QUEUE AWARE PRECODER DESIGN FOR SPACE FREQUENCY RESOURCE ALLOCATION

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ABSTRACT

The paper considers coordinated multi-cell multi-user multiple-input multiple-output (MU-MIMO) transmission using orthogonal frequency division multiplexing (OFDM) technique for downlink channels. Linear beamforming and receiving are employed at BS and corresponding users, respectively. The design criterion is to minimize the number of queued packets, since the transmission is mainly guided by the backlogged packets. An indirect way to solve this problem is to associate the weights of the traditional weighted sum rate maximization scheme with the current status of the queue size, i.e., the longer queue, the higher priority. We deal with this problem directly by formulating it as a noncovex optimization problem and then applying a sequential convex approximation method to find beamformers. In particular, we propose an efficient resource allocation scheme based on jointly optimizing beamformers over the space and frequency domain. We refer to this scheme as queue minimizing (QM) joint space-frequency resource allocation (JSFRA) scheme. The proposed solutions are compared to the traditional queue weighted sum rate maximization (Q-WSRM) approaches mentioned above in terms of the rate of convergence and the backlogged packets remaining after a scheduling instant.

I. INTRODUCTION

We consider the problem of resource allocation for a multi-cell multi-user multiple-input multiple-output (MU-MIMO) transmission over an orthogonal frequency division multiplexing (OFDM) system with the objective of minimizing the total number of backlogged packets of all users at a given instant. The available space and frequency resources in the considered system are shared among the users by base station (BS) cooperation in order to minimize the number of packets waiting for transmission from each BS to the respective users. In this paper, beamforming technique is utilized at BSs and linear single-user detection is employed at each receiver, i.e., the inter-user interference is treated as background noise. The queue minimizing network optimization objective is used to design beamformers across the coordinating BSs, since the transmissions are guided by the available backlogged packets. To achieve the best performance, we propose a joint resource allocation scheme over the space and frequency dimensions among the coordinating BSs to minimize the time that the packets stay in queues prior to transmission, and, hence, to avoid packet drops as an indirect objective.

Many existing beamformer designs for similar system models addresses the problem of weighted sum rate maximization (WSRM) objective. By adjusting the weights properly, we can use the WSRM schemes to achieve other performance measures. For example, if the weight of each user is set to be inversely proportional to his/her data rate, a WSRM scheme can maintain fairness among users. Similarly, the WSRM schemes can be used to solve the design problem considered in this paper. Specifically, to find a rate vector that minimizes the number of queued packets, we should assign weights based on the current queue size of users. More explicitly, the queue states can be incorporated to traditional weighted sum rate objective $\sum_k w_k R_k$ by replacing the weight w_k with the corresponding queue state Q_k or a function depending on it [1], where the queue weighted sum rate maximization (Q-WSRM) scheme is the outcome of minimizing the Lyapunov drift between the current and the future queue states.

The topic of multiple-input multiple-output (MIMO) broadcast channel (BC) precoder design has been studied extensively with different performance criteria in the literature. For the problem of WSRM utility, due to the nonconvex nature of the linear MIMO BC precoder design, [2], [3] addressed the problem using a reformulation via minimum mean squared error (MMSE), casting the problem as a convex one for fixed receivers. In this way, the original problem is expressed in terms of the mean squared error (MSE) weight, precoders, and decoders. Then the problem is solved using an alternating optimization method, i.e., finding a set of variables while the remaining others are fixed. The WSRM problem using an alternative MMSE reformulation along with the additional rate constraints is considered in [4]. A fast converging algorithm for the WSRM problem is proposed in [5] using a surrogate for a convex program at each iteration.

Earlier work on the queue minimization problem was addressed in the survey paper [6] and in particular [7], where the problem of optimal power allocation is considered to minimize the number of backlogged packets via geometric programming formulation. Since the problem considered in [7] assumes multi-user OFDM model without multi-antenna support, the queue minimizing scheduling reduces to the problem of optimal power allocation.

