A NOVEL RESOURCE ALLOCATION STRATEGY FOR DISTRIBUTED MIMO MULTI-HOP MULTI-COMMODITY COMMUNICATIONS

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ABSTRACT

In this paper, we present a near-optimum resource allocation strategy for distributed multiple-input-multiple-output multiple hops multiple commodities OFDMA wireless networks. The novel per-hop-optimization strategy aims to reduce the total transmission power of the network while meeting the individual end-to-end outage probability constraint of each commodity, i.e. for each link of the network. It utilizes the Greedy edge-coloring algorithm to determine reused orthogonal subbands for overlapping hops and allows a distributed implementation per hop. In comparison to other bandwidth allocation strategies like equal or dynamic bandwidth for each commodity, our Per-Hop-Bandwidth-Allocation (PHBA) approach uses the bandwidth in a near-optimum way and reduces the total transmission power significantly.

1. INTRODUCTION

Recently, it has been shown that the channel capacity of a wireless mesh network can be drastically increased by applying multiple-input-multiple-output (MIMO) techniques with respect to spatially separated relaying nodes [1]. These MIMO techniques are a natural extension to the concept of virtual antenna arrays (VAAs) [2] and are named distributed MIMO. Fig.1 shows its application in wireless multi-hop multi-commodity communications, where 3 sources communicate with 3 destinations via a various number of relaying VAAs. While the MIMO techniques that are applied to improve single link performance are well understood (e.g. [3],[4]), the application of distributed MIMO in wireless mesh networks [5][6] is still an open and challenging task. Particularly, Quality-of-Service (QoS) constraints like link reliability, delay, data rate and also the power assignment per node are all entangled through the performance (capacity or outage probability) of the distributed MIMO scheme.

In [1] Dohler et al. have developed a resource allocation approach to maximize the end-to-end (e2e) ergodic capacity

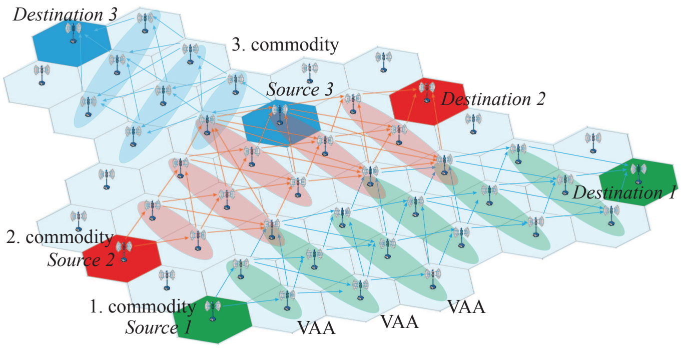

Fig. 1. Distributed MIMO multi-hop multi-commodity transmission with 3 commodities.

for a distributed MIMO *single-commodity* (single-link) transmission scheme. In [7] the authors have derived throughput-maximizing resource-allocation strategies for various sensor network configurations. In both papers a fixed total power $\mathcal{P}$ consumed in the whole network is assumed. Instead, similar to [8] we focus on resource allocation strategies with more practical meanings, i.e. minimize the total power consumption while meeting an end-to-end QoS constraint. To this end, we derive resource allocation strategies for a *multi-commodity* (multi-link) case under an individual e2e outage probability constraint for each commodity and carry a comparative study of different bandwidth allocation strategies. We will formulate the optimization problem and analyze different bandwidth allocation concepts, e.g., equal, dynamic and per-hop-bandwidth-allocation. It will be shown that our novel PHBA strategy exploits network resources in a near-optimum way. Particularly, the strategy is investigated for the wireless backhaul networks, where each base station is placed in the middle of a cell. However, it is also applicable to any wireless meshed networks in principle, e.g., wireless sensor networks or ad-hoc networks.

The aim of this paper is to develop a resource allocation strategy, thus, for the further investigation a given fixed network topology is assumed. In particular, the task of forming the VAAs or searching of optimal routing path is not within the scope of this paper. Furthermore, we focus on the multi-commodity case, where a number of source-destination pairs (commodities or links) are active in the network. As depicted in Fig. 1, some nodes serve for more than one commodities. In order to separate the commodities, we will apply different orthogonal frequency division multiple access (OFDMA) schemes, namely equal bandwidth, dynamic bandwidth, and per-hop-bandwidth-allocation, which will be discussed in detail in the following sections. Such a network is often referred to as a distributed MIMO-OFDMA network.

The remainder of the paper is organized as follows. In Section 2 the system model of the distributed MIMO multi-hop multi-commodity transmission scheme is introduced. The mathematical description of the end-to-end outage probability and an approximated form will be given in Section 3. Two resource allocation problems for distributed MIMO multi-hop multi-commodity systems will be formulated in Section 4, namely equal bandwidth, dynamic bandwidth. In Section 5 the novel per-hop-bandwidth-allocation (PHBA) strategy is proposed, which is shown to use the bandwidth in an efficient way. Finally, simulation results and conclusions will be given in Section 6 and 7, respectively.

