Interference suppression in heterogeneous massive MIMO systems with imperfect CSI

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Abstract
Interference management is of paramount importance in heterogeneous massive mimo networks (HetNet). In this paper, an algorithm has been suggested to suppress the interference in large-MIMO HetNets with imperfect channel state information (CSI). The proposed technique controls both the intra-tier and cross-tier interference of the macrocell as well as the small cells. The intra-tier interference of the macrocell as well as the cross-tier interference have been minimized under maximum transmission power and minimum signal to interference and noise ratio (SINR) constraint. The channel estimation error matrix has also been modeled using the joint sparsity property. The precoding algorithm is thus achieved through the application of semi-definite relaxation and block coordinate descent techniques. The intra-tier interference of the small cells are addressed with the aid of the zero forcing scheme. The proposed method has been validated through various simulations which confirm the superiority of the algorithm over its counterparts.

Keywords Massive MIMO system · Heterogeneous networks (HetNet) · Interference suppression · Interference management

1 Introduction

Due to the increasing number of users and data traffic, the massive MIMO systems as well as the heterogeneous network (HetNet) have emerged as proper solutions to achieve reliable communication, spectral efficiency and energy efficiency in the next generation wireless cellular networks [1]. The advantages of massive MIMO systems and HetNet technology include increasing the transmission rate, and improving the channel capacity and cell coverage using a large number of antennas and small cells. In HetNets, the usage of multiple small cells across a macro cell with lower transmit power improves the quality of service and leads to a marked decline in the total power consumption, simultaneously. The interference and energy efficiency (EE) are two important factors in these systems which should be handled in order to gain the aforementioned benefits. The small base stations (SBS) and macro base stations (MBS) share the frequency resource which leads to the cross-tier interference [2].

Various techniques have been suggested in the literature to solve this issue. The interference coordination in HetNets has been accomplished by uplink power control and cell radius extension [3]. Interference alignment has been used as an efficient method to manage the inter-layer interference [4,5]. Using nested arrays offers high degrees of freedom (DOF) which enables the BS to remove its interference to the neighboring users [6].

The trade-off between inter-cell interference cancellation and sum-rate maximization has been modeled as an integer programing problem [6,7]. Due to the lack of instantaneous channel information from MBS to small users, statistical channel information has been used in [8] to design the minimum mean square error (MMSE) precoder for interference elimination. In [9], by utilizing the DOF provided by MBS, the corresponding signal of small users have been precoded in the null space of MBS to avoid interference. In [10], the interference mitigation and load balancing have been achieved by optimizing the precoding matrix, user association and scheduling, and power allocation. Another way for interference cancellation is to identify the small users which are severely suffering from the MBS interference and eliminate their corresponding interference while designing the MBS precoding matrix [11]. The cooperative interference mitigation in HetNet based on almost blank sub-frame
is considered [2]. In [12], a resource allocation scheme has been provided with using game-theory that takes into account both the energy efficiency and interference reduction in the presence of inaccurate channel state information in HetNets. Improving the energy efficiency by minimizing the total power consumption and designing the optimal precoder is suggested in [13]. The energy efficient zero forcing (ZF) precoder for coordinated multi-point transmission of HetNets has been considered in [14]. Energy efficiency maximization is achieved by deactivating some of the small cells using the Dinkelbach method [15]. Another energy efficiency maximization algorithm has been suggested in [15] where the complexity of the optimization problem has been decreased. In [16], the beamforming matrix is designed to optimize the network energy efficiency under the constraints of quality of service and power allocation. The compromise between spectral efficiency and energy efficiency has been established in [17] with capacity-constrained backhaul links. In [18], the ZF precoding and block diagonalization (BD) schemes have been used in the MBS and SBS, respectively, to reduce the downlink interference. In [19], the sparse precoding matrix is designed to suppress the interference and improve the energy efficiency in homogeneous networks in the presence of channel estimation error. A signal is called sparse where the most of its entries are zero in some domain [20]. In [21], the interference cancellation from an edge user in a heterogeneous network is addressed by designing a precoding matrix. The reduction of the cross-tier interference in HetNets occurs by using the channel statistical information and considering the interfering signals of MBS in the dominant channel space of SUE. In [22], the channel correlation matrix is used to specify the beamforming weights aiming at neutralizing the cross-tier interference signal. The interference reduction algorithm between different BSs is presented in a heterogeneous network based on their minimum allowed distance. In [23], a user allocation algorithm is introduced for the sake of load balancing and achieving high SINR in the HetNets. The performance and efficiency of successive interference cancellation (SIC) has been investigated as one of the efficient interference elimination techniques in homogeneous and hybrid networks [24].

