Distributed Optimization of Transceiver Weights in MIMO Two-way Multihop Networks

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***Abstract*—We investigate the joint optimization of power allocation and transceiver weights in multiple-input multiple-output (MIMO) two-way multihop networks. The objective is to maximize the minimum weighted signal-to-interference-plus noise power ratio (SINR) of the multihop links while satisfying general linear power constraints at the transmit nodes. First, we derive a distributed power allocation algorithm by extending the notion of link SINR metric and analyze its convergence and optimality. Using that result, we propose an alternating optimization algorithm for solving the more complex MIMO transceiver weight optimization. We compare its performance against those of centralized and conventional schemes through numerical simulations. Our results show that the proposed algorithm provides considerable improvement to the end-to-end rate of multihop networks. In fact, it achieves, with low complexity and low coordination overhead, a rate performance close to an upper-bound that was obtained from a centralized optimization with a relaxed power constraint.**

I. Introduction

Wireless mesh networks have several benefits including a distributed architecture, coverage extension, and ease of deployment [1]. These features make them particularly suitable for new mobile applications. However, current mesh networks suffer from a low spectral efficiency due to the multihop transmission and to interference avoidance protocol [2].

Instead of assigning orthogonal channels for the multihop links, we employ multiple-input multiple-output (MIMO) communication to enable the links to share the same spectrum. In fact, it creates parallel subchannels on which the links simultaneously transmit their streams [3]. A fundamental problem is that the degrees of freedom, or the maximum number of non-interfering streams, is limited by the number of antennas at the transmit and receive nodes. Considering this fact, an early idea in [4] cancels only the adjacent interference along the multihop path and treats the weaker interference from far nodes as additional noise. This *baseline scheme* in [4], [5] was extended with power control in [6] .

Interference alignment is known to achieve, in high SINR, the full degrees of freedom of MIMO interference networks [7] by aligning the interfering streams in a low dimensional subspace at each non-intended receiver. Since analytical solutions are in general difficult to find, iterative interference alignment schemes, such as the *max-SINR* algorithm, were proposed in [8]. However, the *max-SINR* algorithm only searches for the interference-aligned transceiver weights and ignores the power allocation problem.

Most studies on MIMO transceiver optimization in interference channels have focused on maximizing the system efficiency or minimizing the power consumption under QoS constraints. For instance, a game theoretical approach was investigated in [9], [10] to maximize the sum rate. On the other hand, alternating algorithms for power minimization were developped in [11], [12] by using the SINR duality or reciprocity concept. Since this later only works with a sum power constraint, it is not suitable for distributed MIMO networks such as multihop networks. In reality, the transmit nodes in two-way multihop networks have multiple linear power constraints.

This work investigates the problem of maximizing the weighted minimum link SINR while satisfying general linear power constraints. This objective is relevant and practical for MIMO multihop networks. First, it makes the optimization problem always feasible in contrast to power minimization problem, which can be infeasible with stringent QoS constraints. In addition, the weights corresponding to the link SINRs allow to define link priorities which are desired when the traffic loads at the nodes may be different, or when there are multiple source/destination pairs in the network. Importantly, we take into account general linear power constraints which naturally occur in distributed MIMO networks.

For simplicity, we use beamforming, i.e. a single stream is transmitted in each multihop link. This assumption is reasonable since multiplexing more streams results in more interference given the limited number of antennas [13].

Since this optimization problem is non-convex and hard to solve, we optimize the power allocation and the transceiver weights in an alternating and iterative manner. In other words, the power allocation is solved while keeping the transceiver weights fixed, and vice versa. To optimize the power allocation, we derive a new distributed algorithm that provably converges to the optimal solution. Although we borrow the notion of SINR metric introduced in [14], our algorithm works with multiple weighted linear power constraints. As a special case, it implies the per-link power constraints in [14]. Then, we employ iterative MMSE filters to optimize the transmit and receive weights.