2. SYSTEM DESCRIPTION

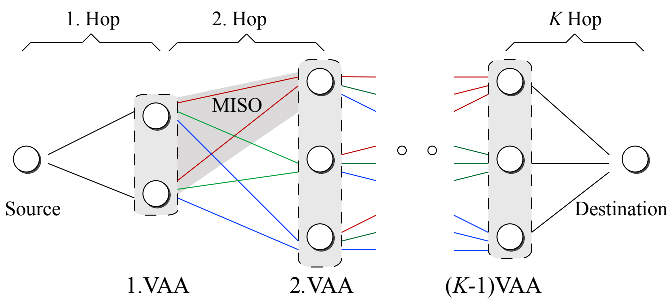

Fig. 2. System model of a distributed MIMO multi-hop single-commodity transmission.

A multi-commodity system is constructed by several single-commodity systems. In order to explain the overall system, the functionality of single commodity is considered first in detail. As shown in Fig. 2, the source node desires to communicate with the destination node via $K-1$ dedicated relaying VAAs in K hops. Note that we limit to one antenna element per node and the general case is straightforward. We consider a time-slotted transmission scheme, i.e., time-diversion multiple-access (TDMA) between hops. Due to the half-duplex constraint, one node can't transmit and receive signals simultaneously because the power of the transmitted signals is about $100-150$ dB greater than that of the received signals. Moreover, the relaying protocol Decode-and-Forward (D&F) at each relaying node is applied [9].

The information is broadcasted from the source to the first VAA at the first time slot over the entire frequency band W. At the first VAA, each node decodes the received information separately, i.e., there is no information exchange between the relaying nodes. Then they re-encode the decoded information "cooperatively" according to a space-time code word, where each node uses only a spatial fraction of the space-time code word. At the second time slot, the first VAA transmits the information to the second VAA over the entire frequency band W. Each node of the second VAA decodes the information separately, re-encodes, and retransmits it to the next VAA in the same manner as in the first time slot. The information is transmitted from one VAA to another VAA until it reaches the destination, where we assume each time slot has the same duration.

Due to the spatially disposed relaying nodes, the distances between the nodes within two VAAs are different, which leads to different pathloss for the subchannels. We refer to such network as an *asymmetric* network. Mention that if one VAA is far away from another VAA, due to the strong pathloss both VAAs can transmit information at the same time slot without interference. Such network is often referred to as a distributed MIMO multi-hop network. As described above, the nodes within the same VAA decode the information separately but re-encode the information with respect to the same space-time code word. To this end, the transmission within one hop can be modeled as multiple-input single output (MISO) systems, as highlighted for the 2nd hop in Fig. 2.

In order to describe the MISO system, we let m index the commodity, M is the number of commodities, k index the hop, K_m denotes the number of hops in the mth commodity, $t_{m,k}$, $r_{m,k}$ denote the number of transmit nodes and receive nodes at the kth hop in the mth commodity, respectively. For simplicity we consider a pathloss model, where the power attenuation $\gamma_{m,k} = 1/d^{\epsilon}_{m,k,i,j}$ is proportional to the distance, where $d_{m,k,i,j}$ denotes the distance between the ith transmit node and the the jth receive node at the kth hop and ϵ is the pathloss exponent within range of 2 to 5 for most wireless channels. We define $\mathbf{S}_{m,k} \in \mathbb{C}^{t_{m,k}\times T_{m,k}}$ as the space-time encoded signal with length $T_{m,k}$ from the $t_{m,k}$ nodes at the kth hop. The received signal $\mathbf{y}_{m,k,j} \in \mathbb{C}^{1\times T_{m,k}}$ at the jth node at the kth VAA with different pathlosses and different transmission power level is given by

$$\mathbf{y}_{m,k,j} = \mathbf{h}_{m,k,j} \cdot \mathbf{\Lambda}_{m,k} \cdot \mathbf{S}_{m,k} + \mathbf{n}_{m,k,j}, \qquad (1)$$

with the diagonal matrix

$$\mathbf{\Lambda}_{m,k} = \mathrm{diag}\left\{\sqrt{\frac{\mathcal{P}_{m,k,1}}{d^{\epsilon}_{m,k,1,j}}}, \cdots, \sqrt{\frac{\mathcal{P}_{m,k,t_{m,k}}}{d^{\epsilon}_{m,k,t_{m,k},j}}}\right\},$$

where $\mathbf{n}_{m,k,j} \sim \mathcal{N}_C(0,\, N_0) \in \mathbb{C}^{1\times T_{m,k}}$ denotes the Gaussian noise vector with power spectral density N_0 and $\mathcal{P}_{m,k,i}$ is the transmission power of the ith node at the kth VAA. The channel from the $t_{m,k}$ transmit nodes to the jth receive node within the kth hop is expressed as $\mathbf{h}_{m,k,j} \in \mathbb{C}^{1\times t_{m,k}}$. Its elements $h_{m,k,i,j}$ obey the same uncorrelated Rayleigh fading statistics, i.e. complex zero-mean circular symmetric Gaussian distribution with variance 1.