In this paper, we consider the problem of designing the precoders for a MU-MIMO OFDM scenario jointly across space-frequency dimension to minimize the number of queued packets associated with the users. We compare the performance of the proposed queue minimizing (QM) joint space-frequency resource allocation (JSFRA) scheme over the Q-WSRM scheme performed over each sub-channel, where the weights are updated after each sub-channel with the unserved packets. We show that the JSFRA scheme provides better performance over the sub-channel wise resource allocation technique like Q-WSRM scheme.

II. SYSTEM MODEL

We consider an OFDM system with N sub-channels and N_B BSs each equipped with N_T transmit antennas, serving K users

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each with N_R receive antennas. The users associated with BS b is denoted by $\mathcal{U}_b$ and the set $\mathcal{U}$ represents all users in the system, i.e., $\mathcal{U} = \underset{b\in\mathcal{B}}{\cup}\mathcal{U}_b$, where the set $\mathcal{B}$ holds the coordinating BSs. The serving BS of user k is denoted by $b_k \in \mathcal{B}$. We denote by $\mathcal{C} = \{1, 2, \ldots, N\}$ the set of all sub-channel indices available in the system.

In this paper we adopt linear beamforming technique at BSs. Specifically, the data symbols $d_{l,k,n}$ for user k on the l^{th} spatial stream over the sub-channel n is multiplied with the beamformer $\mathbf{m}_{l,k,n} \in \mathbb{C}^{N_T\times 1}$ for transmission. In order to detect multiple spatial streams at the receiver, a receive beamforming vector $\mathbf{w}_{l,k,n}$ is employed at each user. Consequently, the received signal of the l^{th} spatial stream over sub-channel n^{th} at user k is given by

$$y_{l,k,n} = \mathbf{w}_{l,k,n}^H \mathbf{H}_{b_k,k,n}\,\mathbf{m}_{l,k,n} d_{l,k,n} + \mathbf{w}_{l,k,n}^H \sum_{i\in\mathcal{U}\setminus\{k\}} \mathbf{H}_{b_i,k,n} \sum_{j=1}^{L} \mathbf{m}_{j,i,n} d_{j,i,n} + \tilde{n}_{l,k,n} \quad (1)$$

where $\mathbf{H}_{b,k,n} \in \mathbb{C}^{N_R\times N_T}$ with rank $L = \min(N_R, N_T)$ is the channel between the BS b and user k on the sub-channel n, and $\tilde{n}_{l,k,n} = \mathbf{w}_{l,k,n}^H \mathbf{n}_{k,n}$, where $\mathbf{n}_{k,n} \sim \mathcal{CN}(0, N_0)$ is the additive noise vector for the user k on the n^{th} sub-channel and l^{th} spatial stream. Assuming $||\mathbf{w}_{l,k,n}||_2^2 = 1$ and independent detection of data streams, we can write the signal-to-interference-plus-noise ratio (SINR) as

$$\gamma_{l,k,n} = \frac{\left|\mathbf{w}_{l,k,n}^H\,\mathbf{H}_{b_k,k,n}\,\mathbf{m}_{l,k,n}\right|^2}{N_0 + \sum_{(j,i)\neq(l,k)} |\mathbf{w}_{l,k,n}^H \mathbf{H}_{b_i,k,n}\mathbf{m}_{j,i,n}|^2}. \quad (2)$$

With the infinite buffer model assumption, let Q_k be the number of backlogged packets which are destined for the user k at a given scheduling instant. The queue dynamics of the user k are modeled using the Poisson arrival process with the average packet arrivals of $A_k = \mathbf{E}_i\{\lambda_k\}$ pkts/bits, where $\lambda_k(i) \sim \text{Pois}(A_k)$ represents the instantaneous number of packets arriving for the user k at the i^{th} instant. The total number of queued packets at the i^{th} instant for the user k depend on the fresh arrivals at the i^{th} instant and the total number of backlogged packets $Q_k(i-1)$ as given by

$$Q_k(i) = \Big[Q_k(i-1) - t_k(i-1)\Big]^+ + \lambda_k(i), \quad (3)$$

where t_k denote the transmissions in packets/bits and $[x]^+ = \max\{x, 0\}$. The total number of transmitted bits for the user k is given by $t_k(i) = \sum_{n=1}^{N}\sum_{l=1}^{L} t_{l,k,n}(i)$, where $t_{l,k,n}$ is the total number of bits that can be transmitted over l^{th} spatial stream and on n^{th} sub-channel at the i^{th} instant. Note that the units of t_k and Q_k are in pkts/bits defined per channel use.