The rest of this paper is organized as follows. Section II presents the multihop network model and formulates the optimization problem. In Section III, we derive a direct solution to the power allocation problem, then we propose a distributed algorithm for the joint optimization problem in Section IV.

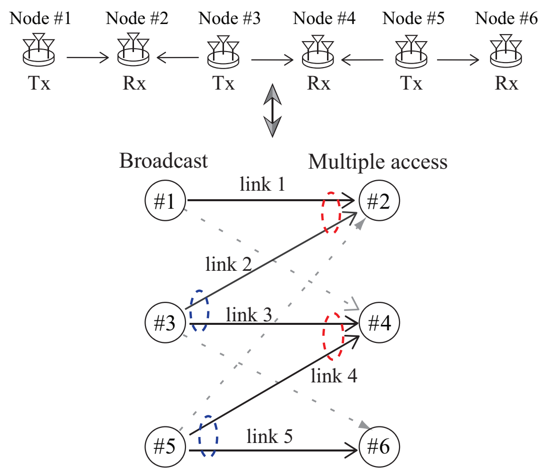

Figure 1. Model of MIMO two-way multihop network.

Finally, numerical results are presented in Section V to verify the effectiveness of our scheme and compare its performance against those of conventional ones.

II. Network model and Problem formulation

We consider a general MIMO network model in which the transmit and receive nodes form a combination of multiple interfering broadcast and multiple access channels. In this network, a transmit node can send independent streams to different intended receive nodes whereas a receive node can decode multiple streams from different transmit nodes. An example of such network is the MIMO two-way multihop network illustrated in Figure 1.

We assume here that only one data stream is transmitted within each MIMO link, and that each node is equipped with M antennas. In the network, the received signal $\mathbf{y}_l$ at the receive node of link l is then:

$$\begin{aligned}\mathbf{y}_l &= \sum_{k=1}^{L} \mathbf{H}_{l,k}\mathbf{x}_k + \mathbf{n}_l \\ &= \sqrt{p_l}\mathbf{H}_{l,l}\mathbf{t}_l s_l + \sum_{k\neq l} \sqrt{p_k}\mathbf{H}_{l,k}\mathbf{t}_k s_k + \mathbf{n}_l \qquad (1)\end{aligned}$$

where L is the total number of links in the network; $\mathbf{H}_{l,k} \in \mathbb{C}^{M\times M}$ denotes the channel matrix between the receive node r_l of link l and the transmit node t_k of link k; and $\mathbf{n}_l \in \mathbb{C}^M$ is a Gaussian noise vector with a covariance matrix $\sigma^2\mathbf{I}_M$; p_k is the power allocated for link k.

Before transmission, the unit power signal s_l of link l is amplified by $\sqrt{p_l}$, then precoded by the unit-norm transmit weight vector $\mathbf{t}_l \in \mathbb{C}^M$. Then, the intended receive node filters the signal $\mathbf{y}_l$ with a receive weight vector $\mathbf{r}_l \in \mathbb{C}^M$ to extract the desired signal.

Therefore, the SINR for the link l can be written as:

$$\begin{aligned}\mathrm{SINR}_l &= \frac{p_l \left|\mathbf{r}_l^\dagger \mathbf{H}_{l,l}\mathbf{t}_l\right|^2}{\sum_{k\neq l} p_k \left|\mathbf{r}_l^\dagger \mathbf{H}_{l,k}\mathbf{t}_k\right|^2 + \sigma^2} \qquad (2)\\ &= \frac{p_l G_{l,l}}{\sum_{k\neq l} p_k G_{l,k} + \sigma^2} \qquad (3)\\ &= \frac{p_l \mathbf{r}_l^\dagger \left(\mathbf{H}_{l,l}\mathbf{t}_l\mathbf{t}_l^\dagger\mathbf{H}_{l,l}^\dagger\right)\mathbf{r}_l}{\mathbf{r}_l^\dagger \mathbf{\Omega}_l \mathbf{r}_l} \qquad (4)\end{aligned}$$

