Capacity Scaling Laws in Interference-Limited Multiple-Antenna AF Relay Networks With User Scheduling

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***Abstract*— The ergodic capacity of multiuser multiple-antenna amplify and forward relay networks with co-channel interference is investigated. Notwithstanding the system complexity, the proposed capacity analysis framework was made possible owing to the newly found complementary moment generating function transform. First, the exact expression for the ergodic capacity, under interference-aware opportunistic scheduling and Rayleigh fading, is derived for finite antenna and user counts. In addition, using extreme value theory, closed-form expressions for the asymptotic ergodic rates are derived for an unlimited number of users or/and antennas at the source. The large-scale analysis embodies, through new insightful formulas, common popular observations so far disclosed intuitively or empirically. Capitalizing on these novel scaling laws, we have been able to derive new closed-form expressions for capacity losses due to intercell interference at the relay and all users. Simulation results suggest a rather fast convergence of the capacity gains to the new asymptotic limits, thereby demonstrating the practical importance of our novel scaling results.**

***Index Terms*— Amplify-and-forward, MIMO, multiuser diversity, opportunistic scheduling, co-channel interference.**

I. Introduction

DRIVEN by the surge of shared data volume and connected devices, multiuser multiple-antenna (MU-MIMO) relaying networks have recently drawn a significant attention as one promising solution to cope with the necessities of more efficient and larger networks. Aiming to enhance multiuser capacity, multiple-antenna communications have been actually identified as a key enabling technique to secure the unprecedented data deluge these large networks are deemed to convey [1], [2]. As such, there has been prominent activity in the past decade toward understanding the fundamental system capacity limits of such architectures, most notably when limited by interference [3], [4].

Manuscript received December 4, 2015; revised May 2, 2016; accepted June 6, 2016. Date of publication June 20, 2016; date of current version August 12, 2016. This work supported by the DG and the CREATE PERSWADE Programs of NSERC and a Discovery Accelerator Supplement Award from NSERC. The associate editor coordinating the review of this paper and approving it for publication was G. Bauch.

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Digital Object Identifier 10.1109/TCOMM.2016.2582480

Many contributions spearheaded this line of research by considering the combination of cooperative and multiuser diversities in the context of single-antenna communications [5]–[7]. In [5], the authors explicitly derived the multiuser diversity orders of several relaying protocol including AF. In [7], the authors showed that the end-to-end signal-to-noise ratio (SNR) is an inadequate criterion for reduced-feedback approaches with SNR-based scheduling in multiuser dual-hop amplify-and-forward (AF) relaying networks. Alternatively, the SNR of the second-hop which requires less complexity at the relay turns out to be a more promising criterion for achieving capacity.

Aiming to further increase the system capacity and reliability, another line of work dedicated to multiuser relay-assisted networks with multi-antenna communications has been longing for understanding such systems [8]–[11]. Assuming multiple antennas at the source, the authors of [8] investigated the optimization problem for joint precoding design in a multiuser downlink system using relaying. Employing opportunistic scheduling, in which the destination with the highest instantaneous SNR is scheduled, the authors of [9] studied the transmit antenna selection and maximal ratio combining (TAS/MRC) scheme in MIMO relay networks. In [10], the authors evaluated the average capacity of multiuser MIMO AF relaying using receive antenna diversity. In [11], the authors derived the exact and asymptotic performance of multiuser MIMO relaying networks under non-identical Nakagami-*m* fading.

Although these works have made great strides toward understanding MU-MIMO relay-assisted communications, they all rely on the absence of the harmful effect of co-channel interference (CCI). The recognition of the interference-limited nature of emerging communication systems has motivated several works to investigate the impact of CCI on the performance of relay networks for different fading models and communication setups [12]–[15]. For instance, in [13], a novel analytical capacity expression for two-hop multiple antenna AF relaying systems was proposed. The more general case of multihop interference-limited communications has also been treated in [14]. However the works in [12]–[15] only consider a single-user scenario. Only recently in [16] was CCI assessed in the context of multiuser relaying networks with opportunistic scheduling. However, this work provided only bounds on the system capacity without characterizing its exact expression and scaling laws.

In contrast, this paper quantifies more accurately the capacity of MU-MIMO relay-assisted networks when opportunistic scheduling among users and transmit selection between the sources's antennas are implemented in a cellular environment. More importantly, its newly derived scaling laws reveal with unprecedented clarity how CCI affects multiuser and spatial diversity gains. The main contributions of this work are summarized as follows. To compute the channel capacity, we establish a novel single-integral relationship in terms of the CMGFs of the per-hop signal-to-interference ratios (SIRs). This relation is resolved in closed form, thereby offering a useful add-on to the framework proposed by [16] which only claims some capacity bounds. For finite large numbers of users, we derive tight average capacity approximations in closed form. We also establish the capacity scaling law when the number of antennas and users grow without bounds. We show that while a $\ln\ln(K)$ [17] scaling law is obtained for interference-oblivious scheduling, a much higher growth rate in $\ln\left(K^{1/Q}-1\right)$ is achieved when interference is accounted for. Most importantly, the performance degradation caused by interference is quantified by deriving the corresponding asymptotic loss.

The rest of the paper is organized as follows. Section II introduces the system model of downlink multiuser AF relay-assisted networks with opportunistic scheduling. Section III introduces the CMGF transform and derives the exact expression for the system capacity. Sections IV and V characterize the system capacity and its scaling laws with massive antenna selection and interference-aware user scheduling. Section VI presents some numerical results and discusses the impact of the numbers of users and interferers on capacity. Finally, Section VII concludes the paper. Technical details and proofs are placed in appendices.

Notation: $\dagger$ is the transpose complex conjugate operator. $\overset{d}{=}$ denotes an equality in distribution, and $\mathbb{E}\{\cdot\}$ is the expectation operator. $M_X(s)=\mathbb{E}\{e^{-sX}\}$ is the MGF of RV X. $F_X(z)=Pr(X\le z)$ is the Cumulative Distribution Function (CDF) of X and $F_X^{(c)}(z)=1-F_X(z)$ is its Complementary Cumulative Distribution Function (CCDF). $M_X^{(c)}(s)=(1-M_X(s))/s$ is the complementary MGF of X while $f_X(x)$ is its Probability Density Function (PDF). $\Gamma(z,x)$, $\Psi(a,b,z)$, and ${}_2\mathrm{F}_1(a,b,c,x)$ denote the upper incomplete gamma function [18, eq. (8.350.2)], the Triconomi confluent hypergeometric function [18, eq. (9.211.1)], the Gauss hypergeometric function [18, eq. (9.100)], respectively. The second-type Bessel function of order ν and the exponential integral function are, respectively, denoted by $\mathrm{K}_\nu(x)$ and $\mathrm{E_i}(x)$ [18, eq. (8.222.1)]. $\mathrm{W}(a,b,z)$ is the Whittaker hypergeometric function [18, eq. (9.222.1)] and $\mathrm{G}^{p,q,k,r,l}_{A,[C,E],B,[D,F]}(\cdot,\cdot)$ is the generalized Meijer-G-function of two variables [19]. "$\chi(2p)$" denotes a chi-square random variable with $2p$ degrees of freedom.