III. PROBLEM FORMULATION

Since beamformers are designed to minimize the number of backlogged packets at each scheduling instant without considering future arrivals, we will drop the time index i in the sequel for notational simplicity. For practical and tractability reasons, we impose a constraint that the maximum number ofr transmitted bits for the user k is limited by the packets available at the transmitter. As a result, the number of backlogged packets remaining in the system is given by

$$v_k = Q_k - \sum_{n=1}^{N}\sum_{l=1}^{L} t_{l,k,n} \geq 0 \;\forall\; k \in \mathcal{U}. \quad (4)$$

The problem of weighted queued packet minimization is formulated as a q-norm minimization as follows

$$\begin{aligned} \underset{t_{l,k,n},\mathbf{m}_{l,k,n},\,\mathbf{w}_{l,k,n}}{\text{minimize}} \quad & \|\tilde{\mathbf{v}}\|_q && (5a)\\ \text{subject to} \quad & t_{l,k,n} \leq \log_2(1+\gamma_{l,k,n}) && (5b)\\ & \sum_{n=1}^{N}\sum_{k\in\mathcal{U}_b} \text{tr}\left(\mathbf{M}_{k,n}\mathbf{M}_{k,n}^H\right) \leq P_{\max},\ \forall\, b, && (5c) \end{aligned}$$

where $\tilde{v}_k \triangleq a_k^{1/q} v_k$, a_k is the weighting factor which is incorporated to control user priority based on their respective quality of service (QoS), $\gamma_{l,k,n}$ is defined in (2), and $\mathbf{M}_{k,n} \triangleq [\,\mathbf{m}_{1,k,n}\,\mathbf{m}_{2,k,n}\ldots\mathbf{m}_{L,k,n}\,]$ comprises the beamformers associated with the user k for n^{th} sub-channel transmission. The constraint in (5b) is due to the assumption of Gaussian signalling, so that the maximum achievable rate is $\log_2(1+\gamma_{l,k,n})$ for a given signal-to-interference-plus-noise ratio (SINR) $\gamma_{l,k,n}$. In (5c), we consider the sum power constraint for each BS across all sub-channels. The proposed solution presented in the next section also applies to the sub-channel power constraint by replacing (5c) by corresponding formulations. Before proceeding further, we note that the constraint in (4) is handled implicitly by the definition of the q-norm in the objective of (5). As a proof, suppose that $t_k > Q_k$ for a certain k at optimum, i.e., $-v_k = t_k - Q_k > 0$. Then there exists $\delta_k > 0$ such that $-v_k' = t_k' - Q_k < -v_k$ where $t_k' = t_k - \delta_k$. Since $\|\tilde{\mathbf{v}}\|_q = \||\tilde{\mathbf{v}}|\|_q = \||-\tilde{\mathbf{v}}|\|_q$, this means that the newly created vector $\mathbf{t}'$ achieves a smaller objective which contradicts with the fact that an optimal solution has been obtained. We comment on the choice of the norm q on the objective as below [6], [7].

- With $q = 1$, the objective results in greedy allocation *i.e*, emptying the queue of users with good channel condition before considering the users with worse channel conditions. For this case, it is easy to see that (5) reduces to the WSRM problem when the queue size is large enough for all users.
- With $q = 2$, the objective prioritizes users with higher queued packets before considering the users with a smaller number of backlogged packets. This is ideal for the delay limited scenario when the packet arrival rates of the users are similar, since the backlogged packets is proportional to the delay in the transmission.
- With $q = \infty$, the objective minimizes the maximum number of queued packets with the current transmission, thereby providing queue fairness by allocating the resources proportional to the number of backlogged packets.

