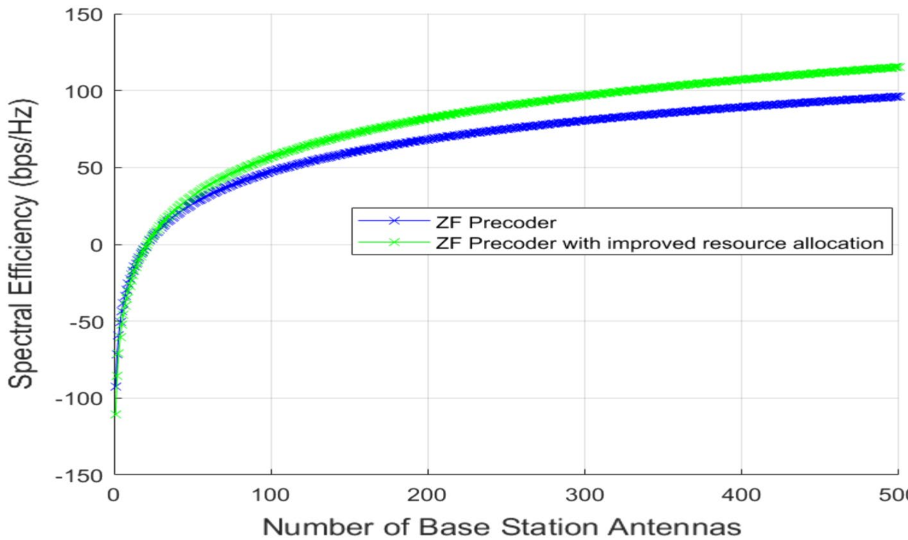

Fig. 5 Variation of spectral efficiency with the number of base station antennas

improves, while reducing the need for allocating more resources for channel estimation hence increasing the spectral efficiency.

Spectral efficiency against the coherence interval

Figure 6a shows the variation of the spectral efficiency with the proportion of coherence interval allocated for data. The figure depicts the variation between the spectral efficiency and the coherence interval assigned to data ($\tau_c - \tau_p$). The coherence interval was set at 200 samples, the power was 0 dB, 18 user terminals, and 128 base station antennas. The Figure shows how spectral efficiency increases as more time–frequency resources are assigned to data transmission; while, fewer resources within the coherence interval were provided to pilots' signals for estimations. The length of the pilot training sequence varies inversely proportional to the average spectral efficiency. Figure 6 shows the spectral efficiency reaches up to 103.3 bps/Hz per cell with resource optimization and up to 80.3 bps/Hz per cell without resource optimization. When the coherence interval is divided equally between pilots and data, the spectral efficiency reaches 51.4 bps/Hz per cell with resource optimization and 39.9 bps/Hz per cell without resource optimization.

As the number of base station antennas increases, the spectral efficiency rises toward saturation as it is constrained by the coherence interval (τ_c). Figure 6b depicts the spectral efficiency after increasing the number of base station antennas to 256; while, the coherence interval was set at 200 samples, and the power was 0 dB, and 18 user terminals. Figure 6b shows the spectral efficiency reaches 118.7 bps/Hz per cell with resource optimization and 92.3 bps/Hz per cell without resource optimization. According to the literature, the increase in the number of base station antennas influences the increase in the beamforming gain [28]. When the coherence interval is divided equally between pilots and data, the spectral efficiency reaches 59.1 bps/Hz per cell with resource optimization and 45.9 bps/Hz per cell without resource optimization.