As the definition for a single-commodity communication is done, it can be extended to the multi-commodities case in Fig. 1. In order to avoid interference between commodities, each commodity should share the entire frequency bandwidth. The bandwidth fraction for the kth hop of the mth commodity is denoted by $\alpha_{m,k}$.

3. OUTAGE PROBABILITY

3.1. Exact form for outage probability

According to the capacity of a MIMO channel exposed in [4], the capacity of each MISO link described above is given by

$$\begin{aligned} C_{m,k,j} =& \alpha_{m,k} W \log_2 \\ & \left(1 + \frac{1}{\alpha_{m,k} W N_0} \sum_{i=1}^{t_{m,k}} \frac{\mathcal{P}_{m,k,i} |h_{m,k,i,j}|^2}{d^{\epsilon}_{m,k,i,j}}\right). \end{aligned} \tag{2}$$

where $\alpha_{m,k}$ denotes the bandwidth fraction of the link. Since the channel capacity $C_{m,k,j}$ is a random variable with respect to the fading channel $\mathbf{h}_{m,k,j}$, it is particularly meaningful to consider its statistical distribution, namely the outage probability. The outage probability is the probability that the transmission rate R is higher than the channel capacity $C_{m,k,j}$, when the decoding error rate (e.g., BER, SER, FER) can't be made arbitrarily small. Hence, for a system with $\alpha_{m,k} W$ bandwidth and information bit rate R, the outage probability can expressed as

$$\begin{aligned} P_{\text{out},m,k,j} &= \Pr\left(R > C_{m,k,j}\right) \\ &= \Pr\left(X_{m,k,j} < (2^{\frac{R}{\alpha_{m,k}W}} - 1)\alpha_{m,k} W N_0\right), \end{aligned} \tag{3}$$

where $X_{m,k,j} = \sum_{i=1}^{t_{m,k}} \frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}} |h_{m,k,i,j}|^2$ is the linear combination of independent χ^2 (i.e., exponential distributed) variables $|h_{m,k,i,j}|^2$ with various weights $\mathcal{P}_{m,k,i}/d^{\epsilon}_{m,k,i,j}$. Closed-form expressions for the probability density function (PDF) with respect to the random variable $X_{m,k,j}$ in terms of the hypergeometric function are derived in [10][11][12],

$$p(x_{m,k,j}) = \frac{\prod_{i=1}^{t_{m,k}} \frac{d^{\epsilon}_{m,k,i,j}}{\mathcal{P}_{m,k,i}}}{\Gamma(t_{m,k})} \cdot x_{m,k,j}^{t_{m,k}-1} \cdot {}_0F_0(-\mathbf{\Sigma}^{-1}, x_{m,k,j}), \tag{4}$$

with the diagonal matrix

$$\mathbf{\Sigma} = \operatorname{diag}\left\{ \frac{\mathcal{P}_{m,k,1}}{d^{\epsilon}_{m,k,1,j}}, \cdots, \frac{\mathcal{P}_{m,k,t_k}}{d^{\epsilon}_{m,k,t_k,j}} \right\}$$

and ${}_0F_0(-\mathbf{\Sigma}^{-1}, x_{m,k,j})$ denotes the complex hypergeometric function. Due to the complex form of the hypergeometric function, it is difficult to achieve a simple and closed form for (3). In order to simplify further analysis and achieve a near-optimum solution to our optimization problem, an approximation to the outage probability will be used for further investigations. The accuracy of this approximation will also be evaluated.

3.2. Approximations for outage probability

As shown in [13] a linear combination of independent χ^2 variables can be approximated by a gamma variable. This technique has been widely used in statistics to determine the pdf of a weighted sum of χ^2 variables [14][15]. In the literature, a linear combination of independent χ^2 variable with various weights is approximated by a gamma variable with arithmetic mean

$$X_{m,k,j} \overset{\approx}{\sim} \text{Gamma}\left(t_{m,k}, \frac{1}{t_{m,k}} \sum_{i=1}^{t_{m,k}} \frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}}\right). \tag{5}$$

where $\overset{\approx}{\sim}$ means the random variable obeys the Gamma distribution approximately.