IV. PROPOSED SOLUTION

This section presents an iterative algorithm to solve (5) locally based on the idea of alternating optimization and successive convex approximation. For this purpose, from (2), we can explicitly reformulate (5) as

$$\begin{aligned} \text{minimize} \quad & \|\tilde{\mathbf{v}}\|_q && (6a)\\ \text{subject to} \quad & \gamma_{l,k,n} \leq \frac{\left|\mathbf{w}_{l,k,n}^H\,\mathbf{H}_{b_k,k,n}\,\mathbf{m}_{l,k,n}\right|^2}{\beta_{l,k,n}} \triangleq f(\tilde{\mathbf{u}}_{l,k,n}), && (6b)\\ & \beta_{l,k,n} \geq N_0 + \sum_{(j,i)\neq(l,k)} |\mathbf{w}_{l,k,n}^H \mathbf{H}_{b_i,k,n}\mathbf{m}_{j,i,n}|^2, && (6c)\\ & \text{(5b)}, \text{(5c)} && (6d) \end{aligned}$$

where $\tilde{\mathbf{u}}_{l,k,n} \triangleq \{\mathbf{w}_{l,k,n}^H, \mathbf{H}_{b_k,k,n}, \mathbf{m}_{l,k,n}, \beta_{l,k,n}\}$. In fact we have replaced the equality in (2) by the inequalities in (6b) and (6c). However, this step is without loss of optimality since it can be easily proved that the inequalities in (6b) and (6c) are active for an optimal solution, following the same arguments as those in [5]. Intuitively, (6b) denotes the SINR constraint for $\gamma_{l,k,n}$, and (6c) gives an upper bound for the interference seen by the user $k \in \mathcal{U}_b$. The problem in (6) is known to be NP-hard even for the single antenna case [3], [4]. The reformulation in (6) allows a tractable solution as presented below. First, we note that the constraints (5b) and (5c) are convex with involved variables. Thus, we only need to deal with (6b) and (6c). Towards this end, we resort to the traditional coordinate descent technique by fixing the transmit beamformers, and find the optimal linear receivers. The optimal linear receiver for the fixed transmit precoders $\mathbf{M}_{i,n}\, \forall i \in \mathcal{U}$, $\forall n \in \mathcal{C}$ is obtained by minimizing (5), as given by

$$\mathbf{w}_{l,k,n} = \mathbf{R}_{l,k,n}^{-1}\, \mathbf{H}_{b_k,k,n}\, \mathbf{m}_{l,k,n}, \tag{7a}$$

$$\mathbf{R}_{l,k,n} = \sum_{(j,i)\neq(l,k)} \mathbf{H}_{b_i,k,n}\mathbf{m}_{j,i,n}\mathbf{m}_{j,i,n}^H\mathbf{H}_{b,k,n}^H + \mathbf{I}_{N_R}, \tag{7b}$$

which is the MMSE receive beamformers [2]–[4].

Algorithm 1: Algorithm of JSFRA scheme

Input: $a_k,\, Q_k,\, \mathbf{H}_{b,k,n},\ \forall\, b \in \mathcal{B},\ \forall\, k \in \mathcal{U},\ \forall\, n \in \mathcal{C}$
Output: $\mathbf{m}_{l,k,n}$ and $\mathbf{w}_{l,k,n}\ \forall\, l \in \{1, 2, \ldots, L\}$
Initialize: $i = 0$ and the transmit precoders $\tilde{\mathbf{m}}_{l,k,n}$ randomly satisfying the total power constraint (5c)
update $\mathbf{w}_{l,k,n}$ with (7b) and $\tilde{\mathbf{u}}_{l,k,n}$ with (9) using $\tilde{\mathbf{m}}_{l,k,n}$
repeat
  solve for the transmit precoders $\mathbf{m}_{l,k,n}$ using (10)
  update $\tilde{\mathbf{u}}_{l,k,n}$ with the current update of $\mathbf{u}_{l,k,n}$ using (9)
  update the receive beamformers $\mathbf{w}_{l,k,n}$ using (7b) with the recent precoders $\mathbf{m}_{l,k,n}$
  $i = i + 1$
until *convergence or* $i \geq I_{\max}$