where $G_{l,k} = \left|\mathbf{r}_l^\dagger \mathbf{H}_{l,k}\mathbf{t}_k\right|^2$ is the effective channel gain between node r_l and node t_k, and $\mathbf{\Omega}_l = \sum_{k\neq l} p_k \mathbf{H}_{l,k}\mathbf{t}_k\mathbf{t}_k^\dagger\mathbf{H}_{l,k}^\dagger + \sigma^2\mathbf{I}_M$ is the interference-plus-noise covariance matrix.

Now, our aim is to balance the weighted SINRs of the links in the network while satisfying the multiple linear power constraints at the transmit nodes. It results in the following max-min optimization problem:

$$(\mathcal{P}_1)\begin{cases} \underset{\mathbf{p},\mathbf{T},\mathbf{R}}{\text{maximize}} & \min_l \frac{\mathrm{SINR}_l}{\Gamma_l} \\ \text{subject to} & \mathbf{w}_{t_l}^\intercal \mathbf{p} \leq P_{t_l}, \;\; l = 1, ..., L \end{cases} \qquad (5)$$

in which the optimization variables are the power allocation vector $\mathbf{p} = [p_1 \cdots p_L] \in \mathbb{R}^L$, the transmit antenna weights $\mathbf{T}_l = [\mathbf{t}_1 \cdots \mathbf{t}_L] \in \mathbb{C}^{M\times L}$ and the receive antenna weights $\mathbf{R}_l = [\mathbf{r}_1 \cdots \mathbf{r}_L] \in \mathbb{C}^{M\times L}$ of every links. In our formulation, a general linear power constraint is imposed on each transmit node. The linear constraint at the node t_l is defined by the weight $\mathbf{w}_{t_l} = [w_{t_l,1} \cdots w_{t_l,L}] \in \mathbb{R}^L$, and P_{t_l} denotes its maximum power. Note that two different links l and k may originate from a same transmit node so that $t_l = t_k$. Moreover, the parameters Γ_l define the priorities assigned to the links, and they can be determined, for instance, based on the traffic load at each node. Clearly, problem $(\mathcal{P}_1)$ is hard to solve since the SINR is a non-convex function of the transceiver weights, which are coupled through the interference-plus-noise covariance matrix $\mathbf{\Omega}_l$. In the following sections, we present our solution which is based on an alternating optimization method.

III. Power allocation problem

In this section, we first consider the simple case in which the transmit and receive antenna weights are fixed. Therefore, we want to solve the following power allocation problem:

$$(\mathcal{P}_2)\begin{cases} \underset{\mathbf{p}}{\text{maximize}} & \min_l \frac{\mathrm{SINR}_l}{\Gamma_l} \\ \text{subject to} & \mathbf{w}_{t_l}^\intercal \mathbf{p} \leq P_{t_l}, \;\; l = 1, ..., L \end{cases} \qquad (6)$$

In short, we optimize only the power allocation vector $\mathbf{p} \in \mathbb{R}^L$ to maximize the minimum weighted link SINR. We should note that problem $(\mathcal{P}_2)$ is a geometric program [15], and it is always feasible. Thus, it can be recast as a convex optimization problem and solved using general-purpose algorithms such as interior-points methods [16]. However, such approach requires a global channel knowledge and has a relatively high computational cost for our application. Instead, distributed and more efficient algorithms are desired in multihop networks.

A. SINR metric-based power allocation algorithm

By extending the notion of SINR metric in [14], we therefore derive a new distributed power allocation algorithm which solves directly the weighted SINR balancing problem $(\mathcal{P}_2)$ with multiple linear constraints.