II. System Model

We consider a downlink of an AF multi-user half-duplex relay network featuring a number K of users (i.e., destinations) U_j, $j=1,\ldots,K$, one source S, and one relay R. The users are single-antenna terminals uniformly distributed in space. The MIMO-enabled source and relay are equipped with M and N antennas, respectively. We assume that the source communicates with the users in a dual-hop fashion using an orthogonal multiple access scheme within the cell so that a single user per cell is supported in any given spectral resource slot (time slot, frequency slot, code slot, etc.). In this paper we focus on the impact of intercell multiple access which is simply superposed, due to full reuse of spectrum (see Fig. 1 for illustration).

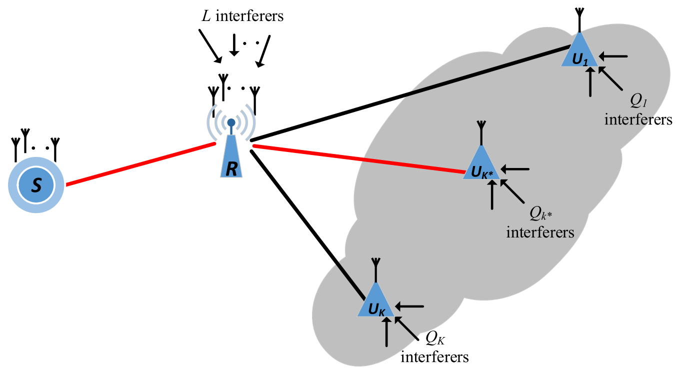


Fig. 1. Two-hop MU-MIMO AF relay network. Direct and interfering links toward the relay and the scheduled user are indicated in red and black arrows, respectively.

We denote by $\mathbf{h}_{i,r}$, $\mathbf{h}_{r,j}$, $\mathbf{h}_j$, and $h_{j,\upsilon}$ the complex downlink flat-fading Rayleigh channel gains with unit average power between the ith antenna of S and R, R and U_j, I_j^R and R, I_υ^j and U_j, respectively. Let x, x_j, and $x_{j,\upsilon}$ be the complex message-carrying signal from S, I_j^R, and I_υ^j, respectively; Then, the received signal from i-th source antenna to the relay R is given by

$$y_{i,r}=\mathbf{w}_i^\dagger\left(\mathbf{h}_{i,r}x+\sum_{j=1}^{L}\mathbf{h}_jx_j\right),\quad i=1,\ldots,M, \tag{1}$$

where $\sum_{j=1}^{L}\sqrt{\mu_j}\mathbf{h}_jx_j$ is the sum of L interfering signals from other cells at the relay. After applying a gain factor G_i at the relay, the received signal at the j-th destination U_j is given by

$$y_{r,j}=\mathbf{w}_j^\dagger\mathbf{h}_{r,j}G_iy_{i,r}+\sum_{\upsilon=1}^{Q_j}h_{j,\upsilon}x_{j,\upsilon},\quad j=1,\ldots,K, \tag{2}$$

where $\sum_{\upsilon=1}^{Q_j}h_{j,\upsilon}x_{j,\upsilon}$ is the sum of Q_j interfering signals from other cells at U_j. Assuming perfect forward and backward channel state information (CSI) at the relay, the latter apply the normalized MRC and MRT precoding vectors given, respectively, by $\mathbf{w}_i=\frac{\mathbf{h}_{i,r}}{\|\mathbf{h}_{i,r}\|}$, $i=1,\ldots,M$ and $\mathbf{w}_j=\frac{\mathbf{h}_{r,j}}{\|\mathbf{h}_{r,j}\|}$, $j=1,\ldots,K$. For variable gain relaying scheme, the relaying gain G_i is given by

$$G_i=\sqrt{\frac{\lambda}{\rho|\mathbf{w}_i^\dagger\mathbf{h}_{i,r}|^2+\sum_{j=1}^{L}\mu_j|\mathbf{w}_i^\dagger\mathbf{h}_j|^2}}, \tag{3}$$

where λ is the transmit power at the relay, $\rho=\mathbb{E}|x|^2$ and $\mu_j=\mathbb{E}|x_j|^2$, $j=1,\ldots,L$ denote the transmit powers at the source and the j-th interferer at the relay, respectively. We also denote by $\nu_{j,\upsilon} = \mathbb{E}|x_{j,\upsilon}|^2, \upsilon = 1, \ldots, Q_j$ the transmit power of the υ-th interferer I_υ^j at user U_j, $j = 1, \ldots, K$. Using (3) in (2), the instantaneous end-to-end SIR of the $\{i, j\}$-th relaying link can be derived as

$$\Gamma_{i,j} = \frac{\Gamma_{i,r}\Gamma_{r,j}}{\Gamma_{i,r} + \Gamma_{r,j} + 1}, \tag{4}$$

where

$$\Gamma_{i,r} = \frac{\rho|\mathbf{h}_{i,r}|^2}{\sum_{j=1}^{L} \mu_j |\mathbf{w}_i^\dagger \mathbf{h}_j|^2}, \tag{5}$$

whereby $|\mathbf{h}_{i,r}|^2$ is the channel power gain from the i-th antenna at the source to the relay and

$$\Gamma_{r,j} = \frac{\lambda|\mathbf{h}_{r,j}|^2}{\sum_{\upsilon=1}^{Q_j} \nu_{j,\upsilon}|h_{j,\upsilon}|^2}. \tag{6}$$

whereby $|\mathbf{h}_{r,j}|^2$ is the channel power gain from the relay to the j-th user U_j.

Having a perfect knowledge of its forward and backward channels (coherent MIMO relaying), the relay selects the antenna with the best channel quality [20], yielding

$$\Gamma_{i^*,r} = \frac{\rho \max\limits_{i=1,\ldots,M}|\mathbf{h}_{i,r}|^2}{\sum_{j=1}^{L} \mu_j |\mathbf{w}_{i^*}^\dagger \mathbf{h}_j|^2} = \Gamma^{(M)}. \tag{7}$$

The relay is also in charge of selecting the user with the largest SIR (maximum relay-user rate scheduler) and feeding back its index to the source. Consequently, we have

$$\Gamma_{r,j^*} = \max_{j=1,\ldots,K} \frac{\lambda|\mathbf{h}_{r,j}|^2}{\sum_{\upsilon=1}^{Q_j} \nu_{j,\upsilon}|h_{j,\upsilon}|^2} = \Gamma^{(K)}. \tag{8}$$

It is worth noting that if the relay scheduler is interference oblivious, then each cell only needs to know the realization of the direct gain $|\mathbf{h}_{r,j}|^2$ and the scheduler is, therefore, trivially distributed (i.e., depends on locally available information only). This task is unarguably difficult for interference-aware schedulers since the achievable rates observed in different cells are cross-coupled through the interference terms. Therefore, it becomes crucial to understand how much performance losses could one expect by sticking to algorithms that solely require local CSI? In the general case, this problem is a difficult one, but some light can be shed here in some asymptotic cases. From this perspective, we assume first of all a homogenous network where all users served by the source are assumed to be located at the same distance from the relay (clustered users). This situation results in all users experiencing the same average SIR. Thus $\frac{\lambda}{\sum_{\upsilon=1}^{Q_j} \nu_{j,\upsilon}} = \frac{\lambda}{\sum_{\upsilon=1}^{Q} \nu_\upsilon} = \text{SIR}$ is a constant independent of the user index j; an assumption often made by previous authors works (e.g., [17], [21], [22]). We also assume interference coming with the same power from every transmitter in the network. In this scenario, all interferers lie on a sphere of the same radius around the user (worst or best interference location). Hence, we can also drop the index υ thereby yielding the second-hop average SIR $= \frac{\lambda}{\nu}$.