The problem now is to find optimal transmit beamformers for a given set of linear receivers which is a challenging task. We note that for fixed $\mathbf{w}_{l,k,n}$, (6c) can be written as a second-order cone (SOC) constraint. Thus, the difficulty is due to the non-convexity in (6b). To arrive at a tractable formulation, we adopt the successive convex approximation (SCA) method to handle (6b). Note that the function $f(\tilde{\mathbf{u}}_{l,k,n})$ in (6b) is convex for fixed $\mathbf{w}_{l,k,n}$ since it is in fact the ratio between a quadratic form (of $\mathbf{m}_{l,k,n}$) over an affine function (of $\beta_{l,k,n}$) [8]. According to the SCA method, we relax (6b) to a convex constraint in each iteration of the iterative procedure. Since $f(\tilde{\mathbf{u}}_{l,k,n})$ is convex, a convex approximation of (6b) can be easily found by considering the first order approximation of $f(\tilde{\mathbf{u}}_{l,k,n})$ around the current operation point. For this purpose, let the real and imaginary component of the complex number $\mathbf{w}_{l,k,n}^H\mathbf{H}_{b_k,k,n}\mathbf{m}_{l,k,n}$ be represented by

$$p_{l,k,n} \triangleq \Re\left\{\mathbf{w}_{l,k,n}^H\mathbf{H}_{b_k,k,n}\mathbf{m}_{l,k,n}\right\}, \tag{8a}$$

$$q_{l,k,n} \triangleq \Im\left\{\mathbf{w}_{l,k,n}^H\mathbf{H}_{b_k,k,n}\mathbf{m}_{l,k,n}\right\}, \tag{8b}$$

and hence $f(\tilde{\mathbf{u}}_{l,k,n}) = (p_{l,k,n}^2 + q_{l,k,n}^2)/\beta_{l,k,n}$. Note that $p_{l,k,n}$ and $q_{l,k,n}$ are just symbolic notation and not the newly introduced optimization variables. In CVX [9], we declare $p_{l,k,n}$ and $q_{l,k,n}$ with the 'expression' qualifier. Suppose that the current value of $p_{l,k,n}$ and $q_{l,k,n}$ at a specific iteration are $\tilde{p}_{l,k,n}$ and $\tilde{q}_{l,k,n}$, respectively. Using the first order Taylor approximation around the local point $[\,\tilde{p}_{l,k,n}, \tilde{q}_{l,k,n}, \tilde{\beta}_{l,k,n}\,]^T$, we can approximate (6b) by the following linear inequality constraint

$$2\frac{\tilde{p}_{l,k,n}}{\tilde{\beta}_{l,k,n}}\,(p_{l,k,n} - \tilde{p}_{l,k,n}) + 2\frac{\tilde{q}_{l,k,n}}{\tilde{\beta}_{l,k,n}}\,(q_{l,k,n} - \tilde{q}_{l,k,n}) + \frac{\tilde{p}_{l,k,n}^2 + \tilde{q}_{l,k,n}^2}{\tilde{\beta}_{l,k,n}}\left(1 - \frac{\beta_{l,k,n} - \tilde{\beta}_{l,k,n}}{2\,\tilde{\beta}_{l,k,n}}\right) \geq \gamma_{l,k,n}. \tag{9}$$

In summary, for fixed linear receivers, the optimization problem to find transmit beamformers is written as

$$\underset{\substack{t_{l,k,n},\gamma_{l,k,n}\\ \mathbf{m}_{l,k,n},\beta_{l,k,n}}}{\text{minimize}} \quad \|\tilde{\mathbf{v}}\|_q \tag{10a}$$

$$\text{subject to} \quad (5\text{b}), (5\text{c}), (6\text{c}), \text{and } (9). \tag{10b}$$

The proposed algorithm is referred as QM JSFRA scheme with a sum power constraint which is outlined in Algorithm 1. The iterative procedure repeats until the improvement on the objective is less than a predetermined tolerance parameter or the maximum number of iterations is reached. Instead of initializing $\tilde{\mathbf{u}}_{l,k,n}$ arbitrarily to a feasible point, transmit precoders can also be initialized with any feasible point $\tilde{\mathbf{m}}_{l,k,n}$, which is then used to find $\tilde{\mathbf{u}}_{l,k,n}$ in an efficient manner as briefed in Algorithm 1.