First, we need to extend the definition of the SINR metric of link l at the iteration n by the following equation:

$$M_l^{(n)} = \frac{\mathrm{SINR}_l^{(n)}}{\Gamma_l} \times \frac{P_{t_l}}{\mathbf{w}_{t_l}^\intercal \mathbf{p}^{(n)}}. \qquad (7)$$

By sharing this single parameter, the transmit nodes can iteratively coordinate their outgoing links' power update and achieve a maximum uniform weighted link SINR. The algorithm is summarized below:

Algorithm 1: Weighted SINR balancing with multiple linear constraints

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Initialize $p_l^{(0)} = \frac{P_{t_l}}{N_{t_l}}$ where N_{t_l} is the number of links of t_l.

Iterate until convergence:

1) The weighted SINR metric is computed for all streams:

$$M_l^{(n)} = \frac{\mathrm{SINR}_l^{(n)}}{\Gamma_l} \cdot \frac{P_{t_l}}{\mathbf{w}_{t_l}^{\mathsf{T}} \mathbf{p}^{(n)}},\ l = 1, 2, \ldots, L$$

2) The minimum weighted SINR metric is shared between the nodes:

$$M_{\min}^{(n)} = \min_k M_k^{(n)}$$

3) Transmit power update for the next iteration:

$$p_l^{(n+1)} = M_{\min}^{(n)} \cdot \frac{\Gamma_l}{\mathrm{SINR}_l^{(n)}} \cdot p_l^{(n)},\ l = 1, 2, \ldots, L$$

The weighted SINR metric $M_l^{(n)}$ can be interpreted as the increased weighted SINR of a link l at the n-th iteration if its corresponding node's power level is scaled to the maximum P_{t_l} while its received interference power remain fixed. In our extended definition, we take into account that each transmit node is subject to a linear power constraint. Since the objective is to achieve an uniform weighted SINR for all links, the idea is to use the minimum SINR metric as a fair reference for deciding which links need to increase or decrease their power. Through this single parameter, the optimization can be carried out with a low level of coordination. In two-way multihop network topology, the nodes can reduce the overhead by computing the minimum SINR metric locally with their neighboring nodes and passing the new minimum value in a distributed manner.

B. Convergence analysis and optimality

The properties, convergence and optimality of the above algorithm will be briefly presented. Due to lack of space, most proofs are omitted in this paper.

Theorem 1. *First, it can be verified that a power allocation $\mathbf{p}^\star$ is optimal, if and only if the following conditions are satisfied:*

1) The weighted SINRs of every links are equal, i.e. $\forall l : \frac{\mathrm{SINR}_l^{(n)}}{\Gamma_l} = \gamma^\star$
2) At least, one node transmits at its maximum power, i.e. $\exists k,\ \mathbf{w}_{t_k}^{\mathsf{T}} \mathbf{p}^\star = P_{t_k}$.

Our proposed algorithm shares some similar properties with the algorithm in [14], which is restricted to simple interference networks with individual link power constraints:

Property 1: Once the above optimality conditions are satisfied, the power allocation becomes stable, i.e. if $\forall l : \frac{\mathrm{SINR}_l^{(n)}}{\Gamma_l} = \gamma^\star$ and $\exists k : \mathbf{w}_{t_k}^{\mathsf{T}} \mathbf{p}^{(n)} = P_{t_k}$, then $\forall l : p_l^{(n+1)} = p_l^{(n)}$.

Property 2: The power updates always satisfy the linear power constraints, i.e. $\forall n, l :\ \mathbf{w}_{t_l}^{\mathsf{T}} \mathbf{p}^{(n)} \leq P_{t_l}$.

The following lemma easily follows from Property 2.

Lemma 1. *The minimum SINR metric is always equal or greater than the actual minimum weighted SINR, i.e,*

$$\forall n : M_{min}^{(n)} \geq \gamma_{min}^{(n)} = \min_k \frac{SINR_k^{(n)}}{\Gamma_k} \tag{8}$$

with equality only if $\frac{\mathrm{SINR}_{j^\star}^{(n)}}{\Gamma_{j^\star}} = \gamma_{\min}^{(n)}$ and $\mathbf{w}_{t_{j^*}}^{\mathsf{T}} \mathbf{p}^{(n)} = P_{t_{j^*}}$ where $j^\star = \underset{k}{\operatorname{argmin}} M_k^{(n)}$.