The motivation of this paper is to present an algorithm for interference suppression in massive MIMO HetNet with imperfect channel state information. The interference minimization is modeled as an optimization problem with two constraints to guarantee the minimum signal to interference and noise ratio (SINR) and maximum transmission power for each of the users. The channel estimation error has also been modeled in the suggested problem with the joint sparsity term. This is based on the assumption that only a few of the user channels have considerable channel estimation error. Using the semidefinite relaxation, the problem has been converted to a convex problem which is solved with the aid of the block coordinate descent scheme. The simulation results have confirmed the outperformance of the algorithm from the perspective of energy efficiency and sum-rate. The main contributions and novelty of this manuscript are as follows:

(1) **Modeling the channel estimation error**: Up to now, most of the work in the field of HetNet have been done assuming that the CSI is perfect on the transmitter side. However, due to the density of the HetNets, the perfect and accurate CSI many not be reasonably available. In other words, the user’s channel vectors may be erroneous. By considering the erroneous channel vectors for some of the users, we obtain a more robust interference managing system. Accordingly, we model the channel estimation error as a joint sparse matrix. To satisfy this assumption, we added mixed $L_2/L_1$ norm of the error matrix as a penalty term to the cost function of the optimization problem.

(2) **Interference mitigation in presence of imperfect CSI**: We introduce a new algorithm to address the cross-tier and inter-tier interference in HetNets. Regarding these two types of interference, we design the optimal precoding on the MBS side using the information of the imperfect interfering channels. We illustrate the objectives and assumptions in the form of an optimization problem. Using the semidefinite relaxation, the problem has been converted to a convex problem which is solved with the aid of the block coordinate descent scheme. The simulation results have confirmed the outperformance of the algorithm from the perspective of energy efficiency and sum-rate.

The rest of the paper is organized as follows: Sect. 2 describes the system model. Section 3 introduces the proposed interference management scheme. The simulation results have been given in Sect. 4 and the paper is concluded in Sect. 5.

## 2 System model

A heterogeneous massive MIMO network with downlink scenario is considered with one MBS and $S$ SBSs which are randomly deployed in the macro cell as shown in Fig. 1. The MBS uses a very large array of $N_m$ antennas to serve $M$ macro users (MU) that are randomly distributed in the macro-cell. Each SBS with $N_s$ antennas only transmits data to the $K$ small users (SU) located in its coverage area. Also, all the users are single antenna. In the downlink data transmission mode, the received signal in the $m$th MU is represented as:

$$y^M_m = (h^M_m)^H v^M L x^M_l + \sum_{l \neq m}^{M} (h^M_l)^H \psi^M_l x^M_l + n^M_m$$  \hspace{1cm} (1)$$