Motivated by the gamma approximation with arithmetic mean, we introduce an approximation with geometric mean

$$X_{m,k,j} \overset{\approx}{\sim} \text{Gamma}\left(t_{m,k}, \sqrt[t_{m,k}]{\prod_{i=1}^{t_{m,k}} \frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}}}\right). \tag{6}$$

With this result, the outage probability (3) can be approximated by

$$\begin{aligned} P_{\text{out},m,k,j} &\approx \Pr\Bigg(\sqrt[t_{m,k}]{\prod_{i=1}^{t_{m,k}} \frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}}} \sum_{i=1}^{t_{m,k}} |h_{m,k,i,j}|^2 \\ &\qquad < (2^{\frac{R}{\alpha_{m,k}W}} - 1)\alpha_{m,k} W N_0 \Bigg) \\ &= \Pr\left(\sum_{i=1}^{t_{m,k}} |h_{mk,i,j}|^2 < \underbrace{\frac{(2^{\frac{R}{\alpha_{m,k}W}} - 1)\alpha_{m,k} W N_0}{\sqrt[t_{m,k}]{\prod_{i=1}^{t_{m,k}} \frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}}}}}_{x'_{m,k,\text{Geo}}} \right) \\ &= \frac{\gamma(t_{m,k}, x'_{m,k,\text{Geo}})}{\Gamma(t_{m,k})}. \end{aligned} \tag{7}$$

where $\gamma(\cdot,\cdot)$ is the incomplete Gamma function, and $\Gamma(\cdot)$ is the complete Gamma function. Similarly, the approximation (5) can also be used

Comparing (3) with (7), the gamma approximation transfers the asymmetric transmission structure to a symmetric case approximately. Note that the less the difference between the weights of the linear combination, the more accurate the approximation. For a symmetric case both approximations (5)(6) lead to same result due to

$$\frac{1}{t_{m,k}}\sum_{i=1}^{t_{m,k}}\frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}}=\sqrt[t_{m,k}]{\prod_{i=1}^{t_{m,k}}\frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}}}=\frac{\mathcal{P}_{m,k,i}}{d^{\epsilon}_{m,k,i,j}}. \quad (8)$$

In order to evaluate the accuracy of the Gamma approximations, we consider an asymmetric 4×1 MISO system, where two case will be examined. In the first case the non-negative weights $\mathcal{P}_{m,k,i}/d^{\epsilon}_{m,k,i,j}$ are almost similar, i.e., a near-symmetric case is given. Since only the relative ratios of the weights $\mathcal{P}_{m,k,i}/d^{\epsilon}_{m,k,i,j}$, $\forall i$ rather than the absolute value of the weights are important for the approximation, the normalized vector

$$\frac{[\mathcal{P}_{m,k,i}/d^{\epsilon}_{m,k,i,j},\,\forall i]}{\min(\mathcal{P}_{m,k,i}/d^{\epsilon}_{m,k,i,j},\,\forall i)}=[1,\,2,\,2,\,1], \quad (9)$$

is used, i.e., the weights are within roughly an 3 dB difference. In the second case the weights are of great difference, i.e., a strongly asymmetric case is considered. The normalized vector is

$$\frac{[\mathcal{P}_{m,k,i}/d^{\epsilon}_{m,k,i,j},\,\forall i]}{\min(\mathcal{P}_{m,k,i}/d^{\epsilon}_{m,k,i,j},\,\forall i)}=[1,\,8,\,1,\,8], \quad (10)$$

i.e., the weights are roughly within 9 dB difference.

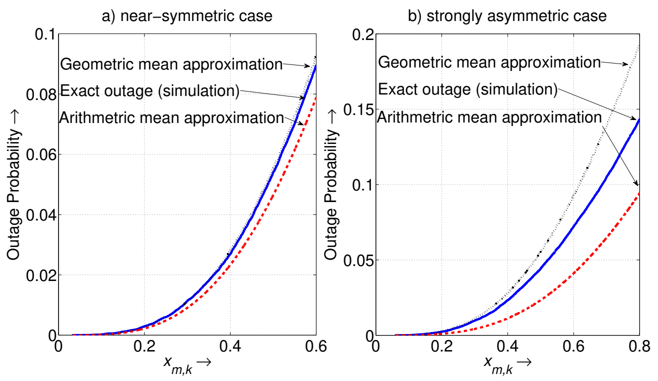

Fig. 3. Exact and approximated outage probability for 4×1 MISO system in case of (a) near-symmetric and (b) strongly asymmetric.

Fig. 3 shows both approximations (5)(6) and the exact outage probability obtained by Monte-Carlo simulations. From Fig. 3(a) we can observe for the near-symmetric that for low outage probability the approximation with geometric mean is better than the approximation with arithmetic mean. Note that low outage probabilities are of more concern than high outage probabilities in practical systems. Fig. 3(b) shows the performance of the approximations in a strongly asymmetric case. Although both approximations perform worse at asymmetric cases, the approximation with geometric mean is still the better one. As we remarked in the figures, the exact outage probability is upper bounded by the approximation with geometric mean (the worst case) and lower bounded by the approximation with arithmetic mean. Therefore, it is reasonable to choose the approximation with geometric mean as the measurement of the outage probability.