Then, it can be shown that the minimum weighted SINR $\gamma_{\min}^{(n)}$ will always converge to the optimal value.

Theorem 2. *The minimum weighted SINR is monotonically increasing, i.e. $\forall n : \gamma_{min}^{(n+1)} \geq \gamma_{min}^{(n)}$. Furthermore, once γ_{min} converges to a constant value $\gamma^\star$ after N iterations, the updated power allocation will satisfy the optimality conditions in Theorem 1.*

Proof: To prove the first part, it is sufficient to show that $\forall n, l : \gamma_l^{(n+1)} \geq \gamma_{\min}^{(n)}$, which easily follows from Lemma 1. The second part is proved as follows. Let us suppose that after the N-th iteration, we have convergence, i.e. $\gamma_{\min}^{(N+1)} = \gamma_{\min}^{(N)}$. If we denote $l^\star = \underset{k}{\operatorname{argmin}} \gamma_k^{(n)}$, then the following equation must hold:

$$\gamma_{l^\star}^{(N+1)} = \gamma_{l^\star}^{(N)}$$

$$\frac{p_{l^\star} G_{l^\star, l^\star} \frac{M_{\min}^{(n)}}{\gamma_{l^\star}^{(N)}}}{\sum_{k \neq l^\star} p_k G l^\star, k \cdot \frac{M_{\min}^{(n)}}{\gamma_k^{(N)}} + \sigma^2} = \frac{p_{l^\star} G_{l^\star, l^\star}}{\sum_{k \neq l^\star} p_k G l^\star, k + \sigma^2}$$

$$\frac{M_{\min}^{(n)}}{\gamma_{l^\star}^{(N)}} \left(\sum_{k \neq l^\star} p_k G l^\star, k + \sigma^2 \right) = \left(\sum_{k \neq l^\star} p_k G l^\star, k \cdot \frac{M_{\min}^{(n)}}{\gamma_k^{(N)}} + \sigma^2 \right)$$

$$\sum_{k \neq l^\star} p_k G l^\star, k \cdot M_{\min}^{(n)} \left(\frac{1}{\gamma_{l^\star}^{(N)}} - \frac{1}{\gamma_k^{(N)}} \right) = \sigma^2 \left(1 - \frac{M_{\min}^{(n)}}{\gamma_{l^\star}^{(N)}} \right)$$

Since $\gamma_{l^\star}^{(N)} \leq \gamma_k^{(N)}\ \forall k$, the left hand side of the last equation is non-negative. On the other hand, it follows from Lemma 1 that the right hand side is non-positive. Thus, the convergence is attained only if $\forall k : \gamma_k^{(N)} = \gamma_{l^\star}^{(N)}$ and $M_{\min}^{(n)} = \gamma_{l^\star}^{(N)}$. Since, we have by definition $M_{\min}^{(n)} = \min_k \left(\gamma_k^{(N)} \cdot \frac{P_{t_k}}{\mathbf{w}_{t_k}^{\mathsf{T}} \mathbf{p}^{(n)}} \right)$, the last condition $\left(M_{\min}^{(n)} = \gamma_{l^\star}^{(N)} \right)$ and Property 2 implies that there exists a link $l^\star$ whose corresponding node transmits at maximum power, i.e. $\mathbf{w}_{l^\star}^{\mathsf{T}} \mathbf{p}^{(n)} = P_{l^\star}$. As a result, the obtained power allocation vector satisfies the optimality conditions in Theorem 1. ■

Remark. In contrast to the algorithm in [14], our algorithm does not enforce that at least one node must transmit at maximum power in each iteration. Instead, the previous result says that after convergence, it is guaranteed that a node will use its maximum power.