$x^M_l$ is the transmission signal from the MBS to the $l$th MU and $v^M_l \in C^{N_m \times 1}$ is the corresponding precoding vec-
tor. $\mathbf{h}_m^{M} \in \mathbb{C}^{N_m \times 1}$ is the channel vector from the MBS to the $m$th MU. $n_m \sim \mathcal{CN}(0, \sigma_m^2)$ denotes the additive white Gaussian noise at the $m$th MU. The second term in (1) represents the interference from the MBS received by the MU. In addition, since the SBSs have small radiation power with low altitude antennas, the interference from the SBS to the MUs or the SUs of the other small cells (SC) can be neglected. The altitude antennas, the interference from the SBS to the MUs is small due to low transmission power. In this section, the proposed method is illustrated. We would design a precoding matrix to mitigate the interference at the same time of ensuring a minimum data rate as well as a constraint on the maximum transmission power in the presence of imperfect CSI. Due to the large transmission power and coverage radius of the MBS, it causes strong interference in the MUs and SUs. We try to limit this interference through designing an optimal precoding matrix in the MBS. Suppose that $\mathbf{v}_l^{M}$ is the precoding vector of the $l$th MU. The desired signal of the $l$th MU shall be precoded in a way that its interference to any other MUs and SUs be zero. In other words, in order to nullify the second term in (1) and the third term in (2), we shall have:

$$\mathbf{h}_m^{M} \mathbf{v}_l^{M} = 0 \quad \forall l \neq m$$

(5)

We can rewrite the constraints in (5) in the matrix form as:

$$\mathbf{H}_l^H \mathbf{v}_l^{M} = 0 \quad \forall k$$

(6)

where $\mathbf{H}_l \in \mathbb{C}^{N_m \times (M-1+S_K)}$ is the interference channel matrix of the $l$th MU defined as:

$$\mathbf{H}_l = [\mathbf{h}_1^{M}, \mathbf{h}_2^{M}, \ldots, \mathbf{h}_{l-1}^{M}, \mathbf{h}_{l+1}^{M}, \ldots, \mathbf{h}_M^{M}, \mathbf{h}_1^{MS}, \ldots, \mathbf{h}_K^{MS}]$$

(7)

The constraint in (6) removes the interference from the MBS to the other MUs and SUs. Moreover, in order to eliminate the interference from the SBS to the other SUs, the common ZF precoder is applied in the SBS. In other words, three types of interference in a HetNet have been eliminated in the proposed method. The interference between MUs and the inter-tier interference from the MBS to SUs have been

as $P_{Tra} + P_{Cir}$ where the transmission power $P_{Tra}$ and circuit power $P_{Cir}$ terms are [13,25]:

$$P_{Tra} = \rho_0 \sum_{m \in M} \mathbf{Tr}(\mathbf{v}_m^{M} \mathbf{v}_m^{M H}) + \sum_{s \in S} \rho_s \sum_{k \in K} \mathbf{Tr}(\mathbf{v}_k^{S} \mathbf{v}_k^{S H})$$

(4)

$$P_{Cir} = \frac{\eta_0}{C} N_m + \sum_{s=1}^{S} \frac{\eta_s}{C} N_s$$

where $\rho_0$, $\rho_s$ are the amplifier power efficiency factors of MBS and SBS, respectively. In the circuit power term, $\eta_0$ and $\eta_s$ denote the power dissipation in the circuit of each transmitter antenna in the MBS and SBS, respectively. $C$ represents the number of subcarriers ($C \geq 1$) applied to normalize the circuit power.

3 The proposed method

In this section, the proposed method is illustrated. We would design a precoding matrix to mitigate the interference at the same time of ensuring a minimum data rate as well as a constraint on the maximum transmission power in the presence of imperfect CSI. Due to the large transmission power and coverage radius of the MBS, it causes strong interference in the MUs and SUs. We try to limit this interference through designing an optimal precoding matrix in the MBS. Suppose that $\mathbf{v}_l^{M}$ is the precoding vector of the $l$th MU. The desired signal of the $l$th MU shall be precoded in a way that its interference to any other MUs and SUs be zero. In other words, in order to nullify the second term in (1) and the third term in (2), we shall have:

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$$\mathbf{H}_l = [\mathbf{h}_1^{M}, \mathbf{h}_2^{M}, \ldots, \mathbf{h}_{l-1}^{M}, \mathbf{h}_{l+1}^{M}, \ldots, \mathbf{h}_M^{M}, \mathbf{h}_1^{MS}, \ldots, \mathbf{h}_K^{MS}]$$

(7)
mitigated with the optimal precoding matrix of the MBS. Also, the ZF precoder is applied to remove the intra-cell interference of the small cells. Due to the arrangement of the small cells within the macro cell and the limited power and low altitude of the SBSs, the interference from SBSs to the MUs can be neglected.