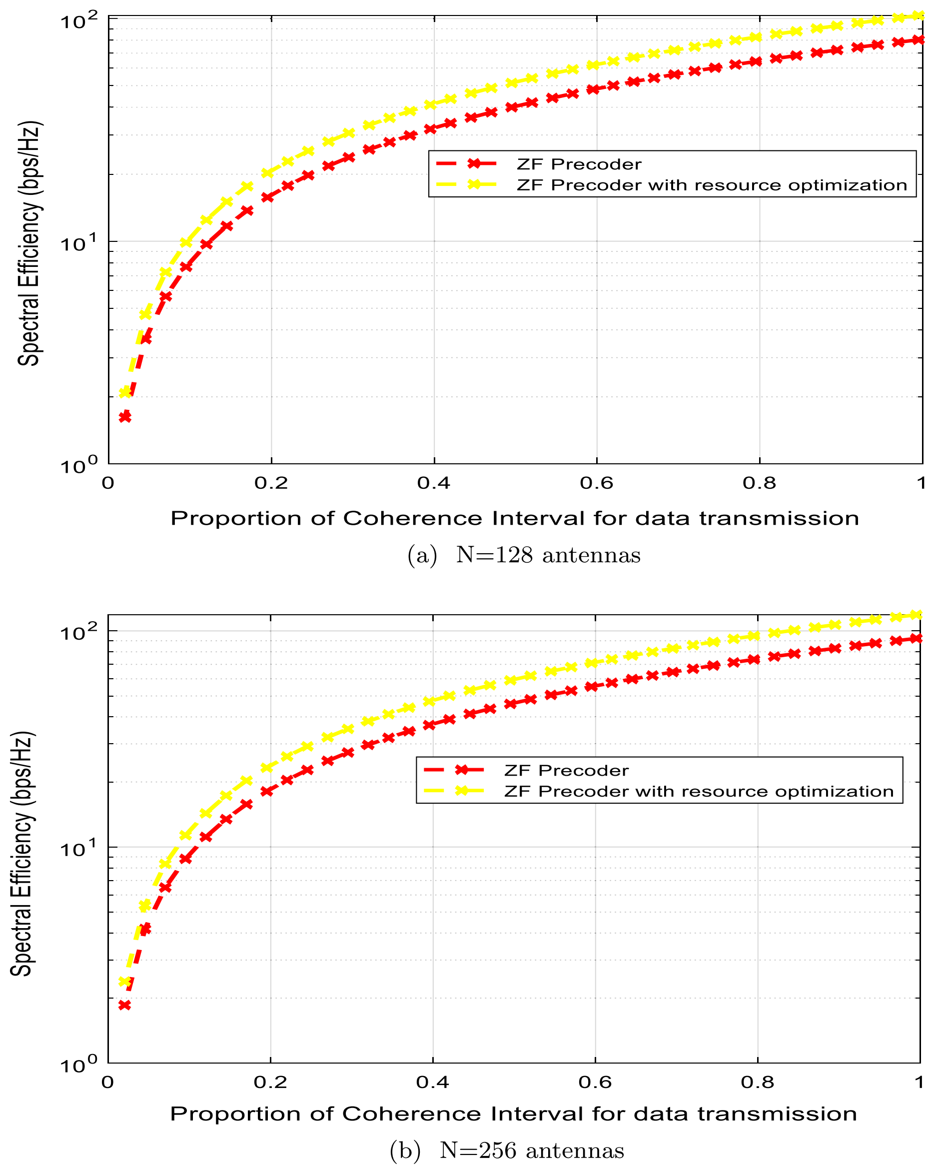

Fig. 6 Variation of spectral efficiency with the proportion of coherence interval allocated for data

Spectral efficiency per user against the number of users and the size of frequency reuse pattern

Related works illustrate the role of cell densification in mitigating interference and improving the system performance as depicted in the analysis by [29]. Figure 7 shows the instantaneous spectral efficiency. The figure depicts the compromise between the three parameters. As was previously mentioned, the objective is to increase spectral efficiency; however, a tradeoff between the number of user terminals and the size of the frequency reuse pattern was required. According to the literature, as the number of user terminals increases, the spectral efficiency decreases as the limited resources are shared between users and pilots [27].