Unless mentioned otherwise, the entire discussions of this contribution are developed under the above conditions leading to the following end-to-end SIR of the network:

$$\Gamma(M, K) = \frac{\Gamma^{(M)}\Gamma^{(K)}}{\Gamma^{(M)} + \Gamma^{(K)} + 1}, \tag{9}$$

where $\Gamma^{(M)} = \frac{\rho \max_{i=1,\ldots,M}|\mathbf{h}_{i,r}|^2}{\sum_{j=1}^{L} \mu_j |\mathbf{w}_{i^*}^\dagger \mathbf{h}_j|^2}$ and $\Gamma^{(K)} = \frac{\lambda}{\nu} \max\limits_{j=1,\ldots,K} \frac{|\mathbf{h}_{r,j}|^2}{\sum_{\upsilon=1}^{Q} |h_{j,\upsilon}|^2}$.

III. Exact Analysis of the Capacity

In this section, the performance of the MU-MIMO relay network under the setting described in Section II is studied. Assuming Gaussian input distribution, we use the ergodic capacity as the performance metric, defined as $C = \frac{1}{2}\mathbb{E}[\ln_2(1 + \Gamma(M, K))]$, where the factor $\frac{1}{2}$ penalty in the multiplexing gain comes from the fact that communication takes place over two time slots (i.e., half-duplex protocol).

Proposition 1: (A Novel CMGF-Based Approach to Compute C): Let the system model of Section II. Then, C is given by

$$C = \frac{1}{2\ln(2)} \int_0^\infty s \exp\{-s\} M_{\Gamma^{(M)}}^{(c)}(s) M_{\Gamma^{(K)}}^{(c)}(s) ds, \tag{10}$$

where

$$M_X^{(c)}(s) \triangleq \int_0^\infty \exp\{-sx\} F_X^{(c)}(x) dx \triangleq \mathcal{L}_{F_X^{(c)}}(s), \tag{11}$$

where $\mathcal{L}$ stands for the Laplace transform.

Proof: We have

$$\begin{aligned} C &= \frac{1}{2}\mathbb{E}\left[\log_2\left(\frac{(1+\Gamma^{(M)})(1+\Gamma^{(K)})}{1+\Gamma^{(M)}+\Gamma^{(K)}}\right)\right] \\ &= C_{\Gamma^{(M)}} + C_{\Gamma^{(K)}} - C_{\Gamma^{(M)}+\Gamma^{(K)}}, \end{aligned} \tag{12}$$

where $C_{Y \in \{\Gamma^{(M)}, \Gamma^{(K)}, \Gamma^{(M)}+\Gamma^{(K)}\}} = \mathbb{E}[\ln(1 + Y)]$. The latter expectation can be evaluated using [23, Lemma 1] as

$$C_{Y \in \{\Gamma^{(M)}, \Gamma^{(K)}, \Gamma^{(M)}+\Gamma^{(K)}\}} = \frac{\int_0^\infty \frac{\exp\{-s\}}{s} (1 - M_Y(s))\, ds}{\ln(2)}. \tag{13}$$

Let $M_Y(s) = s\int_0^\infty \exp\{-sy\} F_Y(y) dy = 1 - s\int_0^\infty \exp\{-sy\} F_Y^{(c)}(y) dy$, then $M_Y(s) = 1 - sM_Y^{(c)}(s)$. By inserting this last expression in (12), we obtain

$$\begin{aligned} C = \frac{1}{2\ln(2)} &\Bigg(\int_0^\infty \exp\{-s\} M_{\Gamma^{(M)}}^{(c)}(s) ds \\ &+ \int_0^\infty \exp\{-s\} M_{\Gamma^{(K)}}^{(c)}(s) ds - \int_0^\infty \exp\{-s\} \\ &\times \frac{1 - \left(1 - sM_{\Gamma^{(M)}}^{(c)}(s)\right)\left(1 - sM_{\Gamma^{(K)}}^{(c)}(s)\right)}{s} ds \Bigg). \end{aligned} \tag{14}$$

Finally, simplifying (14) concludes the proof.

Capitalizing on the CMGF-based representation in (10), whose rational relies upon exploiting the CMGF of the per hop SIR, enables an equivalent system model representations that are mathematically tractable. In the sequel, we will prove that this new methodology can lead to closed-form expressions for the ergodic capacity.

$$C = \frac{1}{2\ln(2)} \sum_{n=0}^{M-1} \sum_{\Omega(n,N)} \sum_{i=1}^{\rho(\mathbf{D})} \sum_{j=1}^{\tau_i(\mathbf{D})} \sum_{k=0}^{N+\delta_n-1} \frac{M\Theta_n \Gamma(k+j)(N+\delta_n-1)!\zeta_i^j(\mathbf{D})}{\Gamma(N)(n+1)^{N+\delta_n}(j-1)!} \frac{\frac{\rho}{\mu_{\langle i \rangle}}}{(n+1)} \frac{\lambda}{\nu} \Bigg(\sum_{m=0}^{K(Q+N-1)-1} \frac{\binom{K(Q+N-1)}{m}}{\Gamma(K(Q+N-1))}$$
$$\times G^{1,1,1,1,2}_{1,[1,1],0,[1,2]}\left[\frac{\frac{\rho}{\mu_{\langle i\rangle}}}{n+1}, \frac{\lambda}{\nu} \,\middle|\, \begin{matrix} \ldots; 1+k; 1+m; \\ \ldots; 0, j-1; 0, K(Q+N-1)-m-1 \end{matrix}\right] + \sum_{p=1}^{K} \sum_{\Omega(p,Q-1)} \frac{\binom{K}{p} \prod_{l=1}^{Q-1} \left(\frac{(1-Q)_l(-1)^l}{(1+N)_l}\right)^{p_l}}{(NB(N,Q))^p}$$
$$\times \frac{\frac{p!}{\prod_{l=1}^{Q-1} p_l!}}{\Gamma(K(Q+N-1)+p(Q-1))} G^{1,1,1,1,2}_{1,[1,1],0,[1,2]}\left[\frac{\frac{\rho}{\mu_{\langle i\rangle}}}{n+1}, \frac{\lambda}{\nu} \,\middle|\, \begin{matrix} \ldots; 1+k; 1+\delta_p+K(Q+N-1)+p(1-Q); \\ 0, j-1; 0, -\delta_p-1+p(1-Q) \end{matrix}\right]\Bigg) \tag{15}$$

Corollary 1 (Closed-Form Expression for C): The ergodic capacity is given by (15) shown at the top of the next page.