In most of the works in the literature, the precoding matrix is designed based on the assumption of perfect CSI. However, due to the density of users and SBSs in the massive MIMO HetNet, this assumption is not reasonable and the channel estimation is done erroneously. As a result, to have a more realistic modeling, we assume that imperfect CSI is available in the transmitter side. With this in mind, we consider a channel estimation error vector for each user. Hence, the perfect channel vector for the $m$th user is modeled as follows:

$$ h_m^M = \hat{h}_m^M + e_m $$

where $\hat{h}_m^M$ is the estimated channel vector and $e_m$ is the estimation error vector. Similarly, the accurate interference channel matrix of the $m$th MU, $\hat{H}_m$, can be represented as:

$$ \hat{H}_m = \hat{H}_m + E_m $$

where $E_m = [e_1, e_2, \ldots, e_{m-1}, e_{m+1}, \ldots, e_M, e_{M+1}, \ldots]$ is the corresponding estimation error matrix, and $\hat{h}_m$ is the corresponding estimated interference channel matrix. Using (9), the interference suppression term in (6) can be rewritten as:

$$ (\hat{H}_m + E_m)^H v_m^M = 0 $$

Moreover, in the modeling of the channel estimation error, we assume that only a few of the user channel vectors have been erroneously estimated. Hence, only a few of the rows of the error matrix, $E_m$, would be non-zero which yields the joint sparsity structure for this matrix [26,27]. To impose the joint sparsity property on a matrix, its mixed $L_2/L_0$ norm is minimized ($\|E_m\|_{2,0}$). In other words, the $L_2$ norm of the matrix rows are calculated, then the $L_0$ norm of those $L_2$ norms are obtained. This value indicates the number of non-zero rows of a matrix. However, the mixed $L_2/L_0$ norm is not convex; thus, its convex relaxation which is the mixed $L_2/L_1$ norm would be minimized ($\|E_m\|_{2,1}$). Considering the interference suppression term as well as the joint sparsity property of the error matrix, we can write the optimization problem for the optimal precoder design as follows:

$$ \min_{\hat{H}_m^M, E_m, e_m} \| (\hat{H}_m + E_m)^H v_m^M \|^2_2 + \lambda \| E_m \|_{2,1} \quad \forall m \in M $$

s.t.

$$ C_1 : \| v_m^M \|_2^2 \leq \frac{P_{max}}{M} $$

$$ C_2 : \| (\hat{h}_m^M + e_m)^H v_m^M \|^2_2 - \gamma_{min} \sum_{l \neq m} \| (\hat{h}_m^M + e_m)^H v_l^M \|^2_2 \geq \gamma_{min} \sigma_m^2 $$

where $\| . \|_2$ indicates for the $L_2$ norm of the vector and $\lambda$ is the relaxation parameter which controls the effect of the joint sparsity term. The constraint (C1) is to guarantee the maximum transmission power of the MBS to each of the MUs, $P_{max}$ is the maximum transmission power of the MBS. The constraint (C2) ensures the MUs to have SINR higher than $\gamma_{min}$. As a result, this constraint guarantees a minimum data rate of $\log_2(1 + \gamma_{min})$ transmitted for each macro user.

Note that the optimization problem in (11) is non-convex due to the coupling of the optimization variables in the cost function and the $C_2$ constraint. Hence, the block coordinate descent (BCD) algorithm in [28] is adopted to evaluate the convexity of the problem with respect to each of variables. The main idea of the coordinate descent algorithm is to alternately optimize the problem with respect to one block of the variables while the others are fixed. In the convexity analysis of the problem (11) with respect to each of the variables separately, the problem (11) is convex in respect of the variable $E_m$, while the other two sub-problems with respect to $v_m^M$, and $e_m$ are non-convex due to the non-convexity of the $C_2$ constraint. Indeed, if the BCD method is applied to the problem (11) in its current form, the optimization problem will still be non-convex. Hence, in order to tackle the non-convexity and also unify the variables in the whole problem, the $C_2$ constraint and the cost function are rewritten as:

$$ \| (\hat{H}_m + E_m)^H v_m^M \|^2_2 - \gamma_{min} \sum_{l \neq m} \| (\hat{h}_m^M + e_m)^H v_l^M \|^2_2 $$

$$ = Tr \left( W_m - \gamma_{min} \sum_{l \neq m} W_l \right) \left( \hat{h}_m^M (\hat{h}_m^M)^H \right) $$

$$ + 2Re \left\{ \hat{h}_m^M e_m^H + e_m e_m^H \right\} $$

and

$$ \| (\hat{H}_m + E_m)^H v_m^M \|^2_2 $$

$$ = Tr \{ W_m (\hat{H}_m \hat{H}_m^H) $$

$$ + \hat{H}_m E_m^H + E_m \hat{H}_m^H + E_m E_m^H \} $$

where $Tr\{\}$ indicates for the trace of the matrix and $W_m \triangleq v_m^M v_m^M^H$ is a positive semidefinite (psd) matrix with $rank(W_m) = 1$. By lifting the vector $v_m^M$ to the matrix $W_m$, the sub-problem with respect to $W_m$ would be convex since
the cost function as well as the constraint would be an affine function. However, the sub-problem with respect to \( e_m \) is still non-convex since the constraint \( C_2 \) is a concave-convex function. In order to solve this issue, the \( C_2 \) constraint is restated as:

\[
\begin{align*}
&||\hat{h}_m^M + e_m^M||_2^2 - \gamma_{\min} \sum_{l \neq m} ||\hat{h}_l^M + e_m^M||_2^2 = \\
&\text{Tr}\left\{ (W_m - \gamma_{\min} \sum_{l \neq m} W_l) (\hat{h}_m^M (\hat{h}_m^M)^H + 2Re(\hat{h}_m^M e_m^H) + e_m^H e_m^H) \right\} = \\
&\text{Tr}(\bar{e}_m^W \Xi W_m \Xi e_m) - \gamma_{\min} \sum_{l \neq m} \text{Tr}(\bar{e}_l^H \Xi W_l \Xi e_m) = \\
&\text{Tr}(\Gamma_m \Xi W_m \Xi) - \gamma_{\min} \sum_{l \neq m} \text{Tr}(\Gamma_m \Xi W_l \Xi)
\end{align*}
\]

where \( \Xi = [I, \bar{h}_m], \bar{e}_m = [e_m, x]^H \) and \( \Gamma_m = \bar{e}_m \bar{e}_m^H \) is a positive semidefinite (psd) matrix with rank one. In other words, the variable vector \( e_m \) is lifted to the matrix \( \Gamma_m \). By replacing (14) and (13), (11) can be written in the following equivalent form:

\[
\begin{align*}
&\min_{W_m, E_m, \Gamma_m} \text{Tr}(W_m (\hat{H}_m H_m^H + \hat{H}_m E_m^H + E_m \hat{H}_m^H + E_m E_m^H)) \\
&+ \lambda ||E_m||_{2,1} \quad \forall m \in M \\
&\text{s.t.} \ C_1 : \text{Tr}(W_m) \leq \frac{P_{\max}}{M} \\
&\quad \forall m \in M \\
&\quad C_2 : \text{Tr}(\Gamma_m \Xi W_m \Xi) \\
&\quad - \gamma_{\min} \sum_{l \neq m} \text{Tr}(\Gamma_m \Xi W_l \Xi) \geq \gamma_{\min} \sigma_m^2 \\
&\quad C_3 : W_m \in S_m^+ \\
&\quad C_4 : \Gamma_m \in S_m^+ \\
&\quad C_5 : \text{rank}(W_m) = 1 \\
&\quad C_6 : \text{rank}(\Gamma_m) = 1
\end{align*}
\]