3.3. The end-to-end outage probability

In the sequel the e2e outage probability of each commodity is investigated. Similar to the assumption made in [7][8] to describe an e2e error rate, we assume the e2e connection is not in outage, i.e., a packet from the source is received correctly at the destination, only when each hop is not in outage. In other words, the packet is correctly received at each relaying node. The e2e outage probability is therefore given by

$$\begin{aligned}P_{\text{e2e},m}&=1-\prod_{k=1}^{K_m}(1-P_{\text{out},m,k}) \quad (11)\\&=1-\prod_{k=1}^{K_m}\left(1-\left(1-\prod_{j=1}^{r_{m,k}}(1-P_{\text{out},m,k,j})\right)\right).\end{aligned}$$

By inserting (7) into (11), we achieve the approximation for the end-to-end outage probability of an asymmetric distributed MIMO multi-hop network

$$P_{\text{e2e},m}\approx 1-\prod_{k=1}^{K_m}\prod_{j=1}^{r_{m,k}}\left(1-\frac{\gamma(t_{m,k},x'_{m,k,\text{Geo}})}{\Gamma(t_{m,k})}\right). \quad (12)$$

4. OPTIMIZATION PROBLEM

The general power and bandwidth allocation problem can be formaluted as a optimization problem, which aims to minimize the total power of the whole network while meeting the end-to-end outage probability requirement e_m per commodity

$$\begin{aligned}&\text{minimize}\ \sum_{m}^{M}\sum_{k}^{K_m}\sum_{i}^{t_{m,k}}\mathcal{P}_{m,k,i}\\&\quad\text{s.t. } P_{\text{e2e},m}\le e_m,\ \forall m\\&\qquad\sum_{(m,k,i)\,\in\,E^{+}\{n\}}\mathcal{P}_{m,k,i}\le\mathcal{P}^{\max}_n,\ \forall n\\&\qquad f(\alpha_{m,k},\ \forall m,\,k)=0.\end{aligned} \quad (13)$$

e_m represents the maximum allowed e2e outage probability of the mth commodity, $E^{+}\{n\}$ denotes the set of (m,k,i) triples, where the nth node in the network serves for transmission and $\mathcal{P}^{\max}_n$ represents the corresponding power constraint. We define the function $f(\cdot)$ as the equal constraint to describe different bandwidth allocation strategies, where

$\alpha_{m,k}$ is the bandwidth fraction assigned to the mth commodity at the kth hop. Note that it is difficult to find an optimal power and bandwidth allocation solution of the optimization problem (13), since the issues like scheduling, routing path searching are involved. Hence, some simple bandwidth allocation strategies will be introduced.

Simple solutions to avoid mutual interference between commodities are unique bandwidth allocations per commodity, i.e., $\alpha_m = \alpha_{m,k}, \forall\, k$. We have two simple strategies , one is so called equal bandwidth allocation that each commodity use an equal fraction of the total bandwidth. Then f becomes

$$\alpha_m = \frac{1}{M}, \forall\, m \quad \text{(equal bandwidth)}. \tag{14}$$

Alternatively, we can optimize the bandwidth fractions α_m by only satisfying the following equation,

$$\sum_{m=1}^{M} \alpha_m = 1 \quad \text{(dynamic bandwidth)}. \tag{15}$$

Note that (13) can be proven to be convex for typical operation points of networks [16] and can consequently be efficiently solved by standard optimization tools [17]. However, for large number of commodities M the bandwidth fraction α_m is small and each commodity only gets a little of the bandwidth for transmission. As a result, the power consumption of the network will dramatically increase to achieve the end-to-end outage probability requirement. Both bandwidth allocation strategies don't fully exploit the network performance [16]. Instead, a flexible bandwidth allocation to commodities per hop can fully utilize the inherent nature of a multi-hop network. In order to use the bandwidth more efficiently, we will propose a novel resource allocation strategy, namely per-hop-bandwidth-allocation (PHBA).

Before presenting the approach, we investigate the optimal power allocation for a single commodity case, which can be derived from (13) by $M = 1$. Fig. 4 shows the optimal outage probability per hop versus bandwidth and data rate in a single-commodity case. The distributed MIMO multi-hop network consists of $K_1 = 5$ hops with $[1,\, 2,\, 3,\, 3,\, 3,\, 1]$ denoting the number of the nodes per VAA. The distance between two neighboring base-stations is assumed to be 1 km and the pathloss exponent is $\epsilon = 3$. The end-to-end outage probability $P_{\mathrm{e2e},1}$ is required to be smaller than 10%. At each time slot, each transmit node uses the entire frequency band. After solving the optimization problem, we observe the interesting result that the optimal outage probability per hop remains unchanged versus the data rate and bandwidth if the e2e outage probability constraint is fixed. Keeping this in mind, this result motivates our resource allocation strategy for a distributed MIMO multi-commodity communication.

