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Power optimization with low complexity using scaled beamforming approach for a massive MIMO and small cell scenario

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Abstract

Present wireless generation is now evolving from 4G to 5G with a large number of clients. Researchers across the globe are working to sustain the quality of service level, while meeting the increasing demand of the clients. Since, the number of clients are increasing, which give arise to a lot of problems like increased interference, complexity and significant amount of power consumption in the processing and transmission. This paper investigates potential improvements in power optimization by modifying the classical macro-cell with massive multiple input multiple output at the mobile tower, which is overlaid with small cell access points. The main aim of the paper is to optimize the utilization of energy, while maintaining the quality of service at the client end and power optimization at the small cell access point, and base station. But along with power optimization, complexity is also a prime objective of concern. Hence for optimizing or minimizing the power, while maintaining low complexity, a new low complexity algorithm is proposed and is compared with a classical relaxed zero-forcing beam forming algorithm and the optimal solution cases. The complexity analysis of this proposed approach has been done on the basis of change in the base stations and the number of UEs surrounding it. The potential merits of this proposed approach for different deployment scenarios, such as an urban macro heterogeneous deployment scenario in the 3GPP LTE Standard and an urban macro, sub-urban macro, and rural macro deployment scenario in the ITU-R M.2135 standard are analyzed by numerical calculations.

Keywords 5G · Beam forming · Scaled beam forming · Low complexity

1 Introduction

In the present age of gadgets, like smartphones and tablets, the requirement of high data rates in a wireless networks has increased tremendously. But phenomenon like fading and shadowing are rigorously effecting the wireless transmissions. So for increasing the capacity and data rates with no or little fading, Multiple input multiple output (MIMO) technology comes into existence. Installation of large number of transmitter and receiver antennas offers higher data rates due to spatial multiplexing, and robustness against fading due to spatial diversity with the similar time and frequency resources. But when the transmitter side has full information of the channel conditions i.e. channel state information, then it will be very easy for the transmitter to optimize the transmission according to certain different criteria [1].

In [2], eigen-beamforming is used for calculation of the capacity under a sum radiated power constraint of the MIMO channels over all the antennas. Power allocation in different eigen modes is done by having the full information of channel, using water filling algorithm at the transmitter. This very method is not accurate because of the extreme output restraint of every single power amplifier, which is not taken into consideration. But [3] is more accurate as it first considered the each antenna power restraints. Though the power that is consumed in the wireless communication comprises of both the power losses in the hardware as well as the output power. But in the

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process of optimizing capacity for power constraints per-antenna, there is no information available regarding the allocation of power to the antennas given a specific channel. Also, there is no information regarding the overall energy conservation for all the antennas and the total power consumption in each power amplifier. But in [4], an algorithm has been derived which will help in obtaining the ideal input delivery of power constraints in each antenna for a particular channel. It is essential to consider power amplifier while designing the transmitters at the base station (BS) because it is clear in [5, Fig. 12] that power amplifiers are consuming 57% of the energy in the macro BSs, while cooling contributes 10%. Thus total power consumed can be decreased, if dissipating energy from the power amplifier is decreased. This conclusion has recently been set forth by others in [6] and [7]. In spite of the importance, the work done in [8] still supports the concept of optimizing MIMO along with the net consumption of energy conserved in a diagonal input covariance matrix using sub-optimal pseudo code. But the work in [9] and [10], based on net power consumption per-antenna, still meets the conclusion of considering the power amplifier while designing the transmitters at the BSs.

The above issue can be solved using the massive MIMO (MM) [11, 12] and small cell (SC) [13, 14] scenario of 5G. Developing a MM network involves deployment of large number of antenna group at the existing macro BSs [11] which will helps in focusing power emission for definite UEs. This correspond to an increased energy efficiency. But in case the base stations/mobile towers increase, then there will be no role of channel estimation, as it will create large overheads. But to satisfy the need of MM of channel acquirement in regard with misuse of path reversibility, Time division duplexing (TDD) will come into play [15, 16]. But the foremost requisite is of power optimization which will be achieved by deploying small cell access (SCA) points in the network and offload the data traffic of low-mobility clients. This method also helps in increasing the energy efficiency and reducing the propagation losses because of the decrease in the total distance between the clients and transmitters [14]. But deployment of SCA's will form an extremely diverse network topology, which will be tough to control and coordinate and this results in increased inter-client interference. Thus researchers and academicians around the globe have now shifted their focus from client-deployed femto-cells to operator-deployed SCA points [17, 18]. The basic motto for shifting is that the SCA's are dependent on the BS for consistent backhaul connectivity and joint control and coordination among them. But the work on complexity has been identified in [19], the signal processing complexity has been specifically mentioned and it interpreted that it is increasing with the increasing number of antennas. The complexity that has

been increased during channel estimation, can be minimized using pilot power allocation scheme that has been proposed in [20]. While minimizing the complexity, the energy efficiency and spectral efficiency of the system should be maintained by optimally designing the system, as described in [21] and [22], respectively. Apart from the research related to complexity, there is a lot work that has been going on, involving both massive MIMO and small cell. In [23], the designing of an energy efficient wireless backhaul network has been done, which is solving the bandwidth allocation and power allocation problem in a heterogeneous small cell [23]. In [24], the resource allocation and power optimization has been done in a heterogeneous small cell network, while having the incomplete channel state information using a non-cooperative game theoretic approach. In [25], the designing of an energy efficient cognitive small cell optimization framework has been done for optimizing the sensing time and power control using imperfect hybrid spectrum sensing. In [26], the designing of an energy efficient mm Wave based ultra-dense network optimization framework has been done, while solving the user association and power allocation problem using a load-aware scheme. This work has been done while considering the load-balancing constraints, QoS requirements, energy efficiency, energy harvesting by base stations, and cross-tier interference limits. In [27], the designing of an energy efficient software defined heterogeneous VLC and RF small-cell network optimization framework has been done, while solving the sub channel allocation and power control problem. This work has been done while considering the backhaul constraints, QoS requirements, energy efficiency, and inter-cell interference limits.