The problem (15) is still non-convex due to the coupling of the optimization variables in the cost function and \( C_2 \) as well as the presence of rank-one constraints in \( C_5 \) and \( C_6 \). By applying the semidefinite relaxation (SDR) method [29], we get rid of the rank-one constraints. Next, to deal with non-convexity, we separate the variables into two blocks\( \{W_m, \{E_m, \Gamma_m\}\} \). Therefore, the problem becomes convex with respect to each block of variables when the other one is fixed. We apply the BCD technique to solve the problem (15). At the sub-problem of \( W_m \), the variables \( \{E_m, \Gamma_m\} \) are assumed as fixed and the problem is solved with respect to \( W_m \):

\[
\begin{align*}
&\min_{W_m} \text{Tr}(W_m (\hat{H}_m H_m^H + \hat{H}_m E_m^H + E_m \hat{H}_m^H + E_m E_m^H)) \\
&+ \lambda ||E_m||_{2,1} \quad \forall m \in M \\
&\text{s.t.} \ C_1 : \text{Tr}(W_m) \leq \frac{P_{\max}}{M} C_2 : \text{Tr}(\Gamma_m \Xi W_m \Xi) \\
&\quad - \gamma_{\min} \sum_{l \neq m} \text{Tr}(\Gamma_m \Xi W_l \Xi) \geq \gamma_{\min} \sigma_m^2 \\
&\quad C_3 : W_m \in S_m^+ \\
&\quad C_4 : \Gamma_m \in S_m^+ \\
&\quad C_5 : \text{rank}(W_m) = 1 \\
&\quad C_6 : \text{rank}(\Gamma_m) = 1
\end{align*}
\]

(16) is a SemiDefinite Programming (SDP) problem which can be solved by the CVX optimization toolbox [30] or any other SDP solvers. At the second sub-problem, \( W_m \) is fixed and the problem is solved with respect to \( \{E_m, \Gamma_m\} \). Thus, the second optimization sub-problem as:

\[
\begin{align*}
&\min_{E_m, \Gamma_m} \text{Tr}(W_m (\hat{H}_m H_m^H + \hat{H}_m E_m^H + E_m \hat{H}_m^H + E_m E_m^H)) \\
&+ \lambda ||E_m||_{2,1} \quad \forall m \in M \\
&\text{s.t.} \ C_1 : \text{Tr}(\Gamma_m \Xi W_m \Xi) - \gamma_{\min} \sum_{l \neq m} \text{Tr}(\Gamma_m \Xi W_l \Xi) \\
&\quad \geq \gamma_{\min} \sigma_m^2 \quad C_2 : 0_m \in S_m^+
\end{align*}
\]

The problem (17) is convex and can be solved using the CVX optimization toolbox [30].

The beamforming vector can be estimated from the suboptimal matrix \( W_m \) by using the eigenvalue decomposition (EVD) as: \( v_m = u \xi^2 \) where \( \xi \) is the largest eigenvalue of \( W_m \) and \( u \) is its corresponding eigenvector. The same procedure can be implemented to extract \( \bar{e}_m \) from the \( \Gamma_m \) matrix. Therefore, by applying the EVD on the obtained \( \Gamma_m \) matrix, we will have: \( \Gamma_m = U \Sigma U^H \) where \( U \) is the unitary matrix of the eigen vectors and \( \Sigma \) is the diagonal matrix of the eigenvalues. In order to guarantee the rank-one constraint on \( \Gamma_m \), the gaussian randomization technique in [31] is adopted to produce a suboptimal solution of \( \bar{e}_m \) as \( \bar{e}_m = U \Sigma^{1/2} r \) where \( r \sim CN(0_{N_m + 1}, I_{N_m + 1}) \) is a random vector with circularly symmetric complex Gaussian (CSCG) distribution. Finally, the sub-optimal solution of \( e_m \) is given as:

\[
e_m = \frac{[\bar{e}_m]_{1:N M}/[\bar{e}_m]_{(N M + 1)}}{\| [\bar{e}_m]_{1:N M}/[\bar{e}_m]_{(N M + 1)} \|_2}
\]

and \( |z|_{1:L} \) refers to the vector that contains the first \( L \) elements of \( z \).