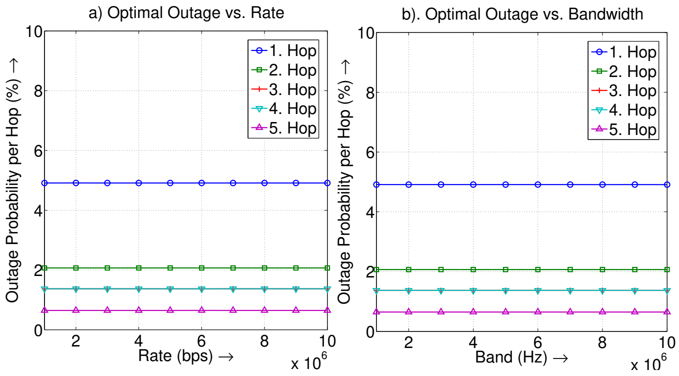

Fig. 4. Optimal outage probability per hop vs. rate and bandwidth for a single-commodity case. $P_{\mathrm{e2e},1} \leq 10\%$

5. PER HOP BANDWIDTH ALLOCATION (PHBA)

5.1. Greedy-edge-coloring algorithm

Before we discuss our approach in detail, we first introduce the standard Greedy-edge-coloring algorithm shortly [18]. The Greedy-edge-coloring algorithm is originally used to assign colors to a graph so that adjacent edges in the graph are differently colored. We apply the algorithm to determine orthogonal bandwidth allocations for overlapping hops in our approach. Since we use a TDMA transmission scheme, a case illustrated in Fig. 5 may happen in a multi-commodity transmission that the hops of 5 commodities are overlapped, where for instance, the 6th hop of the 1st commodity connects with the 3rd hop of the 2nd commodity and the 4th hop of the 5th commodity. According to the graphic theorem [18], the figure can be interpreted as a graph with 5 edges.

By using the Greedy coloring algorithm, the graph can be colored by 3 different colors, i.e., green, red, blue. In other words, it means that the total bandwidth has to be partitioned into $L = 3$ orthogonal parts, denoted as α_1, α_2, α_3 with $\sum_{l=1}^{L=3} \alpha_l = 1$. From the figure it can be seen that the 1st, 3rd commodities, the 2nd, 4th commodities use the same band bandwidth, respectively. We observe that using the Greedy edge-coloring algorithm can furthermore improve the efficiency of the bandwidth usage comparing to the equal and dynamic bandwidth allocation, where for the 5 commodities case the total bandwidth is divided into 5 orthogonal parts. By using the Greedy edge-coloring algorithm reuse of the bandwidth is achieved, since the total bandwidth is only partitioned into 3 parts. For convenience, we define a vector $\Phi_{m,k}$ to describe the mapping relationship between $\alpha_{m,k}$ and α_l. It is represented as $\alpha_{m,k} = \Phi_{m,k} \cdot [\alpha_1, \cdots, \alpha_L]^T$,

$$\begin{aligned}
\alpha_1 &\longrightarrow \alpha_{1,6},\, \alpha_{3,7} \mapsto \Phi_{1,6} = \Phi_{3,7} = [1,\, 0,\, 0] \\
\alpha_2 &\longrightarrow \alpha_{2,3},\, \alpha_{4,3} \mapsto \Phi_{2,3} = \Phi_{4,3} = [0,\, 1,\, 0] \\
\alpha_3 &\longrightarrow \alpha_{5,4} \qquad\quad\; \mapsto \Phi_{5,4} = [0,\, 0,\, 1].
\end{aligned} \tag{16}$$

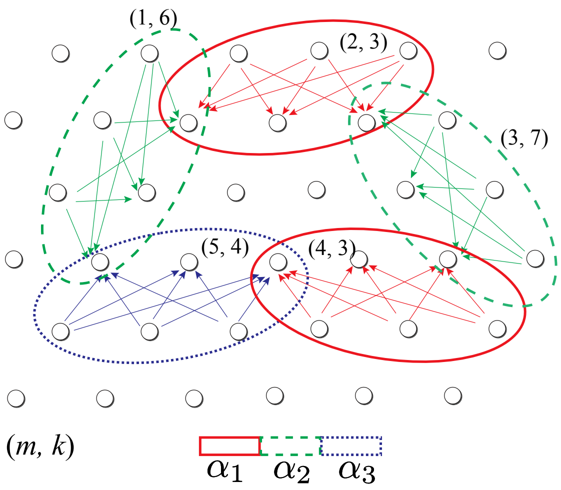

Fig. 5. Edge-coloring algorithm for a 5 commodities case. (m, k) denotes the kth hop of the mth commodity.

5.2. Per hop optimization

After separating bandwidth by the Greedy edge-coloring algorithm, our novel approach will be discussed in detail. The idea of the per-hop-optimization approach is twofold:

- Instead of a unique bandwidth allocation to commodities, we allow for a flexible allocation per hop. Only the overlapping hops between commodities need to share the bandwidth, other hops are allowed to use the entire bandwidth. Furthermore, the reusage of the bandwidth for the overlapping hops can be accomplished by using the Greedy-edge-coloring algorithm, then the equation constraint $f(\cdot)$ in (13) becomes $\sum_{l=1}^{L} \alpha_l = 1$ with the mapping relation $\alpha_{m,k} = \Phi_{m,k} \cdot [\alpha_1, \cdots, \alpha_L]^T$, where L denotes the number of required bandwidth fractions.