Proof: See Appendix A.

The function $G^{p,q,k,r,l}_{a,[c,e],b,[d,f]}(\cdot,\cdot)$ is known as the generalized Meijer's G-function of two variables [19] and can be implemented in most numerical software programs. Moreover in (15), $(x)_n$ stand for the Pochhammer function and $B(x,y) = \Gamma(x)\Gamma(y)/\Gamma(x+y)$ is the Beta function [18].

IV. Large-Scale Analysis of the Capacity

We analyse the ergodic capacity with massive antenna selection and interference-aware user scheduling, i.e., when the number of antennas at the source M and the number of users K grow without bound. The study of asymptotic capacity when the relay antenna number N gets unbounded is interesting, yet beyond the scope of this paper.

Capitalizing on *Proposition 1*, the large-scale capacity analysis boils down to studying the asymptotic CMGF of the SIR in each hop independently. Assuming an isotropic network (i.e., all users experience the same channel statistics), we can simplify the analysis as shown below.

Lemma 1: Let $v_i = \rho|\mathbf{h}_{i,r}|^2, i = 1,\ldots,M$. Assume that $v_i \overset{d}{=} \rho\chi(2N)$ are independent and identically distributed (i.i.d.) across antennas with PDF and CDF given, respectively, by $f_V(x) = \frac{(\frac{x}{\rho})^{N-1}}{N!} e^{-\frac{x}{\rho}}$ and $F_V(x) = 1 - \frac{\Gamma(N,\frac{x}{\rho})}{\Gamma(N)}$. Then for asymptotically large M and fixed N, the CMGF of $\Gamma^{(M)} = \max_{i=1,\ldots,M} \frac{v_i}{\mu \sum_{j=1}^{L} |\mathbf{w}_{i*}^{\dagger}\mathbf{h}_j|^2}$ is given by

$$M^{(c)}_{\Gamma^{(M)}}(s) = \frac{1}{s} - 2\sum_{n=0}^{L-1} \frac{\beta_M^{n+1}}{n!} s^{\frac{n-1}{2}} K_{n-1}\left(2\beta_M\sqrt{s}\right), \tag{16}$$

where $\beta_M = \sqrt{\frac{\rho}{\mu}\left(\ln(M/4) + (N-1)\ln\ln(M)\right)}$.

Proof: See Appendix B.1.

Lemma 2: Let $w_j = \frac{|\mathbf{h}_{r,j}|^2}{\sum_{v=1}^{Q} |h_{j,v}|^2}$ denotes the normalized SIR at user U_j, which is the ratio of two Chi-square distributed variables, i.e., $w_j \overset{d}{=} \frac{\chi(2N)}{\chi(2Q)}$. Assume that w_j, $j = 1,\ldots,K$ are i.i.d. across users. Then we can find their distribution as

$$F_W(x) = \frac{x^N {}_2F_1(N+Q, N, 1+N, -x)}{NB(N,Q)}. \tag{17}$$

Then for fixed N and asymptotically large K, the CMGF of $\Gamma^{(K)} = \frac{\lambda}{\nu} \max_{j=1,\ldots,K} w_j$ is given by

$$M^{(c)}_{\Gamma^{(K)}}(s) \approx \begin{cases} \frac{1}{s}\left(1 - e^{-\frac{NK\lambda}{4\nu}s}\right), & Q = 1, \forall\ N \\ \frac{1}{s}\left(1 - e^{-\frac{\lambda}{\nu}\left(\frac{K^{\frac{1}{Q}}-1}{4^{\frac{1}{Q}}}\right)s}\right), & N = 1, \forall\ Q. \end{cases} \tag{18}$$

Proof: See Appendix B.2.

From the per-hop SIR CMGF asymptotic expressions in (16) and (18), we obtain the large-scale average capacity of the two-hop AF MU-MIMO network as stated in the following theorems.

Theorem 1 (Capacity for Large M and K): For fixed N and asymptotically large M and K, the average ergodic capacity of a two-hop AF MU-MIMO system with antenna selection and interference-aware user scheduling is given by

$$C = \frac{1}{2\ln(2)}\Bigg(\ln(\alpha_K) - e^{\frac{\beta_M^2}{\alpha_K}}\Gamma\left(0, \frac{\beta_M^2}{\alpha_K}\right) - e^{\beta_M^2}\mathrm{E_i}\left(-\beta_M^2\right)$$
$$-\sum_{n=1}^{L-1} \frac{\beta_M^n}{n}\left(e^{\frac{\beta_M^2}{2}} W_{-\frac{n}{2},\frac{n-1}{2}}\left(\beta_M^2\right) - \frac{e^{\frac{\beta_M^2}{2\alpha_K}}}{\alpha_K^{n/2}} W_{-\frac{n}{2},\frac{n-1}{2}}\left(\frac{\beta_M^2}{\alpha_K}\right)\right)\Bigg), \tag{19}$$

where $\alpha_K = 1 + \frac{\widehat{a}_K\lambda}{\nu}$, with

$$\widehat{a}_K = \begin{cases} \frac{NK}{4}, & Q = 1, \forall\ N, \\ \frac{K^{\frac{1}{Q}}-1}{4^{\frac{1}{Q}}}, & N = 1, \forall\ Q, \end{cases} \tag{20}$$

Proof: Substituting (16) and (18) into (10), we obtain

$$C = \frac{1}{2\ln(2)}\Bigg(\int_0^\infty \frac{e^{-s}}{s}\left(1 - e^{-\frac{\widehat{a}_K\lambda}{\mu}s}\right) ds$$
$$-2\beta_M\Phi_0\left(\frac{\widehat{a}_K\lambda}{\nu}, \beta_M\right) - 2\sum_{n=1}^{L-1} \frac{\beta_M^{n+1}}{n!}\Phi_n\left(\frac{\widehat{a}_K\lambda}{\nu}, \beta_M\right)\Bigg), \tag{21}$$

whereby

$$\Phi_n(a,b) \underset{n\geq 0}{=} \int_0^\infty e^{-s} s^{\frac{n-1}{2}}\left(1 - e^{-as}\right) K_{n-1}\left(2b\sqrt{s}\right) ds. \tag{22}$$

The first term in (21) can be solved in closed form by applying [18, eq. (3.421.5)]. The second term can be solved by using the identity [18, eq. (8.486.15)]

$$\frac{d(x^{-\mu}K_\mu(x))}{dx} = -x^{\mu}K_{\mu+1}(x), \tag{23}$$

and integrating by part, yielding

$$\Phi_0(a,b) = \frac{1}{2b}\left(e^{\frac{b^2}{1+a}}\Gamma\left(0,\frac{b^2}{1+a}\right)+e^{b^2}\mathrm{E_i}\left(-b^2\right)\right). \tag{24}$$