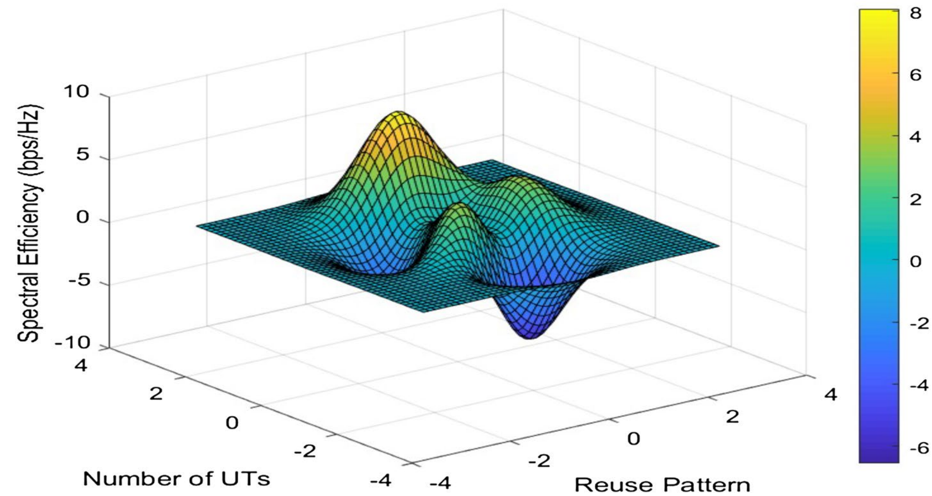

Fig. 7 Instantaneous spectral efficiency

Through analysis of the variation of the number of users and the size of the frequency reuse pattern, the instantaneous spectral efficiency per user is determined. When the number of users and frequency reuse are both minimum, the instantaneous spectral efficiency per user reaches its maximum. Thus, τ_p is decreased along with the product of coherence interval and the spectral efficiency. Consequently, the fraction of bandwidth available for transmission of data is maximized. Figure 4 displays the yellow areas when the number of users and the spectral reuse pattern are minimal.

According to the literature, an increase in the number of user terminals reduces the spectral efficiency as users share finite network resources. In a massive MIMO system with TDD, where the number of user terminals is typically lower than the number of base station antennas, the overhead resulting from the acquisition of the uplink CSI is linearly proportional to the number of user terminals. Pilot overhead would therefore increase as more resources would be allocated to estimation than to data transmission. The proposed technique aimed to reduce pilot contamination while enhancing spectral efficiency.

Figure 8 illustrates the variation of the number of user terminals (K), the size of frequency reuse pattern (η_{reuse}), and the spectral efficiency (C_{net})As previously noted, the aim is to maximize spectrum efficiency; nevertheless, a balance between the number of user terminals and the size of the frequency reuse pattern was required. When the number of user terminals or the size of the frequency reuse pattern rises, or when both of these variables rise at the same time, the associated spectral efficiency decreases. Furthermore, if the number of user terminals or the size of the frequency reuse pattern reduces, the resultant spectral efficiency increases.

The algorithm was simulated with three reuse factors of 1, 3, and 7 (Table 1). The results revealed that when the number of users reached a maximum of twenty-one; while, the size of the frequency reuse pattern was 7, the spectral efficiency improved to 14.5 bps/Hz/cell. On the other hand, the instantaneous spectral efficiency was 6.76 bps/Hz/cell for the frequency reuse pattern of 7. Nevertheless, when the size of the frequency reuse pattern was 1, maximal spectral efficiency could be reached.