Contribution of the paper The study of literature showed that the work for optimizing the power has been done but without thinking about the role of complexity. This paper investigates the potential improvements in power optimization by modifying the classical macro-cell with MM at the BS and overlaying it with SCA points, while maintaining the low complexity. In order to achieve low complexity, a lot of researchers are using classical relaxed zero-forcing (RZF) beam forming in which the orthodox zero-forcing interference leakage constrictions are in undisturbed mode waiting for some preset interference leakages that are allowed to unwanted receivers for increasing the beam design space to achieve larger rates as compared to the orthodox zero-forcing scheme for making beam policy possible, when zero-forcing is impossible. The paper proposed a less complex scaled beamforming approach and compared it with a classical relaxed zero-forcing (RZF) beam forming and optimal solution cases. The complexity analysis of this proposed approach has been done on the basis of varying client number and transmitting antenna

number at BSs. The possible merits of this proposed strategy on the diverse deployment scenarios like urban macro (UM) heterogeneous deployment scenario in the 3GPP LTE Standard (Case 1) and urban macro (UM), sub-urban macro (SUM), and rural macro (RM) deployment scenario in the ITU-R M.2135 standard (Case 2) are analyzed also by numerical calculations.

Organization of the paper The remaining paper is organized as follow. The system model and problem description has been elaborated in Sect. 2. The algorithm for power optimization with low complexity is given in Sect. 3. The simulation parameters has been given in Sect. 4. Section 5 demonstrates the simulation results. The paper finally concludes in Sect. 6.

2 System model and problem depiction

Main objective of the paper is of optimizing the power and reducing the complexity using different approaches given in Sect. 3. In order to achieve this, let us assume a model consisting of a macro BS having $N_{BS} \gg K$ antennas, where K is the number of antennas on clients, and is ranging from 8 to 100 [47]. These macro BS antennas are having a capability of attending K clients and S ≥ 0 total of arbitrarily positioned SCAs to form a heterogeneous network. For optimizing the power, SCAs should be fixed with $1 \leq N_{SCA} \leq 2$ transmitting antennas each and follows the firm energy restraints that leads to the covering of a narrow region. But for high quality of service (QoS) in a vast coverage region, BS should support significant power restraints [47].

In the organization model, there is no need of channel estimation because of the use of TDD, thus aids in optimizing the power. For client k, block fading path is used, while single flat fading path denoted in the baseband as $h_{k,0}^H \in \mathbb{C}^{1 \times N_{BS}}$ and $h_{k,j}^H \in \mathbb{C}^{1 \times N_{SCA}}$, for BS and SCA, in the respective order. Hence, the received signal at client k is

$$y_k = h_{k,0}^H x_0 + \sum_{j=1}^{S} h_{k,j}^H x_j + n_k \tag{1}$$

where x_0 and x_j represents the communicated signals at the BS and jth SCA point. Here, $n_k \sim \mathcal{CN}\left(0, \sigma_k^2\right)$ is the circularly symmetric complex Gaussian received unwanted signal with zero-mean and alteration σ_k^2, calculated in milliwatt (mW) [47].

For obtaining the communicated signals

$$x_j = \sum_{k=1}^{K} w_{k,j} x_{k,j}, \quad j = 0, \dots, S \tag{2}$$

The data symbols to UE k, represented as $x_{k,0}$ and $x_{k,j}$, from the Base Station and the jth SCA respectively, taken from the independent Gaussian codebooks as $x_{k,j} \sim CN(0, 1)$, for j = 0,…,S with unit energy (in mW). Now multiply it with the beam-forming vectors $w_{k,0} \in \mathbb{C}^{1 \times N_{BS}}$ and $w_{k,j} \in \mathbb{C}^{1 \times N_{SCA}}$. These vectors helps in resolving the problem of optimization. As $w_{k,j} \neq 0$, the task of allocating the transmitter is completed on its own and in the best way of reducing the problem for j transmitters that are aiding k number of clients [47].

The key objective of the paper is to achieve power optimization and at the same time maintaining the QoS. The QoS is represented as data rate in bits/s/Hz and is achieved in parallel by each client. These are defined as $\log_2(1 + SINR_k) \geq \gamma_k$, where γ_k is the static QoS target and SINR is the signal to interference noise ratio of the kth client, which is represented as

$$SINR_k = \frac{\left|h_{k,0}^H w_{k,0}\right|^2 + \sum_{j=1}^{S}\left|h_{k,j}^H w_{k,j}\right|^2}{\sum_{\substack{i=1 \\ i \neq k}}^{K}\left(\left|h_{k,0}^H w_{i,0}\right|^2 + \sum_{j=1}^{S}\left|h_{k,j}^H w_{i,j}\right|^2\right) + \sigma_k^2} \tag{3}$$

Here $\log_2(1 + SINR_k)$ is the depiction of the information rate which is achieved when the interference is successively cancelled from the own data symbols, whereas the co-client symbols are treated as unwanted signal [28].

The total energy consumed by each subcarrier can be represented as $P_{dynamic} + P_{static}$ [30–32] where

$$P_{dynamic} = \rho_0 \sum_{k=1}^{K} w_{k,0}^2 + \sum_{j=1}^{S} \rho_j \sum_{k=1}^{K} w_{k,j}^2, \tag{4}$$

$$P_{static} = \frac{\eta_0}{C} N_{BS} + \sum_{j=1}^{S} \frac{\eta_j}{C} N_{SCA}, \tag{5}$$

where, the dynamic power consumption comprehend the emission of energy as, $\sum_{k=1}^{K} w_{k,j}^2$, after multiplication with a constant $\rho_j \geq 1$ demonstrating the less effectiveness of the power amplifier at the definite transmitter [47]. While, the fixed energy/power consumption is proportional to N_{BS} and N_{SCA} both. Here, $\eta_j \geq 0$ in the equation denotes the power dissipation in the baseband processing and in the circuits of each antenna comprises of filters, mixers, and converters. The total number of subcarriers $C \geq 1$ are also have an impact on the equation given above. Thus, each BS and SCA is susceptible to L_j power restraints

$$\sum_{k=1}^{K} w_{k,j}^H Q_{j,l} w_{k,j} \leq q_{j,l}, \quad l = 1, \dots, L_j. \tag{6}$$