Finally, applying [18, eq. (6.643)], a closed-from expression for Φ_n is obtained after some manipulations as

$$\Phi_n(a,b) \underset{n\geq 1}{=} \frac{\Gamma(n)}{2b}\left(e^{\frac{b^2}{2}}W_{-\frac{n}{2},\frac{n-1}{2}}\left(b^2\right) - \frac{e^{\frac{b^2}{2(1+a)}}}{(1+a)^{n/2}}W_{-\frac{n}{2},\frac{n-1}{2}}\left(\frac{b^2}{1+a}\right)\right). \tag{25}$$

Theorem 2 (Capacity for Fixed M and N and Large K): For fixed M and N and asymptotically large K, the ergodic capacity of a two-hop AF MU-MIMO system with antennas selection and interference-aware user scheduling is given by

$$C = \frac{1}{2\ln(2)}\sum_{n=0}^{M-1}\sum_{\Omega(n,N)}\sum_{k=0}^{N+\delta_n-1}\frac{M\frac{\rho}{\mu}\Theta_n(N+\delta_n-1)!}{\Gamma(N)(k+L)(n+1)^{N+\delta_n+1}} \times\left({}_2\mathrm{F}_1\left(k+1,1,k+L+1,1-\frac{\rho}{\mu(n+1)}\right)-\left(\frac{NK\lambda}{4\nu}+1\right)^{-1} \times {}_2\mathrm{F}_1\left(k+1,1,k+L+1,1-\frac{\frac{\rho}{\mu(n+1)}}{\left(\frac{NK\lambda}{4\nu}+1\right)}\right)\right), \tag{26}$$

when $Q=1, \forall\ N$, while it is given by

$$C = \frac{1}{2\ln(2)}\sum_{n=0}^{M-1}\frac{\frac{M}{L}\frac{\rho}{\mu}\Theta_n}{(n+1)^2}\left({}_2\mathrm{F}_1\left(1,1,1+L,1-\frac{\rho}{\mu(n+1)}\right) -\left(\frac{\lambda}{\nu}\left(\frac{K^{\frac{1}{Q}}-1}{4^{\frac{1}{Q}}}\right)+1\right)^{-1}{}_2\mathrm{F}_1 \times\left(1,1,1+L,1-\frac{\frac{\rho}{\mu(n+1)}}{\left(\frac{\lambda}{\nu}\left(\frac{K^{\frac{1}{Q}}-1}{4^{\frac{1}{Q}}}\right)+1\right)}\right)\right), \tag{27}$$

when $N=1, \forall\ Q$.

Proof: The result follows after substituting (18) and (55) into (10) and invoking [18, eq. (8.380.1)] with some algebraic manipulations.

Corollary 2: For MU-MIMO relay networks, the capacity achieved by the AF protocol as described in section II, in the large K limit, is given by

$$C^{\infty} = \frac{1}{2\ln(2)}\sum_{n=0}^{M-1}\sum_{\Omega(n,N)}\sum_{k=0}^{N+\delta_n-1}\frac{M\frac{\rho}{\mu}\Theta_n(N+\delta_n-1)!}{\Gamma(N)(k+L)(n+1)^{N+\delta_n+1}} \times {}_2\mathrm{F}_1\left(k+1,1,k+L+1,1-\frac{\rho}{\mu(n+1)}\right). \tag{28}$$

Proof: Applying $x\,{}_2\mathrm{F}_1(a,b,c,1-x) \underset{x\to 0}{\to} 0$ in the $K\to\infty$ limit bears the result. Note that (28) only holds when $K^{1/Q}-1\to\infty$, i.e., when $\log(K)\gg Q$.

This corollary suggests that intercell interference on the second hop, no matter how strong, does not affect the scaling of the network capacity when the number of users is large enough ($\log(K)\gg Q$) and when SIR-optimal scheduling is applied.

It is interesting to observe that $C^{\infty} = \frac{1}{2}C^{TAS/MRC}_{M\times N,L}$ where $C^{TAS/MRC}_{M\times N,L}$ denotes the capacity of an $M\times N$ Gaussian MIMO channel using TAS/MRC and subject to L interferers with receive SIR ρ/μ.

V. Scaling Laws

In an effort to understand and gain more physical insight into the impact of key parameters on the system capacity, we investigate and extract from the scaling laws to key design features: 1) multiuser gain due to interference awareness, and 2) capacity losses due to an increased dimensionality of interference.

Corollary 3 (Arbitrary N With M and K $\to\infty$): If K grows faster than $\ln(M)$ (i.e., $\lim_{M,K\longrightarrow\infty} K/\ln(M)=\infty$, which includes the case K=M), it holds that

$$C \approx \frac{1}{2\ln(2)}\left(\ln\left(\frac{\rho}{\mu}\left(\ln(M)+(N-1)\ln\ln(M)\right)\right) + \gamma - H_{L-1}\right), \tag{29}$$

where γ is the Euler-Mascheroni constant [18, eq. (8.367.1)] and H_n is the harmonic number of order n.

Proof: From *Theorem 1*, as $\frac{K}{\ln(M)}\longrightarrow\infty$, we have $\beta_M^2 \underset{M\longrightarrow\infty}{\longrightarrow}\infty$ and $\frac{\beta_M^2}{\alpha_K}\underset{M,K\longrightarrow\infty}{\longrightarrow} 0$. Hence, the following approximations hold: $\Gamma(0,z)\underset{z\longrightarrow 0}{=} -\ln(z)-\gamma$, $e^z \underset{z\longrightarrow 0}{=} 1+o(z)$, $e^zE_i(-z)\underset{z\longrightarrow\infty}{=} 0$ and $e^{z/2}W_{a,b}(z)\underset{z\longrightarrow\infty}{\approx} z^a$, $z^{n/2}e^{z/2}W_{-n/2,b}(z)\underset{z\longrightarrow 0}{=} 0$. Considering all these properties, C reduces after several manipulations to

$$C \approx \frac{1}{2\ln(2)}\left(\ln\left(\beta_M^2\right)+\gamma-\sum_{n=1}^{L-1}\frac{1}{n}\right), \tag{30}$$

proving thereby (29).

Corollary 3 definitely generalizes published results in the context of single-cell single-hop maximum rate user scheduling, found in [17] among others. Moreover, when using massive antenna selection at the source and massive interference-aware user scheduling, this corollary suggests that the received power of each user node can be scaled down inversely proportional to the number of antennas at the relay ($\lambda_E=\lambda/N$) without incurring any performance penalty since $\frac{\beta_M^2}{\alpha_K}\underset{M,K\longrightarrow\infty}{\longrightarrow} 0$ is preserved.