In the proposed solution, we replaced (6b) by a convex constraint using the first order approximation, which basically means that we not solve the problem exactly. According to the traditional block coordinate descent method (BCDM), we need to solve a subproblem when fixing a set of variables to the global optimum to ensure the convergence to a stationary point. If we just approximate the objective, then the convergence is guaranteed [10]. In our case, we solve the subproblem inexactly, so the convergence proof of BCDM does not apply to our problem. Recall that [3] only approximates the nonconvex objective in each iteration. In this problem, using alternating optimization with SCA method provides monotonic convergence since the objective is improved at each step *i.e* $f^{(i)} \geq f^{(i+1)}$, assuming $f^{(i)}$ is the objective function at the i^{th} SCA iteration. In a single receive antenna case, the proposed solution is guaranteed to converge as discussed in [5].

IV-A. Per Sub-Channel Resource Allocation Schemes

In this section, we consider the QM spatial resource allocation (SRA) scheme, which limits the resource allocation over the spatial dimension by limiting the JSFRA design over a single sub-channel only. For a scheduling slot, the precoders are designed for each sub-channel in a sequential manner by updating the queues before designing the spatial precoders with the allocations made from the previous sub-channels on the same scheduling instant.

The queue update is common for SRA and Q-WSRM schemes, which controls the design of precoders for the allocation of spatial resources for each sub-channel. The queues are updated before designing the precoders for each sub-channel n as

$$Q_{k,n} = \max\Big\{Q_k - \sum_{j=1}^{n-1}\sum_{l=1}^{L} t_{l,k,j}, 0\Big\},\ \forall\, k \in \mathcal{U} \tag{11}$$

where Q_k is given by (3) for the user k. The weight for the sub-channel n is given by (11), which uses the allotted transmission bits $t_{l,k,j}$ evaluated from the earlier sub-channels $j < n$.

k	$n=1$			$n=2$			$n=3$		
	h	a	b	h	a	b	h	a	b
1	1.70	0	4.91	0.52	0	0	0.55	2.04	0
2	0.39	0	0	1.41	4.39	4.39	1.02	0	0
3	2.34	5.81	0	1.25	0	0	2.31	0	5.77

Table I. Sub channel wise allocation for a scheduling instant

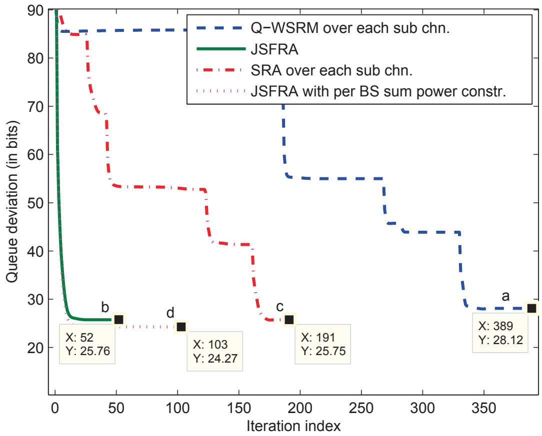

Fig. 1. Queue deviation convergence plot for a 4×1 system

V. SIMULATION RESULTS

First, we consider a system operating at 10 dB signal-to-noise ratio (SNR) with $N_T = N_R = 1$, $N = 3$ sub-channels, and $K = 3$ users, each having $Q_k = 6$ bits to be transmitted. Table I denotes the channel gain over each sub-channel by h and the allocated packets for users by Q-WSRM and JSFRA schemes on each band as a and b respectively. It can be seen that the Q-WSRM scheme with the rates allocated on each sub-channel as shown in Table I, the total number of backlogged packets after the current scheduling is $\zeta = 5.76$ bits, where $\zeta = \sum_{k=1}^{K} [Q_k - t_k]^+$. On contrary, the JSFRA scheme allocates the resource for all users across the sub-channels more effectively leaving only $\zeta = 2.93$ bits after the current instant as shown in Table I. The precoder design for the optimal allocation in Q-WSRM depends on the order of selecting the sub-channels, which leads to an exhaustive search.