The weighting matrices $Q_{0,l} \in \mathbb{C}^{N_{BS} \times N_{BS}}$, $Q_{j,l} \in \mathbb{C}^{N_{SCA} \times N_{SCA}}$ for j = 1,…,S, are positive semi-definite having

a boundary condition of $q_{j,l} \geq 0$. The variables $Q_{j,l}, q_{j,l}$ are fixed and represents per-antenna, per-array, and soft shaping restraints [29]. Generally, the BS provides the coverage, so we have $q_{0,l} \gg q_{j,l}$ for $1 \leq j \leq S$. The mathematical calculation considers per-antenna restraints of q_j [mW] at the jth transmitter, given by $L_0 = N_{BS}, L_j = N_{SCA}, q_{j,l} = q_{j \forall l}$, and $Q_{j,l}$ with one at lth diagonal element and zero, elsewhere.

Hence, for optimization of energy, total power consumption is decreased keeping the QoS limitations and energy limitations for [47]

$$\underset{w_{k,j} \forall k,j}{minimize} \, P_{dynamic} + P_{static}$$

$$\text{Subject to} \quad \log_2(1 + SINR_k) \geq \gamma_k \quad \forall k,$$

$$\sum_{k=1}^{K} w_{k,j}^H Q_{j,l} w_{k,j} \leq q_{j,l}, \quad \forall j, l. \tag{7}$$

The single cell scenario in Fig. 1 depicts the three possibilities of case study 2 as described in Sect. 3 for optimizing the power.

3 Algorithm for power optimization with low complexity

The QoS constraints as given in (7) makes the problem non-convex in its original design because they are complex functions of the beam forming vectors. So (7) can be redesigned as a convex optimization problem which can be solvable in polynomial time with the help of standard algorithms. Additionally, a self-organizing solution for the optimal power-minimization has also been given in which every client will be served by one or a few transmitters. But, it has a fundamental convex structure that can be taken out by making use of semi-definite relaxation. Along with this, the unique method as given in [33] to spatial multiflow transmission is also being generalized. For achieving the convex reformulation of (7), the notation $W_{k,j} = w_{k,j} w_{k,j}^H \forall k,j$ is used. This matrix denoted as $W_{k,j} \geq 0$, should be positive semi-definite with $rank(W_{k,j}) \leq 1$.

But the position can be zero, which infers that $W_{k,j} = 0$. We can redraft (7) efficiently by involving the BS and SCA points in the same sum expressions, as
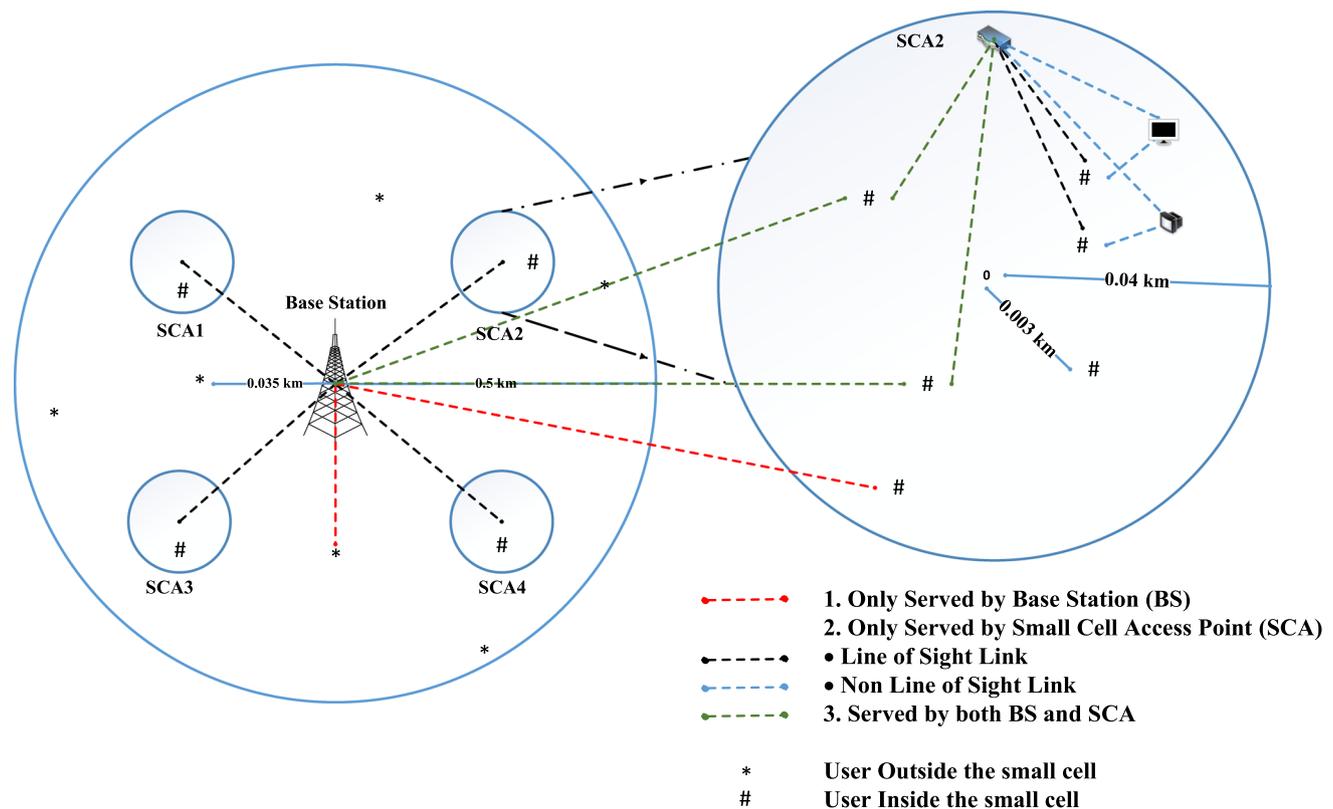
Fig. 1 The single cell scenario for the three possibilities of case study described in Sect. 3

$$\underset{W_{k,j} \geq 0 \forall k,j}{\text{minimize}} \quad \sum_{j=0}^{S} \rho_j \sum_{k=1}^{K} tr(W_{k,j}) + P_{static}$$