Remark 1 (Capacity Loss Due to Intercell Interference at the Relay When $Q=1$): Consider a two-hop MU-MIMO AF relay network subject to either L_1 or L_2 interferences at the relay. Then the capacity degradation due to an increased interference dimensionality ($L_2>L_1$) can be computed as

$$\delta_C = \frac{H_{L_1-1}-H_{L_2-1}}{2\ln(2)}. \tag{31}$$

Proof: The result is readily obtained from (29).

Remark 2 (Increased Dimensionality of Interference): The capacity of large-scale MU-MIMO (with $K \gg \ln(M)$) in the presence of a large number of interferers L behaves as

$$2^{2C} \approx \frac{\rho}{\mu} \frac{\ln(M) + (N-1)\ln\ln(M)}{L}. \quad (32)$$

Proof: Resorting to the approximation of the Harmonic number as L goes large given by

$$H_{L-1} \underset{L\to\infty}{\approx} \gamma + \ln(L-1), \quad (33)$$

it follows from (29) that

$$C \approx \frac{1}{2\ln(2)} \left(\ln\left(\rho\left(\ln(M) + (N-1)\ln\ln(M)\right)\right) - \ln(\mu L)\right), \quad (34)$$

yielding (32) after involving some logarithmic identities.

It can be inferred from *Remark 2* that the capacity loss due to an increased dimensionality of spatial interference is much more pronounced than any improvement resulting form adding more active transmit antennas at the source. In view of this key remark, it is not surprising when some research on spatial multiplexing in cellular systems has reached the common conclusion that adding more transmit antennas or data streams at each base station can actually decrease the capacity due to the increased dimensionality of spatial interference [4], [21].

Corollary 4 [$N = 1$ and $\ln(M^{1/L}) \gg K^{1/Q} - 1$]: If $Q \gg \left\lfloor \frac{\ln(K)}{\ln\ln(M)} \right\rfloor$, where $\lfloor x \rfloor$ denotes the integer part of x, then it holds that

$$C \approx \frac{1}{2\ln(2)} \left(\ln\left(1 + \frac{\lambda}{\nu}\left(K^{\frac{1}{Q}} - 1\right)\right) - L \frac{\frac{\lambda}{\nu}\left(K^{\frac{1}{Q}} - 1\right)}{\frac{\rho}{\mu}\ln(M)} \right). \quad (35)$$

Proof: According to (19), the growth of $K^{1/Q} - 1$ with respect to $\ln(M)$ is crucial for the capacity scaling law. In fact, it is easy to show for $\left\lfloor \frac{\ln(K)}{\ln\ln(M)} \right\rfloor \ll Q$ that we have

$$\frac{\beta_M^2}{\alpha_K} \underset{M,K\longrightarrow\infty}{\approx} \frac{\ln(M)}{K^{1/Q} - 1} \longrightarrow \infty. \quad (36)$$

Then it follows immediately that all the terms but the first in the R.H.S of (19) become vanishingly small as M and K grow large with $\frac{\ln(M)}{K^{1/Q}-1} \longrightarrow \infty$. In fact, considering that $e^z\Gamma(0,z) \underset{z\longrightarrow\infty}{=} \frac{1}{z}$, $e^z E_i(-z) \underset{z\longrightarrow\infty}{=} -\frac{1}{z}$, and $z^{n/2}e^{z/2}W_{-n/2,\frac{n-1}{2}}(z) \underset{z\longrightarrow\infty}{=} 1 - \frac{n}{z}$, it follows after some manipulations that

$$C \approx \frac{1}{2\ln(2)} \left(\ln\left(1 + \frac{\lambda}{\nu}\left(K^{\frac{1}{Q}} - 1\right)\right) - L\left(\frac{1 + \frac{\lambda}{\nu}(K^{\frac{1}{Q}} - 1)}{\frac{\rho}{\mu}\ln(M)} - \frac{1}{\frac{\rho}{\mu}\ln(M)} \right) \right), \quad (37)$$

thereby concluding the proof.

Despite imposing (36), the latter appears to be insufficient to achieve the multiuser diversity gain. In fact, C in (35) is a monotonically increasing function of K if and only if the following condition holds

$$\ln(M^{1/L}) \gg K^{1/Q} - 1, \quad (38)$$

where (38) verifies $\frac{dC}{dK} > 0$.

Corollary 5 [$N = 1$ and $\ln(M^{1/L}) \ll K^{1/Q} - 1$]: When $\frac{\ln(M)}{K^{1/Q}-1} \longrightarrow 0$, valid for small to moderate values of Q, the scaling law for arbitrary L is given by

$$C \approx \frac{1}{2\ln(2)} \left(\ln\left(\frac{\rho}{\mu}\ln(M)\right) + \gamma - H_{L-1} - \frac{1}{L} \frac{\frac{\rho}{\mu}\ln(M)}{\frac{\lambda}{\nu}(K^{1/Q} - 1)} \right). \quad (39)$$

Proof: (39) is obtained along the same lines to derive (29). The fourth term in the R.H.S of (39) follows form resorting to the series expansion of the Whittaker function near zero. It is easy to prove that (39) is an increasing function of M only if

$$\ln(M^{1/L}) \ll K^{1/Q} - 1, \quad (40)$$

thereby avoiding any impediment of the diversity gain.

Equations (35) and (39) unarguably confirm analytically the common intuitive observation that AF relaying performance is ultimately the performance of one of its bottleneck hop among the two. This dominance is usually the output of the system's parametric objective function that quantifies the link's strength. So far, in the literature, several functions defining the link's strength were proposed, namely, the antenna number, the fading shape, or the product of both.[1] Oblivious to the interference number, these rules turn out to be totally inaccurate in interference-limited environments when considering the ergodic capacity as performance metric.

Corollary 6 (Interference Oblivious or IO vs Interference Aware or IA Multiuser Scheduling): In the IA case, neglecting the second term on the R.H.S of (35) yields

$$\begin{cases} 2C_{IA} \approx \ln_2(\frac{\lambda}{\nu}K^{1/Q}), & \text{for small } Q, \quad (a) \\ 2^{2C_{IA}} \approx 1 + \frac{\lambda}{\nu}\frac{\ln(K)}{Q}, & \text{for large } Q, \quad (b) \end{cases} \quad (41)$$

where the first equation in (41) follows form the fact that $\ln(1+x) \approx \ln(x)$ when x is large enough (valid for small Q). Nevertheless, when Q is large, $\ln(1+x) \approx \ln(x)$ no longer holds true. Instead, we have $K^{1/Q} - 1 \underset{Q\gg 1}{\approx} \frac{\ln(K)}{Q}$, thereby yielding the second approximation for large Q.