To study the performance in a MIMO framework, we consider $N = 5$ sub-channels with $N_B = 2$ BSs, each equipped with $N_T = 4$ transmit antennas operating at 10dB SNR, serving $K = 8$ users with N_R antennas each. The users are dropped near the cell-edge of each BS with the maximum path-loss ratio seen by any user is limited to 0.75dB, with $|\mathcal{U}_b| = 4, \forall b \in \mathcal{B}$.

Fig. 1 shows the performance of the above discussed schemes for a single receive antenna system. The figure compares the total number of SCA iterations required by the JSFRA, JSFRA with sum power constraint, SRA and Q-WSRM schemes to achieve the optimal resource allocation to minimize the number of backlogged packets during the given scheduling instant. The convergence of the proposed JSFRA is much quicker compared to the band-wise allocation schemes like Q-WSRM and SRA. The waterfall like behaviour for the band allocation schemes suggests the rapid convergence when there is a transition from the current sub-channel to the next one. The convergence at each sub-channel is iterated for the accuracy $\approx 10^{-4}$ or for predetermined count $I_{\max}$, which creates the flat region between each waterfall behaviour. The backlogged bits and the iteration count by various schemes at the convergence point are marked in the figures using data tips.

q	user indices								ζ
1	12.0	6.15	5.32	12.0	6.95	11.1	11.9	10.8	19.71
2	11.9	7.3	5.9	10.1	9.19	10.1	10.8	10.3	20.48
∞	9.15	9.15	9.15	9.15	9.16	9.15	9.15	9.15	22.75

Table II. Queue information for $N = 5$ sub-channels

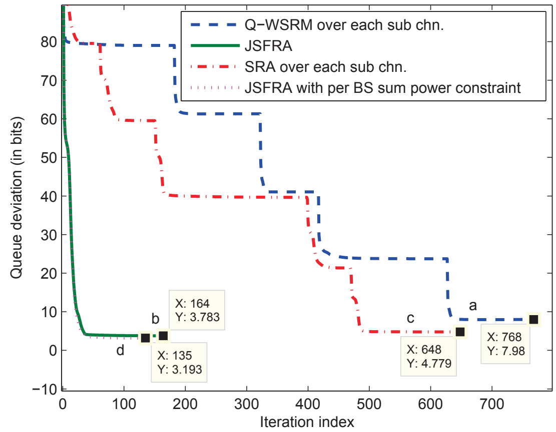

Fig. 2. Queue deviation convergence plot for a 4×2 system

Fig. 2 compares the convergence behaviour of the precoder designs, which allocates the space-frequency resources to the users to minimize the number of backlogged packets. Different values for the exponent q are compared in Table II for the system configuration $\{N_B, K, N_T, N_R\} = \{2, 8, 4, 1\}$. It is evident that the exponent $q = 1$ shows the greedy resource allocation in comparison with the fair scheduling achieved using $q = \infty$. The number of backlogged packets at each user before the current scheduling is fixed to be 12 bits.

VI. CONCLUSIONS

In this paper, we proposed algorithms to minimize the number of queued packets in a coordinated manner by designing the precoders jointly across the space-frequency dimension for a multi-cell multi-user multiple-input multiple-output (MU-MIMO) system. The proposed queue minimizing (QM) joint space-frequency resource allocation (JSFRA) scheme adopting the successive convex approximation (SCA) technique models the nonconvex constraint as a convex constraint in an iterative manner to design the precoders for the QM objective. The JSFRA scheme provides better convergence and performance over the traditional per sub-channel queue weighted sum rate maximization (Q-WSRM) approach with the proper queue updates. The impact of varying the exponent used in the objective were also studied with the number of packets remained after the scheduling instant. The decentralized version, which provides independent precoder design with the minimal information exchange will be addressed in our future work.

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