Subject to $\quad rank(W_{k,j}) \leq 1 \quad \forall k,j,$

$$\sum_{j=0}^{S} h_{k,j}^{H} \left(\left(1 + \frac{1}{\tilde{\gamma}_k}\right) W_{k,j} - \sum_{i=1}^{K} W_{i,j} \right) h_{k,j} \geq \sigma_k^2 \quad \forall k, \qquad (8)$$

$$\sum_{k=1}^{K} tr(Q_{j,l} W_{k,j}) \leq q_{j,l} \quad \forall j, l,$$

Here, the aim that is QoS is converted into SINR targets of $\tilde{\gamma}_k = 2^{\gamma_k} - 1 \ \forall k$.

Now the problem in (8) is convex except for the limitation of position. But optimality can be achieved by relaxing these constraints. To achieve this, two case studies has been explained. Case Study 1 provides the complete analysis of complexity problem while the analysis of power optimization problem is provided in the Case Study 2.

Case Study 1 For achieving a convex semi-definite optimization problem, consider a semi-definite relaxation of (8) in which the limitation of position $rank(W_{k,j}) \leq 1$ are vanished. Additionally, it will always have an optimal solution $\{W_{k,j}^* \forall k,j\}$ where all matrices satisfy rank $(W_{k,j}^*) \leq 1$.

Analysis According to the standard in [34], the relaxed problem is a semi definite optimization problem. But there might exist high-rank solutions, as given in [32, Example 1]. Yet, there always exist a solution with $rank(W_{k,j}) \leq 1 \forall k,j,$. To verify this:

Let us assume that there exist an optimal solution $\{W_{k,j}^{**} \forall k,j\}$ with $rank(W_{k,j}^{**}) > 1$ for some k, j.

So $W_{k,j}^{**}$ can be replaced by any $V \geq 0$ such that it

maximizes $h_{k,j}^{H} V h_{k,j}$

subject to $\quad tr(V) \leq tr(W_{k,j}^{**}), tr(Q_{j,l} V) \leq tr(Q_{j,l} W_{k,j}^{**}) \forall l$

which means that, it is not using more power than $W_{k,j}^{**}$ and for not causing more interference than $W_{k,j}^{**}$

$h_{i,j}^{H} V h_{i,j} \leq h_{i,j}^{H} W_{k,j}^{**} h_{i,j} \quad \forall i \neq k$

So one solution will be $V = W_{k,j}^{**}$, but according to [33, Lemma 3] these types of problems always have rank-one solutions

Hence this case study reveals that the original problem given in (7) can be solved as a convex optimization problem and the optimal solution is certain in polynomial time [34].

Case Study 2. For achieving the optimality, consider $\{W_{k,j}^* \forall k,j\}$ as the optimal solution to (8) and for each client k there are three options:

1. $W_{k,j}^* = 0, \ 1 \leq j \leq S$; *(Only served by the BS)*
2. $W_{k,o}^* = 0$ and $W_{k,i}^* = 0$ for $i \neq j$; *(Only served by the jth SCA point)*
3. $\sum_{k=1}^{K} tr(Q_{j,l} W_{k,j}^*) = q_{j,l}$; *(Served by a combination of BS and SCA points, such that at least one transmitter j has an active power constraint l)*

Analysis Let $A_k = \frac{1}{\sigma_k^2} diag\left(\frac{1}{\rho_0} h_{k,0} h_{k,0}^H, \ldots, \frac{1}{\rho_s} h_{k,s} h_{k,s}^H\right)$ be a block-diagonal matrix and $w_k = \left[\sqrt{\rho_0} w_{k,0}^T \cdots \sqrt{\rho_s} w_{k,s}^T\right]^T$ be the aggregate beam forming vectors. Also, let $\tilde{Q}_{j,l}$ be the block diagonal matrix that makes $w_k^H \tilde{Q}_{j,l} w_k = w_{k,j}^H Q_{j,l} w_{k,j}$ and $w_k^* = \sqrt{p_k} u_k$ is the optimal solution to (7), where u_k is unit-norm.

According to the uplink-downlink duality as given in [32, Lemma 4], is given as

$$\tilde{\gamma}_k = \frac{p_k u_k^H A_k u_k}{\sum_{i \neq k} p_i u_i^H A_k u_i + 1} = \frac{\lambda_k u_k^H A_k u_k}{u_k^H B_k u_k} \qquad (9)$$

where $B_k = \left(\sum_{i \neq k} \lambda_i A_i + \sum_{j,l} \mu_{j,l} \tilde{Q}_{j,l} + I\right)$ and $\lambda_k, \mu_{j,l}$ are the ideal Lagrange multipliers for the QoS and energy limitations, respectively.

Hence it is clear from the expression given in (9) that the uplink SINR targets or QoS targets will achieve their largest value when u_k will be the dominating eigenvector of $B_k^{-1/2} A_k B_k^{-1/2}$. Since B_k and A_k are block diagonal with each block belongs to either the BS or one of the SCA points. So the dominating eigenvalue that arises from one of the blocks with the only non-zero element for this block is the eigenvector, interprets that there must be preferably a UE k by only one transmitter. There also exists another case in which there is diversity in the dominating eigenvalue and at least one energy limitation is active i.e. power constraints are not supporting the single transmitter solutions, then only another u_k is used. This statement now proves the above three cases specified in the case study 2.