Moreover, in the IO case, gathering results from (29) and (32), it follows that

$$\begin{cases} 2C_{IO} \approx \ln_2(\frac{\rho}{\mu}\ln(M)) + \frac{\gamma - H_{L-1}}{\ln(2)}, & \text{for small } L, \quad (c) \\ 2^{2C_{IO}} \approx \frac{\rho}{\mu}\frac{\ln(M)}{L}, & \text{for large } L. \quad (d) \end{cases} \quad (42)$$

Identities (a) and (c) from *Corollary 6* suggest that the capacity obtained with IO and IA scheduling have different scaling laws when the number of interfering sources is small. Remarkably IA scheduling outperforms its IO counterpart since $\ln\left(K^{1/Q}\right) > \ln\ln(M) + \gamma - H_{L-1}$ always holds when $\{M, K\} \gg 1$ and $\{L, Q\}$ are small. This proves the advantage of having global network CSI knowledge, namely through cooperation where the CSI is shared between the transmitting

[1] These rules are usually obtained in terms of a diversity order analysis by assuming equal per-hop average SIRs (cf. [15] and references therein).

nodes so that the interference generated in other cells is taken into consideration.

When the number of interfering sources becomes large, identities (b) and (d) from *Corollary 6* suggest that the capacity obtained with IO and IA scheduling have identical scaling laws in $\ln\ln(U)$, $U \in \{K, M\}$, with a slight advantage for IA since $2^{2C_{IA}} = 1 + 2^{2C_{IO}}$. In fact, the multicell interference in IA scheme becomes negligible because the optimum scheduler tends to select on an instantaneous basis users who have both a strong direct link to the relay and small interfering links from a large number of surrounding interferers. Although this minimization should take away some degrees of freedom in choosing the users with best direct links, it does not sufficiently so to the point of affecting the capacity scaling.

At the relay, the AF protocol tends to favor one of the four scaling laws in *Corollary 6* according to the following decision rules

$$M \overset{(a)}{\underset{(c),(d)}{\substack{\gg \\ \ll}}} \left(\exp\left\{K^{\frac{1}{Q}} - 1\right\}\right)^{L}, \tag{43}$$

and

$$M \overset{(b)}{\underset{(c),(d)}{\substack{\gg \\ \ll}}} K^{\frac{L}{Q}}. \tag{44}$$

Nevertheless, when $\ln(M^{1/L}) \simeq K^{1/Q} - 1$, the AF protocol tends to behave according to (19).

Remark 3 (Capacity Losses Due to Interference): Consider a two-hop MU-MIMO AF relay network with interference-aware scheduling subject to either L_1 and Q_1 or L_2 and Q_2 interferers at the relay and each destination, respectively. For the sake of tractability without loss of generality, we assume $\frac{\rho}{\mu} = \frac{\lambda}{\nu}$. Then capacity losses in the $M, K \to \infty$ limit due to $L_2 > L_1$ and $Q_1 > Q_2$ are given by

$$\begin{cases} \delta_C = \dfrac{\ln\left(\frac{Q_1}{Q_2}\right) - \frac{L_1}{Q_1} + \frac{L_2}{Q_2}}{2\ln(2)}, & \ln(M^{1/L_i}) \gg K^{1/Q_i} - 1, \\ \delta_C = \dfrac{H_{L_1-1} - H_{L_2-1} - \frac{Q_1}{L_1} + \frac{Q_2}{L_2}}{2\ln(2)}, & \ln(M^{1/L_i}) \ll K^{1/Q_i} - 1, \end{cases} \tag{45}$$

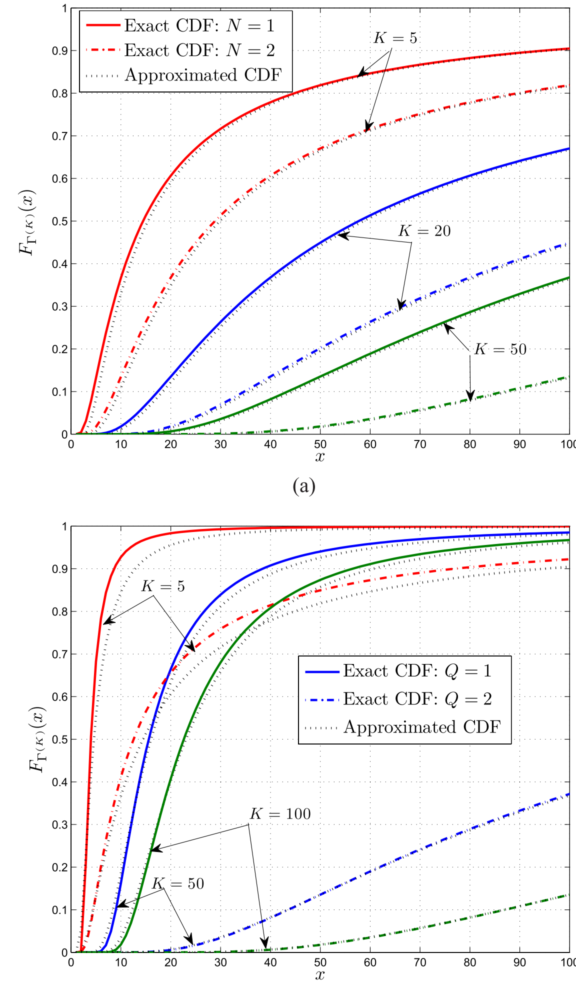
where $i \in \{1, 2\}$.

Proof: (45) is obtained by resorting to (35) and (39) after invoking $K^{1/Q} - 1 \underset{Q \gg 1}{\approx} \frac{\ln(K)}{Q}$ along with some manipulations.

Remarkably, the obtained results not only exemplify the interference nature of the considered system, but also analytically quantify through simple formulas capacity losses due to interference. Such findings are highly desirable for the anticipation in a timely manner of any quality of service (QoS) degradation in wireless communication networks

VI. Numerical and Simulations Results

Here, we provide some numerical examples to illustrate: 1) the tightness of the proposed approximations for large scale MU-MIMO relay networks; and 2) the impact of interference on spatial and multiuser diversity. The simulations set-up consists of an $(M \times N \times K)$ MU-MIMO AF relay network where the relay and each destination is subject to L and Q i.i.d. interferers, respectively. We also assume, without loss of generality, equal per-hop average SIR $\frac{\rho}{\mu} = \frac{\lambda}{\nu}$, shorthanded in the plots as SIR.



(a)

(b)

Fig. 2. The exact and asymptotic distribution of $F_{\Gamma(K)}$ for different values of (a): N, and (b): Q.

Fig. 2 shows the exact and asymptotic CDFs of the second-hop SIR $\Gamma^{(K)}$ for different values of N and Q. We observe that the asymptotic distribution in (71) is a good approximation even for small values of N and Q and becomes more accurate by increasing K.

In Fig. 3, we validate by Monte-Carlo simulations the asymptotic behavior of the two-hop MU-MIMO relay network with optimal SIR scheduling when K grows large. The approximation curves refer to the average capacity using (26) when $Q = 1, \forall\, N$, and (27) when $N = 1, \forall\, Q$. We observe that the analytical curves approach the simulated curves for small to moderate values of K, thereby providing an attractive alternative to the cumbersome expression of the average capacity shown for any K in (15).