The proposed method has been summarized in Algorithm 1.

### 4 Numerical results

In this section, the performance of the suggested algorithm has been investigated through various simulation scenarios. The considered system is a macro cell with a radius of 500 m that includes one MBS located at the center of the macro-cell with 15 MUs. Also, there are 5 SCs where each SBS serves...
The proposed interference suppression algorithm.

1: \( \Delta \leftarrow 0.001 \)
2: \( \Phi^{(0)} \leftarrow 0, \Gamma^{(0)} \leftarrow 0 \)
3: \( n \leftarrow 1 \)
4: \( \Phi \leftarrow 0 \)
5: repeat
6: \( \text{for do } m = 1 : M \)
7: \( \text{Fix } [E_m^{(n-1)}, \Phi^{(n-1)}] \) and optimize (16) to find \( W^{(n)}_m \)
8: \( \text{Fix } W^{(n)}_m \) and optimize (17) to find \( [E_m^{(n)}, \Gamma^{(n)}_m] \)
9: \( (U, \Sigma) \leftarrow EVD(\Gamma^{(n)}_m) \)
10: \( \tilde{e}_m \leftarrow U \Sigma \tilde{r} \) where \( r \sim CN(0, \sigma^2_m, 1, N_m+1) \)
11: \( \text{Apply (18) to obtain } e^{(n)}_m \)
12: \( \Phi \leftarrow \Phi + [E^{(n)}_m(:, 1 : m - 1), e^{(n)}_m, E^{(n)}_m(:, m + 1 : M - 1)] \)
13: end for
14: \( \Phi \leftarrow \Phi / M, \forall m \in 1, \ldots, M \)
15: \( e^{(n)}_m \leftarrow \Phi(:, m) \)
16: \( \theta_{0,m} \leftarrow e^{(n)}_m \)
17: \( n \leftarrow n + 1 \)
18: until \( \|W^{(n)}_m - W^{(n-1)}_m\|_2 \leq \Delta, \|E^{(n)}_m - E^{(n-1)}_m\|_2 \leq \Delta \) \( \forall m \in 1, \ldots, M \)
19: \( \tilde{W}_m \leftarrow W^{(n)}_m \)
	hree SUs within a 40 m range. The channel is modeled as follows [13]: \( h^M_m = \sqrt{\varphi^M_m g^M_m} \), where \( g^M_m \in C^{1 \times N_m} \) is the small scale fading generated from Rayleigh distribution and \( \varphi^M_m \) is the large scale fading which includes the path loss and shadowing.

Throughout the simulations, it is assumed that the SUs are scattered in a cell with a radius much smaller than that of the macro cell (MC). Also, SCs are placed far away from the MBS. Based on these assumptions, the angle of arrival of the signal from MBS to a SBS and its SUs will be almost equal. Thus, it can be claimed that the channel vectors from the MBS to a SBS and its SUs would be highly correlated.

The simulation parameters are presented in Table 1. The following methods have been considered as the benchmarks: the Energy-Efficient Zero-Forcing HetNet Beamforming (EE ZF) technique [16] and the All-BS method [15].

The performance of the proposed precoding matrix is evaluated from the perspective of the MBS transmission power, sum rate \( (\sum_m r_m + \sum_s \sum_k r_{k,s}) \), and energy efficiency. 30 Monte Carlo runs on the channel matrix have been conducted in all of the simulation scenarios. Furthermore, it is assumed that only 5 MU channels (which are selected uniformly at random) have been erroneously estimated. In the first test, the effect of the parameter \( \lambda \) has been investigated. Figure 2 depicts the sum-rate versus SNR curves for various values of the parameter \( \lambda \). The number of transmit antennas has been considered as 40 in this simulation.

As the amount of \( \lambda \) increases from 0.01 to 1, the sum-rate increases and for the \( \lambda \) values greater than 1, the sum-rate curve does not change. Therefore, we have set \( \lambda = 1 \) for the rest of the simulations.