The exact interpretation of the case study 2 reveals that though UEs can be served by multiflow transmission, but, in order to achieving optimality at least one transmitter for each UE is allotted. The clients that are close to a SCA point are solely served by it, while most of the other clients are served by the BS. Since the SCA is not capable of fulfilling the QoS targets, so there will be change in the coverage part surrounding every SCA in which multiflow transmission is applied. Hence case study 2 has come up with a positive outcome of reduced transmission/reception complexity.

Proposed approach Case study 1 is used for computing the optimal beam forming for spatial soft-cell coordination.

The level of complexity related to optimal beam forming is relatively modest, but when N_{BS} and S grow large i.e. for real-time implementation, the algorithm becomes infeasible. Case Study 1 also provides a centralized code that needs the knowledge of path to be collected at the Base Station antenna irrespective of the circulated code that can definitely be obtained using primal or dual decomposition techniques as given in [35]. Circulation of codes are also not suited for real-time implementations because they need iterative backhaul signaling of coupling variables.

Hence case study 1 is considered as the standard for calculating less complex codes for non-coherent coordination. To validate this, a less complex non-iterative multiflow relaxed zero forcing (RZF) beam forming is explained as:

Each transmitter $j = 0, \ldots, S$ computes

$$u_{k,j} = \frac{\left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2} h_{i,j} h_{i,j}^H + \frac{K}{\bar{\gamma}_k q_j} I\right)^{-1} h_{k,j}}{\left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2} h_{i,j} h_{i,j}^H + \frac{K}{\bar{\gamma}_k q_j} I\right)^{-1} h_{k,j}} \quad \forall k,$$

$$g_{i,k,j} = \left| h_{i,j}^H u_{k,j} \right|^2 \quad \forall i,k, \quad Q_{j,l,k} = u_{k,j}^H Q_{j,l} u_{k,j} \quad \forall l,k.$$

The jth SCA sends the scalars $g_{i,k,j}, Q_{j,l,k} \forall k, i, l$ to the BS. The BS solves the convex optimization problem

$$\underset{p_{k,j} \geq 0 \forall k,j}{\text{minimize}} \sum_{j=0}^{S} \rho_j \sum_{k=1}^{K} p_{k,j} + P_{static}$$

$$subject\ to \quad \sum_{k=1}^{K} Q_{j,l,k} p_{k,j} \leq q_{j,l} \quad \forall j,l, \qquad (10)$$

$$\sum_{j=0}^{S} p_{k,j} g_{k,k,j} \left(1 + \frac{1}{\bar{\gamma}_k}\right) - \sum_{i=1}^{K} p_{i,j} g_{k,i,j} \geq \sigma_k^2 \quad \forall k$$

The allotment of energy $p_{k,j}^* \quad \forall k$, which gives solution for (10) is given to the jth SCA, which computes

$$w_{k,j} = \sqrt{p_{k,j}^*} u_{k,j} \quad \forall k$$

The heuristic RZF beam forming as shown in [12, 36] is applied in this algorithm which transforms the problem given in (7) into the power allocation problem given in (10), while keeping it less complex irrespective of the antenna number. Code in this case is does not give any iteration but for maintaining coordination some scalar variables are interchanged among the BS and SCA points. This change between BS and SCA points will effect only to those clients who are in the vicinity of a SCA point. Hence only few variables are interchanged for each SCA point, while all other variables are set to zero.

Relaxed zero forcing (RZF) beam forming approach is briefly explained in [37]. Based on an observation the traditional zero forcing (ZF) method tries to nullify the inter-cell interference of the mobile clients that are at the cell edges. But in order to achieve this, the complexity of the system is increased. But, if the inter-cell interference vanishes, even then thermal noise is there. Hence, there is no need to remove the inter-cell interference, but it is bounded to a certain level analogous to that of the thermal noise. Hence by relaxing the ZF interference limitations, the level of complexity is decreased and now the antenna number is increased for giving a larger rate than that of the ZF scheme.

But along with low complexity, power optimization is also an important concern. So for optimizing or minimizing the power while maintaining the low complexity, a new approach is proposed in which the optimal beam former is obtained by scaling the noise power by a factor of $\varphi_{i,j}$. Case Study 1 and the low-complexity non-iterative multiflow RZF beam forming are considered as the standard for the scaled beam forming (SBF) approach in which power optimization is provided with the low complexity. In this approach, the interference noise power in the unit norm factor is scaled by a factor of $\varphi_{i,j}$ as given in (11), for the optimal and low complex solution and is represented as

$$u_{k,j} = \frac{\left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2} h_{i,j} h_{i,j}^H + (\varphi_{i,j}) \frac{K}{\bar{\gamma}_k q_j} I\right)^{-1} h_{k,j}}{\left(\sum_{i=1}^{K} \frac{1}{\sigma_i^2} h_{i,j} h_{i,j}^H + (\varphi_{i,j}) \frac{K}{\bar{\gamma}_k q_j} I\right)^{-1} h_{k,j}} \quad \forall k, \qquad (11)$$

where $\varphi_{i,j} = (N_{BS} - 1) + (i - j)$, $i = 1, \ldots, K$ and $j = 1, \ldots, S$.

The scaling factor will scale the interference noise power while maintain the original signal power. Thus, Scaled Beam forming approach will maintain the low complexity, while optimizing the power.

The results and interpretations that have come by applying the proposed low complexity scaled beam forming approach on the MM and SC scenario for optimizing energy on different deployment scenarios are presented in Sect. 5.