IV. Joint Power Allocation and Transceiver Weight Optimization

In this section, we propose a simple distributed algorithm for solving the joint power allocation and transceiver weight optimization problem $\mathcal{P}_1$.

A. Distributed Alternating Optimization

The distributed optimization alternates between the primal network and its reverse network in an iterative manner. As shown in Figure 2, the reverse network is simply obtained by reversing the directions of all links, replacing the channel matrix $\mathbf{H}_{l,k}$ by its reciprocal $\widehat{\mathbf{H}}_{k,l} = \mathbf{H}_{l,k}^{\dagger}$, and finally by using the transmit weights of the primal network as the receive weights of the reverse network and vice versa (i.e. $\widehat{\mathbf{R}} = \mathbf{T}$ and $\widehat{\mathbf{T}} = \mathbf{R}$) [11]. This reciprocity concept is particularly useful for TDD wireless networks.

For given transmit weights and power allocation vector, the optimal receive filter $\mathbf{r}_l$ that maximizes the SINR (4) is the Wiener or MMSE filter $\mathbf{r}_l^{\text{MMSE}}$. It is obtained as a solution of the general eigenvalue problem $(\mathbf{H}_{l,l}\mathbf{t}_l,\ \mathbf{\Omega}_l)$ and is of the form:

$$\mathbf{r}_l^{\text{MMSE}} = \beta_l \mathbf{\Omega}_l^{-1}\mathbf{H}_{l,l}\mathbf{t}_l \tag{9}$$

where β_l is a scaling factor which can be chosen to normalize $\mathbf{r}_l^{\text{MMSE}}$. The proposed distributed algorithm is then summarized below:

Algorithm 2: Distributed power allocation and transceiver weight optimization

Initialize Initialize the power allocation vectors $\mathbf{p}^{(0)}$, $\mathbf{q}^{(0)}$ and the transmit weigth $\mathbf{T}^{(0)}$.

Iterate until convergence:

1) Optimize the primal network:
   a) Each RX node computes the optimal MMSE weight $\mathbf{r}_l^{(n)}$ from (9).
   b) Update the power allocation $\mathbf{p}^{(n+1)}$ as follows:
   Let $\gamma_l^{(n)} = \text{SINR}_l\left(\mathbf{T}^{(n)}, \mathbf{R}^{(n)}, \mathbf{p}^{(n)}\right),\ \forall l \in \mathcal{S}$, then the SINR metric of each link is computed locally:
   $$M_l^{(n)} = \frac{\text{SINR}_l^{(n)}}{\Gamma_l}\cdot\frac{P_{t_l}}{\mathbf{w}_{t_l}^{\mathsf{T}}\mathbf{p}^{(n)}}p_l^{(n)},\ l = 1, 2, \ldots, L$$
   c) The minimum SINR metric is computed and shared distributedly between the nodes:
   $$M_{\min}^{(n)} = \min_k M_k^{(n)}$$
   d) Transmit power update for the next iteration:
   $$p_l^{(n+1)} = M_{\min}^{(n)}\cdot\frac{\Gamma_l}{\text{SINR}_l^{(n)}}\cdot p_l^{(n)},\ l = 1, 2, \ldots, L$$
2) Optimize the reverse network, i.e. calculate the receive weights $\mathbf{t}^{(n+1)}$ and update the reverse power vector $\mathbf{q}^{(n+1)}$, using the same procedure as in 1).

Athough our algorithm is heuristic in nature, it takes advantage of the previous results. And as we will see later, it achieves an end-to-end rate close to that of a centralized optimization scheme with a much lower complexity. We note that this distributed algorithm is not based on the SINR duality concept [11] as in the centralized optimization scheme described next.