- Since the optimal outage probability per hop remains unchanged versus the data rate and bandwidth if the e2e outage probability is upper bounded, we can decompose the multi-hop optimization problem into per hop optimization problems.

We summarize the algorithm as follows,

- Step 1: Solve the optimization problem for each commodity separately assuming full bandwidth per commodity,

$$\begin{aligned} \text{minimizing } & \sum_{k}^{K_m} \sum_{i}^{t_{m,k}} \mathcal{P}_{m,k,i} \\ \text{subject to } & P_{\text{e2e},m} \leq e_m, \\ & \alpha_m = 1 \end{aligned} \tag{17}$$

so that the optimal power allocation of $\mathcal{P}^*_{m,k,i}$ is obtained. According to (7), the outage probability constraint per hop of each commodity can be calculated, $P^*_{\text{out},m,k} = e^*_{m,k}, \forall m, \forall k$.

- Step 2: Determine $\Phi_{m,k}$ by the Greedy edge-coloring algorithm. For overlapping hops the bandwidth should be shared between the commodities, otherwise the transmission can use the entire frequency band, i.e., $\alpha_{m,k} = 1$.

- Step 3: Solve the optimization problem per hop for the given outage probability constraint $e^*_{m,k}$,

$$\begin{aligned} \text{minimizing } & \sum_{m}^{M} \sum_{i}^{t_{m,k}} \mathcal{P}_{m,k,i} \\ \text{subject to } & P_{\text{out},m,k} \leq e^*_{m,k} \\ & \sum_{(m,k,i) \in E^+\{n\}} \mathcal{P}_{m,k,i} \leq \mathcal{P}_n^{\max}, \\ & \alpha_{m,k} = \Phi_{m,k} \cdot [\alpha_1, \ldots, \alpha_L]^T, \\ & \sum_{l=1}^{L} \alpha_l = 1. \end{aligned} \tag{18}$$

The near-optimal resource allocation can now be obtained, i.e., the power allocation $\mathcal{P}^*_{m,k,i}$ and the bandwidth allocation $\alpha^*_{m,k}$.

For the next hops of all commodities, goto Step 2 and 3 again. The algorithm ends when the optimization problem (18) for all hops of all commodities has been applied.

6. PERFORMANCE ANALYSIS

In this section we provide some numerical results to show the performance of our approach in a wireless backhaul network. We assume that there is 5 MHz bandwidth available to the network and all commodities share this bandwidth. We consider 4 commodities active in the network, as illustrated in Fig. 6. Each commodity has its individual distributed MIMO multi-hop structure with different number of hops, different source and destination nodes, and end-to-end outage probability requirements, namely 1%, 1%, 10%, 5%, respectively. The power of thermal noise N_0 is assumed to be -174 dBm according the standards of Universal Mobile Telecommunications System (UMTS).

Fig. 7 shows the total power consumption of the network versus data rate from 1 Mbps to 10 Mbps. It can be seen that the dynamic bandwidth allocation strategy consumes less power than the equal bandwidth allocation due to the freedom of differing bandwidth fractions. However, the PHBA outperforms the dynamic and equal bandwidth allocation strategies significantly and achieves nearly the performance of a

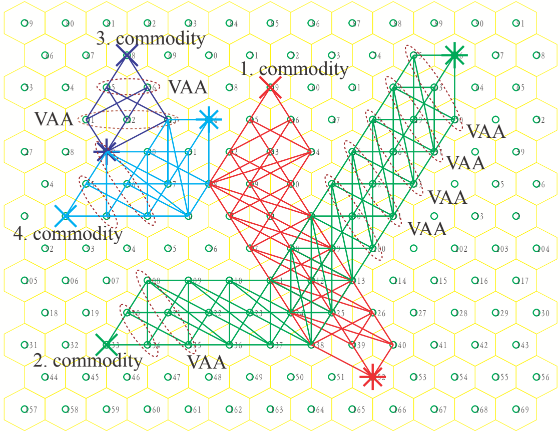

Fig. 6. Distributed MIMO multi-hop multi-commodity transmission (4 commodities) with the e2e outage constraints 1%, 1%, 10%, 5%, respectively. $\times$ denotes source, $*$ is destination. Each commodity is differently colored.