4 Numerical Parameters

Scenario parameters are shown in this section of the paper, which are used for implementing the scenario shown in Fig. 1. It comprises of a circular macro cell having 4 SC access points deployed in a manner to maintain the low power consumption as proved in [47]. This scenario comprises of ten active clients inside the macro cell. Among these active clients, 6 clients are evenly spread in the entire cell, while one client is evenly spread within 40 m range of each SC access point. While the base station transmitting antenna number be $N_{BS} = 50$ and the transmitting antenna number at the SCA be $N_{SCA} = 2$. The overall performance on client locations and the information of channels are

calculated in this paper. Table 1 displays the variables that are used in the numerical calculations. It contains carrier frequency (F_c), iterations (N_I), subcarriers (N_S), bandwidth (B), subcarrier bandwidth (B_s), noise figure (N_F), noise floor (NF), transmitter number (N_T), Client number (N_U), QoS constraint ($QoS_{constraint}$), SINR constraints per client ($SINR_{constraints}$), power amplifiers Efficiency (E_{PA}), circuit power per antenna (P_C), per-antenna constraints (*Per-antenna*$_{constraints}$), UM cell radius (R_{UM}), SUM cell radius (R_{SUM}), RM cell radius (R_{RM}), least distance between the clients and the BS (D_{BS-U}^{min}), least distance between the clients and the SCA point (D_{SCA-U}^{min}) and Standard deviation (SD). It also contains the path loss models for deployment scenarios like UM heterogeneous deployment scenarios in the Case 1 and UM, SUM, and RM deployment scenario in the Case 2 as Penetration loss (P_L), Cluster size (C), Path and penetration loss at distance d (km) (PPL_d), Path and penetration loss within 40 m from SCA point (PPL_{SCA-40}),

Table 1 Numerical parameters for the scenario

	Values
F_c	2 GHz
N_I	5
N_S	600
B	10 MHz
B_s	30 kHz
N_F	5 dB
NF (dBm)	$-174 + 10\log_{10}(B_s) + N_F$
N_T	01 BS + 04 SCA
N_U	10
$QoS_{Constraint}$	2 bits/s/Hz per client
$SINR_{constraints}$	$(2^{QoS_{Constraint}-1}) * ones(N_U, 1)$
E_{PA}	$\frac{1}{\rho_0} = 0.388, \frac{1}{\rho_j} = 0.052 \forall j$
P_C	$\eta_0 = 189$ mW, $\eta_j = 5.6$ mW $\forall j$
Per-antenna$_{constraints}$	$q_{0,1} = 66, q_{j,l} = 0.08$ mW $\forall j, l$
R_{UM}	0.5 km
R_{SUM}	1.299 km
R_{RM}	1.732 km
D_{BS-U}^{min}	0.035 km
D_{SCA-U}^{min}	0.003 km
SD	7 dB
P_L	20 dB
C	0.04 km
PPL_d	$148.1 + 37.6\log_{10}(d)$ dB
PPL_{SCA-40}	$127 + 30\log_{10}(d)$ dB
PL_d^{UM}	$199.5653 + 39.0864\log_{10}(d)$ dB
PL_d^{SUM}	$180.4953 + 38.64\log_{10}(d)$ dB
PL_d^{RM}	$177.8878 + 38.64\log_{10}(d)$ dB

Path loss for UM at distance d (km) (PL_d^{UM}), Path loss for SUM at distance d (km) (PL_d^{SUM}), Path loss for RM at space/distance d (km) (PL_d^{RM}), which has already been standardized in [38–44] and the hardware parameters [31] that characterize the power consumption.

5 Numerical results

This part of paper explains the effect of applying the low complexity scaled beam forming approach on the MM and SC scenario in terms of energy/power conservation for many deployment scenarios has been incorporated. The complexity analysis has been performed on the basis of varying the UE number and transmitter antenna number on mobile towers. The optimization of this problem has been done using convex optimization [46] and algorithmic toolbox SeDuMi [45].

5.1 UM heterogeneous deployment scenario in the Case 1

For the UM heterogeneous deployment scenario in the Case 1, the numerical calculations are performed on the MM and SC scenario. The numerical result shown in Fig. 2 clearly depicts the effect of adding more transmitting antennas in number on both the mobile towers and SC entree point. Addition of extra hardware is decreasing the total power consumption ($P_{static} + P_{dynamic}$), because if there is a decrease in the dynamic part, $P_{dynamic}$, then an rise in the fixed part, P_{static}, from the additional electric circuit systems will equate it for maintaining the energy efficiency and decreasing the propagation losses.

The prime aim of maintaining the energy efficiency has already been achieved by applying the MM approach. This
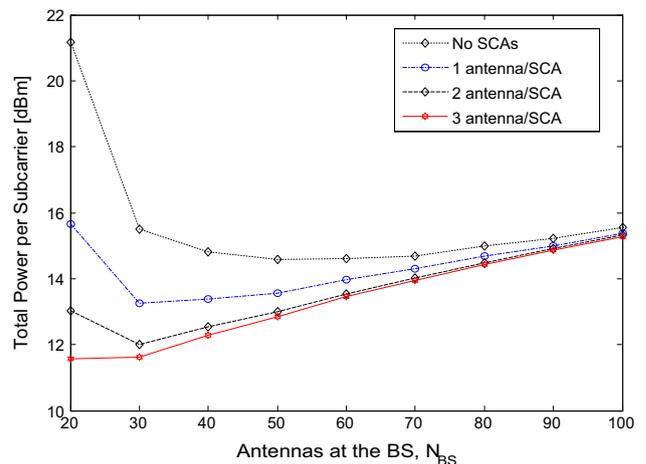
Fig. 2 Overall energy per subcarrier for different N_{BS} and N_{SCA} in the 3GPP LTE standard

can further be enhanced by deploying single antenna SCs in the areas where the density of the active clients, having half the base station transmitting antennas, is very high. This will reduce the power consumption and maintain the energy efficiency. The energy efficiency is further improved by combining and deploying the MM and multi-antenna SCs topology. This combination topology has been implemented in [47] and is also mentioned in Fig. 2. It clearly depicts that, with the increase in the transmitting antenna number on the SCs, the improvement shown is approximately tenfold. But the improvement is having certain saturation points where the increased number of antennas will not further reduce the overall energy. [16, 43].