B. Comparative scheme: centralized optimization

For benchmark purpose, we consider the following centralized optimization problem $(\mathcal{P}_3)$ whose solution is an upper bound to the original problem $(\mathcal{P}_1)$:

$$(\mathcal{P}_3)\begin{cases} \underset{\mathbf{p}}{\text{maximize}} & \min_l \frac{\text{SINR}_l}{\Gamma_l} \\ \text{subject to} & \mathbf{1}^{\mathsf{T}}\mathbf{p} \le \sum_{t=1}^{T} P_t \end{cases} \tag{10}$$

where T denotes the number of transmit nodes in the network. Its solution is an upper-bound to $\mathcal{P}_1$ since we have relaxed this later by replacing the multiple linear power constraints in (6) by a sum power constraint. Therefore, we can use the SINR duality-based algorithm in [11], which allows to solve $(\mathcal{P}_3)$, as a comparative scheme.

As mentioned before, the duality-based algorithm relies on a sum power constraint and on the availability of global channel knowledge between every interfering links. Therefore, this centralized scheme is not practical for distributed MIMO networks and is only useful here for performance comparison.

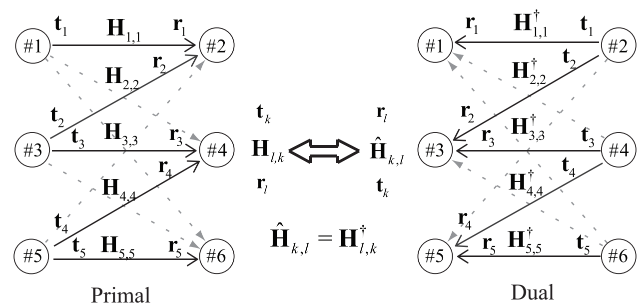

Figure 2. Illustration of network duality in a MIMO two-way multihop network with 6 nodes.

V. Numerical results

Simulation results are presented for a MIMO two-way multihop network with 6 nodes, each equipped with $M = 3$ antennas. In this network, the data streams flow in two directions: forward and backward (see Figure 1). In the reverse network, the directions of the links are simply reversed. To define the linear power constraint at t_l, the elements of the vector $\mathbf{w}_{t_l}$ is set to 0 or 1 depending on whether the corresponding link belongs to t_l or not.

To simplify the analysis, the nodes are aligned and located at equal distance. For a discussion on optimal relay locations, we refer the reader to our previous work [17]. Also, we consider the simple case with equal link priorities $\forall l : \Gamma_l = 1$, i.e. we assume that there is a single source/destination pair of nodes located at the far ends of the linear multihop network. In this case, we can measure the performance by the end-to-end rate defined by [4]:

$$R_{\text{E2E}} = \frac{1}{2}\left[\mathbf{E}\left(R_{\text{E2E}}^{F}\right) + \mathbf{E}\left(R_{\text{E2E}}^{B}\right)\right]\ \text{[bit/s/Hz]} \tag{11}$$

where $R_{\text{E2E}}^{\text{F}} = \min_{l\in I^{\text{F}}} R_l$ and $R_{\text{E2E}}^{\text{B}} = \min_{k\in I^{\text{B}}} R_k$ with $R_l = \log_2(1 + \text{SINR}_l)$ is the achievable rate of link l, and I^{F} and I^{B} respectively denote the set of forward and backward links both in the primal and reverse networks.