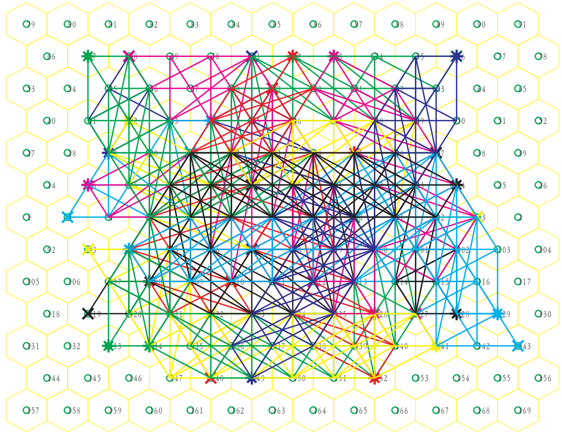

Fig. 8. Distributed MIMO multi-hop multi-commodity transmission (21 commodities) with different e2e outage constraints. $\times$ denotes source, $*$ is destination. Each commodity is differently colored.

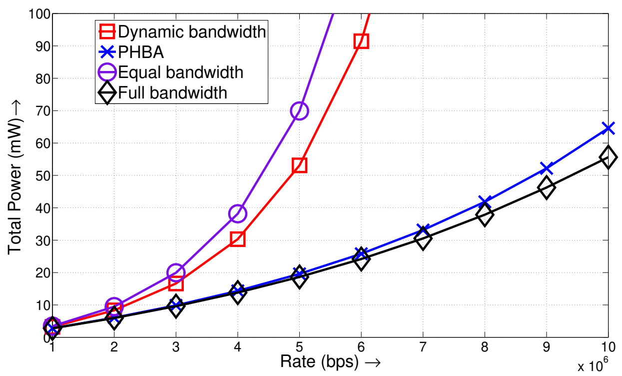

Fig. 7. Total power vs. rate for 4 commodities with the e2e outage constraints 1%, 1%, 10%, 5%.

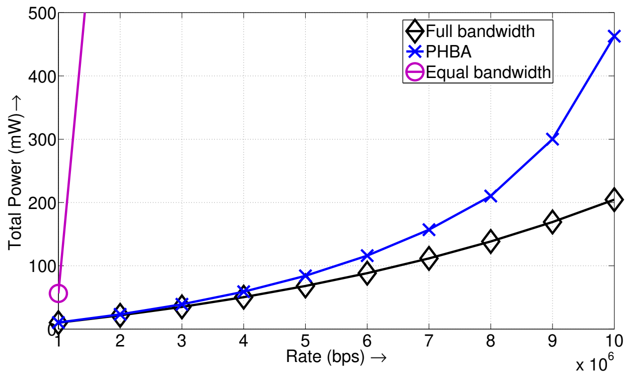

Fig. 9. Total power vs. rate for 21 commodities with different e2e outage constraints.

full bandwidth allocation per commodity. Note that the full bandwidth allocation is only an artificial and unreachable case that each commodity can use the full bandwidth without any interference. It serves as a lower bound for total power consumption.

The performance of the PHBA in a fully occupied network is evaluated next. As depicted in Fig. 8, there are 21 commodities active in the network at the same time. Each commodity has its individual arbitrary end-to-end outage probability requirement. The network setup as shown is randomly chosen. Fig. 9 shows the total power consumption with different resource allocation strategies. It is obvious that the equal bandwidth allocation is not suitable for a large number of commodities, since it leads to an enormous power consumption. In contrast, our novel approach PHBA can support the network with reasonable total power to provide the required QoS for the commodities.

7. SUMMARY

In this paper we have studied the principles of distributed MIMO multi-hop scheme and its applications in wireless backhaul networks. Motivated by the resource allocation strategy to maximize the end-to-end ergodic capacity, we have introduced a strategy based on minimizing the total transmission power while satisfying the end-to-end outage probability requirement for the multi-commodity case. The optimization problems of resource allocation in *asymmetric* distributed MIMO multi-hop networks were investigated, where a Gamma approximation with respect to geometric mean was proposed for simplicity.

Moreover, the multi-commodity transmission of distributed MIMO multi-hop scheme has been considered, which is referred as a distributed MIMO-OFDMA network. The equal and dynamic bandwidth allocation between commodities were investigated. We proposed a novel approach of resource allocation for the distributed MIMO-OFDMA network, i.e. Per-Hop-Bandwidth-Allocation, to overcome the problem of enormous power consumption in the wireless networks with a large number of commodities and improve the efficiency of the bandwidth. In the proposed algorithm, the bandwidth is shared between commodities in a near-optimum way, i.e., if a relaying node is used by only one commodity, then full bandwidth will be allocated to the node; if a node is shared by commodities, then the bandwidth is shared between commodities. We show that by using the proposed algorithm, the total power consumption of the network is significantly reduced. The novel algorithm achieves over 90% power gain compared to the equal bandwidth allocation.

For the distributed and cooperative communications, many research issues still need to be discovered and analyzed, e.g., dynamic forming a VAA based on channel conditions, non-ergodic fading channel, complexity of transceives, and dynamic scheduling, routing and power allocation in wireless mesh network, etc.

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