With a probability of 0–3% of aiding a client by number of transmitters, this system also supports multiflow transmission. Which also satisfies case study 2. The main idea behind increasing the N_{SCA} to allocate more than one client to each SCA for serving completely. It is clear from Fig. 2 that the probability is 20–45% for $N_{SCA} = 3$ but it decreases, if the N_{BS} increases.

Now in Fig. 3 for different QoS constraints, consider $N_{BS} = 50$ and $N_{SCA} = 2$. In this figure, comparison of four beamforming codes is done:

1. *Optimal beamforming using only the BS antennas*
2. *Multiflow-RZF beamforming having low complexity*
3. *Scaled Beamforming explained in Sect. 3 (A)*
4. *Optimal spatial soft-cell coordination from Case Study 1.*

According to [32, Fig. 4], it is clear that by offloading clients to the SCA, power optimization can be achieved. Further improvement in power optimization can be achieved by using sensible low-complexity beam forming techniques. Figure 3 shows the comparison of low complexity techniques in terms of power optimization. The proposed Scaled beam forming approach gives promising results for practical applications as compared to traditional multiflow-RZF beam forming technique.
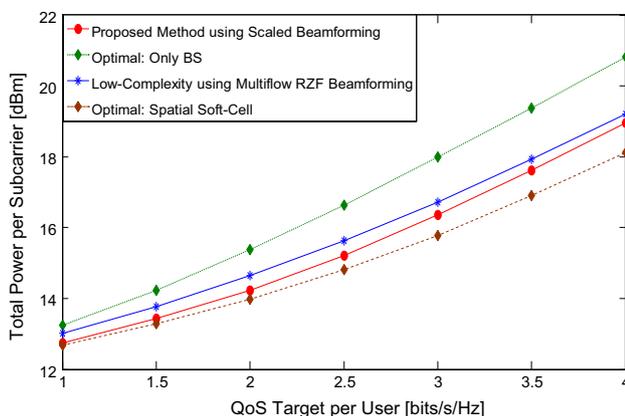
5.2 Deployment scenarios in the Case 2

Figure 3 demonstrates the comparison of low complexity techniques in terms of power optimization for Case 1. But for different deployment scenarios in the Case 2, the low complexity techniques are not optimizing the power and consumes power equals to 1st possibility of case study 2 i.e. optimal beam forming using only the mobile tower antennas. Figure 4 shows that the total power for each subcarrier in the RM scenario, which consumes less power as compared to the SUM and UM, respectively for the 3rd possibility of case study 2 i.e. optimal spatial soft-cell coordination. It is because of the reason that the density of the users according to the area is very less and the inter-ferers in the RM area are very few as compared to the SUM and UM. Hence, the total power per subcarrier in the RM area is less as compared to the SUM and UM.

5.3 Complexity analysis of the proposed approach

The complexity analysis among the four beamforming algorithms has been done on the basis of the varying UE number in the scenario and by varying the transmitting antennas at the mobile tower.

Figure 5 depicts the complexity analysis on the basis of total clients in the scenario. Obviously when the total clients in the network increases, it will correspondingly increases the complexity in the scenario, which further results in the increased power consumption. But our proposed Scaled beamforming approach will helps in achieving low complexity with optimized power, and is performing better than the other used approaches.

Fig. 3 Overall energy for each subcarrier for $N_{BS} = 50$ and $N_{SCA} = 2$ in the 3GPP LTE M.2135 Standard
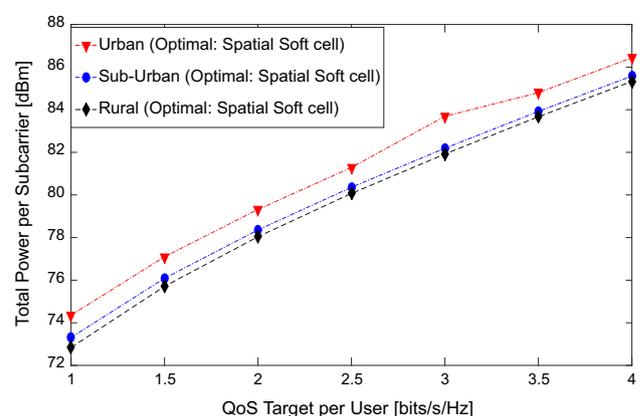
Fig. 4 Overall energy for each subcarrier for $N_{BS} = 50$ and $N_{SCA} = 2$ with different beamforming in the ITU-R M.2135 standard
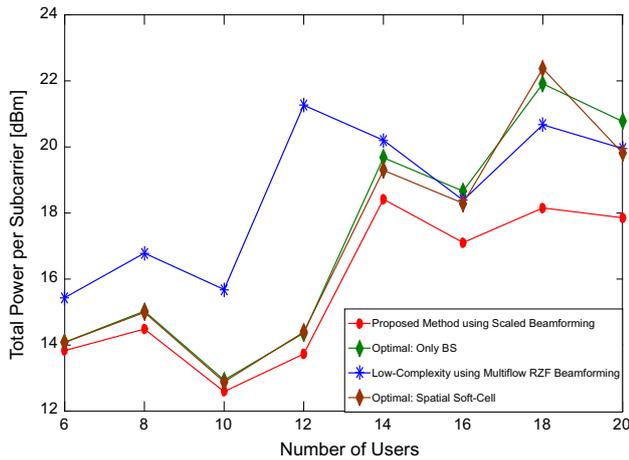
Fig. 5 Total power per subcarrier for $N_{BS} = 50$ and $N_{SCA} = 2$ with different Number of Clients and beamforming in the 3GPP LTE M.2135 Standard

In case the antenna number on the BS increase, it will add extra complexity to the network which will result in the increased power consumption. But, different beamforming techniques are applied to the scenario for reducing the complexity. It is clear from the Fig. 6 that proposed Scaled beamforming approach gives promising results in terms of optimized power for practical applications as compared to traditional RZF beam forming technique.