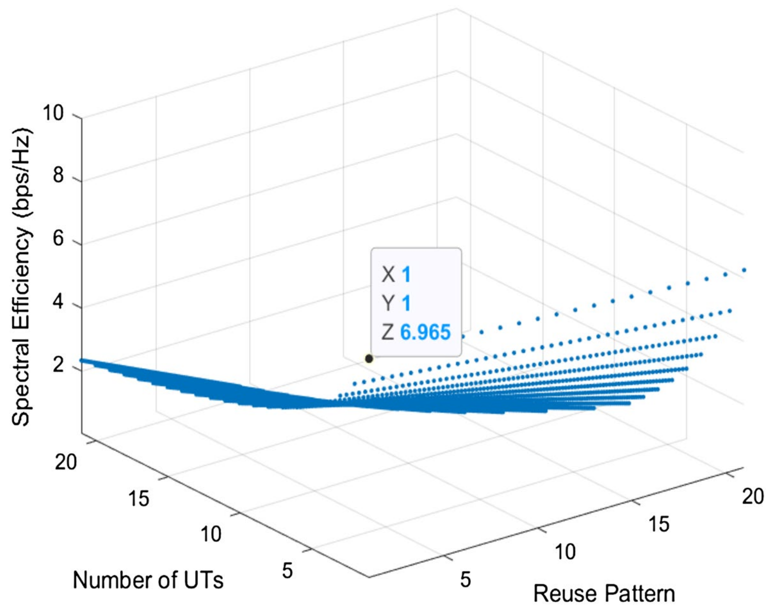

Fig. 8 Variation of spectral efficiency per user with the number of users and the size of frequency reuse pattern

Table 1 Variation of spectral efficiency with the size of frequency reuse pattern

Number of user terminals (K)	Frequency reuse pattern		
	$\eta = 1$	$\eta = 3$	$\eta = 7$
Instantaneous spectral efficiency (bps/Hz/cell) for $K = 1$	6.97	6.90	6.76
Net spectral efficiency (bps/Hz/cell) for $K = 18$	49.01	37.51	14.51

Table 2 Comparison of computational complexity

Literature	Methodology	Computational complexity
Nie and Zhao [10]	Joint pilot allocation and pilot sequences optimization	$O(KL)^3$
Shahabi et al. [12]	CEP with limited cooperation among cells to reduce overheads	$O(MKL^2)$
Ma et al. [31]	Joint optimization pilot allocation	$O(KL^2 \log L)$
Mei et al. [32]	ZF-PCP	$O((K)^L)$
Liu et al. [33]	Near MMSE precoder using the parametric model	$O(TKL)^2$

The results revealed that when the number of users expanded to a maximum of 18, but the size of the frequency reuse pattern remained constant at one, the spectral efficiency reached 49.01 bps/Hz/cell, with a maximum instantaneous spectral efficiency of 6.97 bps/Hz/cell.

Computational complexity comparison

Considering the max–min fairness algorithm, the complexity is $O(n^2)$. For each user (K) and in a multi-cell system, with (L) cells, the complexity of the precoder is $O(MK^2L)$. The combined complexity thus becomes $O(n^2) + O(MK^2L)$. Therefore, the overall complexity upper bound of the proposed method is $O(MK^2L)$. The results are comparable with results obtained in [30]. Table 2 shows a comparison of the proposed algorithm with other approaches in terms of the computational complexity in a massive MIMO multi-cell scenario. From the table, M is the number of base station antennas, K is the number of single-antenna user terminals, L is the number of cells, and T represent the total number of iterations. The works of literature were selected based on the adoption of massive MIMO multi-cell scenario, similar to this study, as opposed to other studies with a focus on single-cell scenario.

Conclusion and future work

In massive MIMO systems, during transmission the channel is estimated using the channel state information (CSI). The CSI uses the pilot overheads from the limited network resources to continuously estimate the channel. Consequently increasing pilot overhead and reducing the spectral efficiency, since more resources are allocated to pilots for estimation as opposed to actual data transmission. As a result of the inefficient use of the available spectra, the benefit of acquiring CSI for estimation is diminished, necessitating the use of effective resource allocation techniques. As a result, the max–min fairness algorithm, pilot frequency reuse, and Zadoff–Chu sequences were adopted in the proposed approach. The Zadoff–Chu sequences reduced pilot contamination during the channel estimation process, through the use of orthogonal codes among pilot sequences across the neighboring cells. The orthogonal codes can be re-used based on the frequency reuse pattern, hence the adoption of pilot frequency reuse. The max–min fairness algorithm ensured the optimal allocation of resources. The numerical results indicate an overall improvement in spectral efficiency. To further improve the performance of massive MIMO systems, the artificial intelligence-based method and Angle of Arrival methods can be further explored.

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AM conducted the literature review, designed the algorithm, performed simulations and results analysis, and wrote the manuscript.

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Declarations

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