In the following, we compare the efficiency of the provided precoder with the other competing methods. Figure 3 shows the sum-rate versus SNR curves for all the 3 methods.

According to the figure, the sum-rate curves have increasing trend with respect to SNR for all of the three methods. The proposed precoding scheme offers higher sum-rate for all SNR values. The outperformance of the proposed scheme is more considerable in high-SNR regimes. This is due to the fact that the proposed scheme has modeled the channel estimation error as well as suppressing the interference.

It should be noted that the All-BS method has very high computational complexity for large antenna array size. Therefore, it could not be compared in the rest of the simula-

| Table 1 The simulation parameters |
|----------------------------------|
| Parameters                      | Values               |
| The bandwidth                  | 10 MHz               |
| The maximum MBS power budget   | 46 dbm               |
| The minimum rate required for each user | 6 Mbps   |
| The standard deviation of shadowing | 7 db     |
| The least distance of the SBSs from the MBS | 150 (m) |
| The MBS penetration loss       | 128.1 + 37.6\log_{10}(d(km)) |
| The SBS penetration loss       | 127 + 30\log_{10}(d(km))  |
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Fig. 3 The comparison of sum-rate versus SNR curves for all the methods with 40 transmission antennas.

Fig. 4 The sum-rate versus SNR for different EECV with 60 antennas.

Fig. 5 The transmission power versus the number of MBS antennas.

Fig. 6 The sum-rate versus the number of MBS antennas.

Fig. 7 The sum-rate versus the number of transmit antennas.

Figure 6 displays the curves of the sum-rate versus the number of transmit antennas.

It is observed that the sum-rate increases for the larger antenna sizes which indicates the advantage of the massive MIMO systems. Furthermore, the proposed method achieves higher sum-rate values compared to the EE-ZF scheme specially in the larger antenna sizes. Meanwhile, the gap between the transmission rates of the two methods depends on the capability of the precoder in eliminating the interference in the presence of channel estimation error. Our proposed method performs better in such situations due to the modeling of channel estimation error in the precoder matrix design.

As another scenario, the energy efficiency curves versus the number of transmit antennas have been plotted in Fig. 7.

According to this figure, the energy efficiency is increasing for less than 70 antennas. This is because of the increasing trend of the spectral efficiency in this range. As the transmit antennas goes beyond 70, the inter-user interference and the...
Fig. 7 The energy efficiency versus the number of transmit antennas

circuit power of the MBS increase as well which leads to a slight decrease in the energy efficiency. The proposed method outperforms the EE-ZF scheme even in the case of energy efficiency.

Another figure assesses the performance of the proposed precoding matrix in the elimination of inter-tier interference between macro-cell users and improving the sum rate.

In Fig. 8, the comparison of the sum rate and the interference ratio is done once by considering the estimation error in the precoding matrix design and another time without the estimation error.

As expected, in both cases, the sum rate increases with the SNR. However, in the case of modeling the estimation error, the interference between MUEs is literally suppressed while for the other case the interference leakage is quite tangible.

As the last test, the proposed method is compared to another competing scheme [22] in the case of several numbers of SCs. In this simulation, the channel estimation error has been considered for both of the methods. The sum rate curves of both schemes for the different number of SCs located in the MC are shown in Fig. 9.

According to this figure, as the number of SCs increases, the total rate also grows. It is obvious that the proposed method achieves higher sum rate compared to its counterpart. This is due to the fact that the proposed method eliminates the inter-tier interference in the presence of channel estimation error.

5 Conclusion

In this paper, a MIMO precoding scheme has been suggested to cope with the interference of the massive MIMO HetNets. The channel estimation error has been modeled in the proposed scheme under the assumption that a few of the channel estimations are imperfect. The simulation results indicate that the proposed method outperforms its rivals in sum rate and energy efficiency.
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**Declarations**

**Conflict of interest** The authors declare that they have no known conflicts of interest that could have appeared to influence the work reported in this paper.

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