Complexity analysis on the basis of the client number (N_{users}) is done using the relation,

$$C = N_{users} \log_{10}(P_{av}) \tag{12}$$

While, on the basis of transmitting antenna number at the mobile towers (N_{BS}) is done using the relation,

$$C = N_{BS} \log_{10}(P_{av}) \tag{13}$$

where C is the complexity, P_{av} is the average total power consumption.
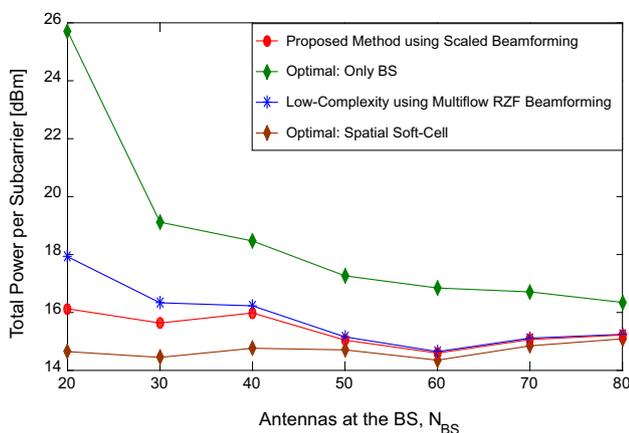
Fig. 6 Overall energy per subcarrier for different N_{BS} and beamforming, in the 3GPP LTE M.2135 standard
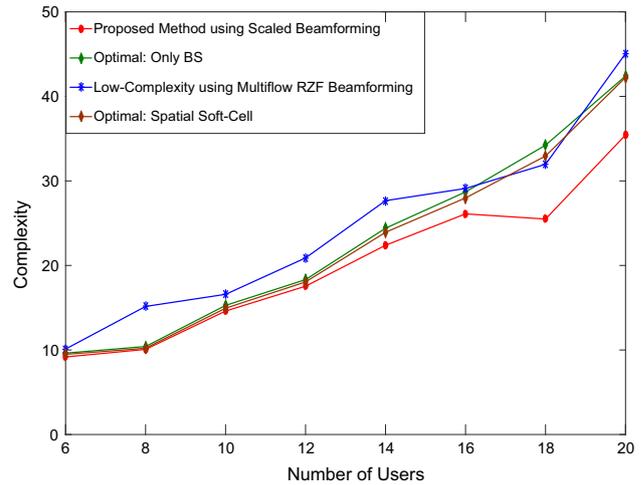
Fig. 7 Complexity analysis on the basis of number of clients, while considering the average total power consumption with $N_{BS} = 50$ and $N_{SCA} = 2$ with different Number of Clients and beamforming in the 3GPP LTE M.2135 Standard
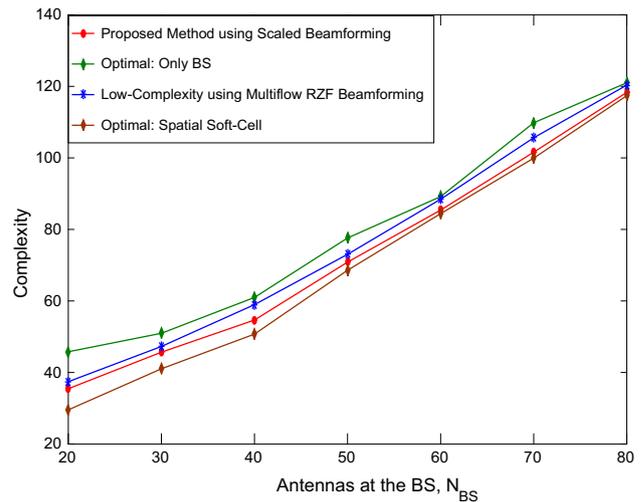
Fig. 8 Complexity analysis on the basis of number of antennas at the base station, while considering the average total power consumption with different N_{BS} and beamforming, in the 3GPP LTE standard

From Figs. 5 and 6, it is clear that, with the addition in total number of client and base station antennas, the average total power consumption increases, which makes the system more complex. Hence the complexity has a direct relation with the increase in the client number and antenna number at the base station, which will further effect the average total power consumption.

Existence of these Eqs. (12) and (13) are being validated with the existence of Shannon capacity theorem, where, the capacity has a direct relation with the bandwidth, which will further effect the SNR. The numerical results can be seen in Figs. 7 and 8 are depicting the complexity analysis

on the basis of the number of clients and number of antennas on the base station in a specific area.

It is clear from the Figs. 7 and 8 that if the number of clients in the network and number of antennas at the base station increases, it will correspondingly increase the complexity in the scenario. Since, different beamforming techniques are applied to the scenario for reducing the complexity, but the proposed Scaled beamforming approach is achieving low complexity with optimized power, and is performing better than the other used approaches.

6 Conclusion

Present day researchers are finding ways to meet the increasing demand of the clients, but are ending up consuming more power and increased complexity. In this paper, work has been done on optimization the power while maintaining low complexity. Power optimization has been achieved by modifying the classical macro-cell with MM at the BS and overlaying it with SCA points. But for maintaining the low complexity, Scaled Beamforming approach has been proposed and compared it with a classical relaxed zero-forcing beamforming, and the optimal solution cases. This paper also analyzes the potential merits of this proposed approach on the different deployment scenarios like UM heterogeneous deployment scenario in the Case 1 and UM, SUM, and RM deployment scenario in the Case 2. This paper concludes that the new proposed low complexity algorithm using scaled beamforming approach gives auspicious results for applied applications, because a bulk of the power optimization improvements are possible by sensible low complexity beamforming techniques for Case 1. But for different deployment scenarios in the Case 2, the low complexity techniques are not optimizing the power. This paper has also done the complexity analysis using the proposed Scaled Beamforming approach on the basis of varying number of clients and number of BS antennas. It is clear from the numerical calculations that the proposed Scaled beamforming approach gives promising results for practical applications as compared to traditional RZF beamforming technique.

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