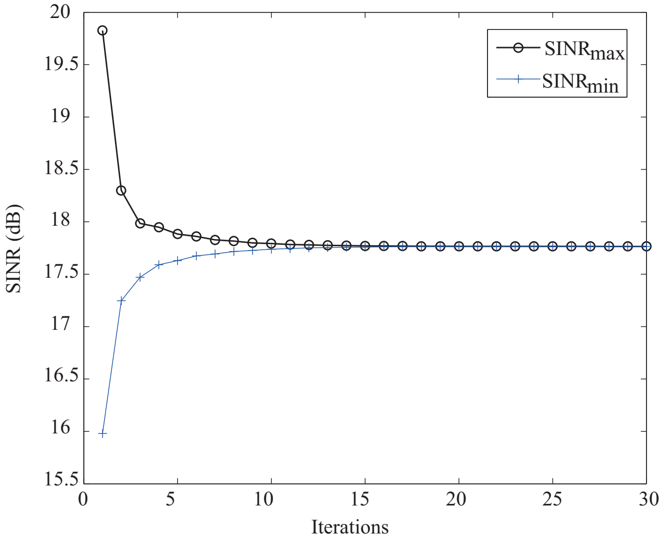

Figure 3. Max-min SINR convergence of the distributed power allocation (Algorithm 1) for $P_{t_l} = 30$dB.

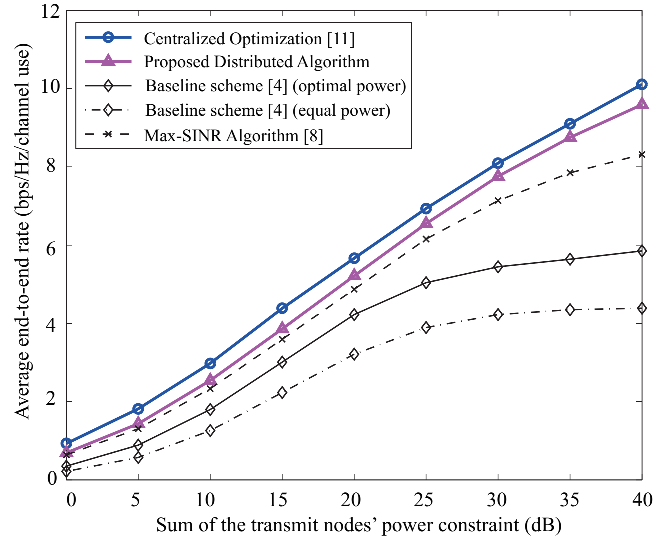

Figure 4. Average end-to-end rate of the distributed algorithm (Algorithm 2) vs. Upper bound centralized algorithm [11] vs. *baseline scheme* in [4] and the *max-SINR algorithm* [8].

First, Figure 3 shows a typical example of the max-min convergence of the power allocation Algorithm 1.

Next, we present the performance benchmark between the proposed distributed algorithm and the centralized one. Also, we show the performance of two conventional schemes: the baseline scheme in [4], which cancels only the adjacent link interference, and of the *max-SINR* algorithm in [8], which employs MMSE filtering but equally allocates the power for the multihop links.

Figure 4 illustrates the end-to-end rate, averaged over 50 realizations of an i.i.d Rayleigh fading channel. Clearly, our proposed distributed algorithm outperforms the conventional schemes. The *baseline scheme* [4] mitigates only the adjacent interference so that the interference from far nodes saturates the end-to-end rate in high SNR. On the other hand, the *max-SINR* algorithm cannot achieve a uniform rate for the multihop links since it equally allocates the power. In contrast, our algorithm optimizes the power allocation and also mitigates the overall received and leaked interference by iterative transmit and receive MMSE filtering.

More importantly, we can see that the proposed distributed algorithm achieves an average end-to-end rate very close to that of the centralized optimization scheme with a lower computational cost. The observed small performance gap can be explained by the relaxation of the transmit power contraints in the centralized scheme.

VI. Conclusion

We studied the joint optimization of power allocation and transceiver weights in MIMO two-way multihop networks. First, we considered the power allocation problem and proposed a direct solution that provably maximizes the minimum weighted SINR of the links. The solution was based on the notion of SINR metric that we extended in this work to cope with the general linear power constraints. From this result, we derived a distributed and alternating algorithm for the MIMO transceiver optimization. Our numerical results confirmed that the proposed algorithm can provide considerable rate gain improvement compared to conventional schemes. Since our distributed algorithm requires a low level of coordination, it is an effective solution for increasing the spectral efficiency of future MIMO multihop networks.

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