In Fig. 3 (a), we highlight the system's behavior under equitable interference conditions on the two hops, i.e., $L = Q = 1$ and for different numbers N of relay antennas. As K goes large, one can see that the capacity of opportunistic scheduling continuously approaches the asymptotic value C^{∞}.

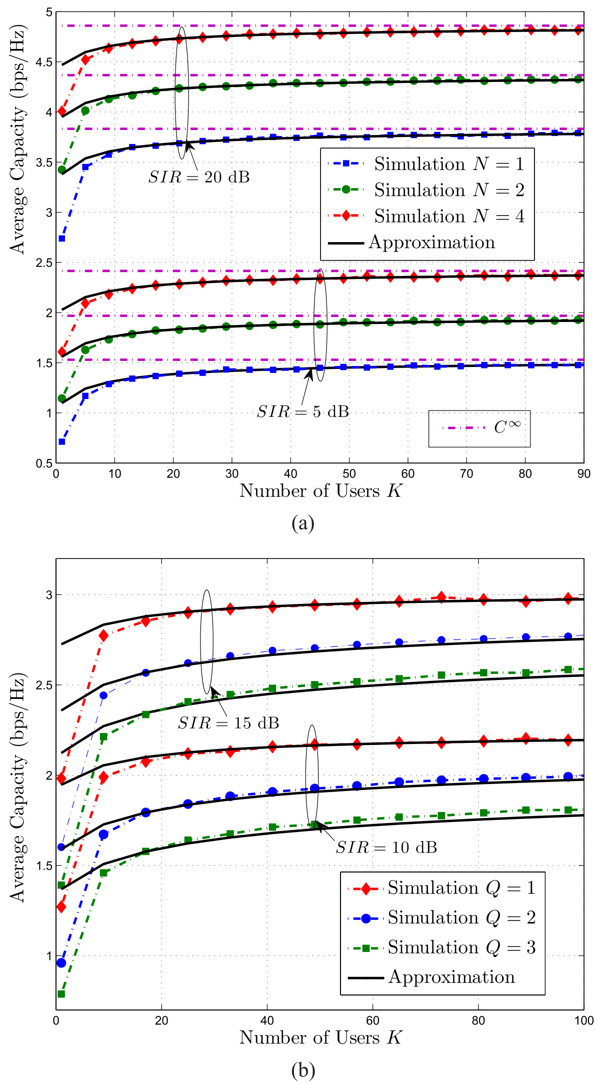


Fig. 3. Average capacity vs. K, for (a): different values of N with $L = Q = 1$, and (b): different values of Q with $N = 1$ and $L = 2$.

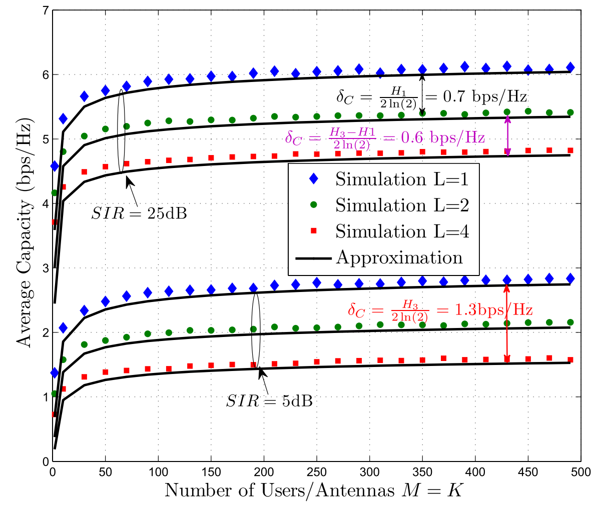


Fig. 4. Average capacity vs. $M = K$ for different values of the number of interferers L at the relay with $Q = 1$, $N = 2$, and $SIR = \{5, 25\}$ dB.

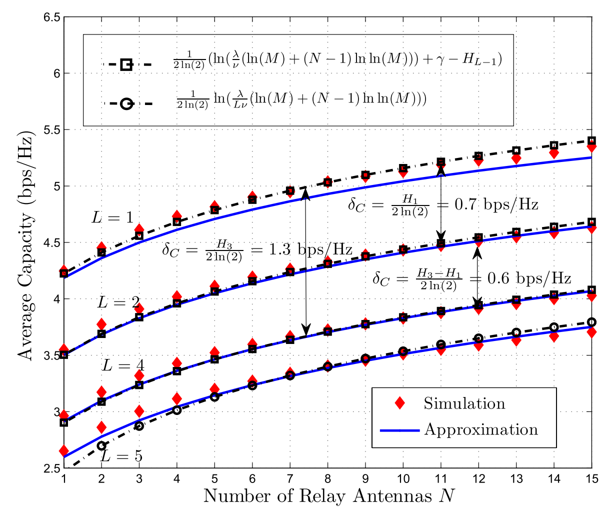


Fig. 5. Average capacity vs. N for different values of the number of interferers L at the relay with $M = K = 500$, $Q = 1$, and $SIR = 5$ dB.

In Fig. 3 (b), the system capacity is depicted for different values of Q with $L = 2$. As Q increases, with fixed K, the capacity gain from multiuser diversity cannot compensate for losses from the harmful interference; thus, the system capacity begins to decline monotonically. Clearly, as Q gets larger, the condition $\frac{\ln(K)}{Q} \to \infty$ becomes harder to attain for moderate values of K, a fact that postpones the ceiling effect to larger values of K.

In Fig. 4, we validate by Monte-Carlo simulations the asymptotic behavior of the two-hop MU-MIMO relay network using TAS and optimal SIR scheduling when M and K grow large. The approximation curves refer to the average capacity using (19). These curves which are in very good match with their stimulated counterparts show the accuracy and effectiveness of the new approximation proposed in (19).

In Fig. 5, we show the large-scale average capacity against the antennas number at the relay for different values of L when $Q = 1$. We observe that the average capacity exhibits the scaling laws in (29) and (32) for small and large L, respectively. Moreover, we validate the degradation caused by intercell interference at the relay using (31).

In Figs. 6 and 7, we plot the capacity of the two-hop MU-MIMO relay network using TAS and optimal SIR scheduling vs. the number of antennas M or users K when $M = K$ for several values L and Q of the numbers of interferers at the relay and users, respectively. In Fig. 6, we observe that capacity exhibits the trend predicted by *Corollary 4* in all $\{L, Q\}$ scenarios but the case $\{L = 2, Q = 3\}$ where the condition $\ln(M^{1/L}) \gg K^{1/Q} - 1$ no longer holds even when $Q > \left\lfloor \frac{\ln(K)}{\ln\ln(M)} \right\rfloor$ is verified. In this figure the capacity losses measured by simulations coincide with those predicted analytically in (45) due to L and Q interferers at the relay and each of the K users, respectively.

In Fig. 7, we observe that capacity exhibits the trend predicted by (35) that neglects the second term on the R.H.S of (35) when $\frac{L(K^{\frac{1}{Q}}-1)}{\ln(M)} \longrightarrow 0$ with $L = 1$. The capacity loss due

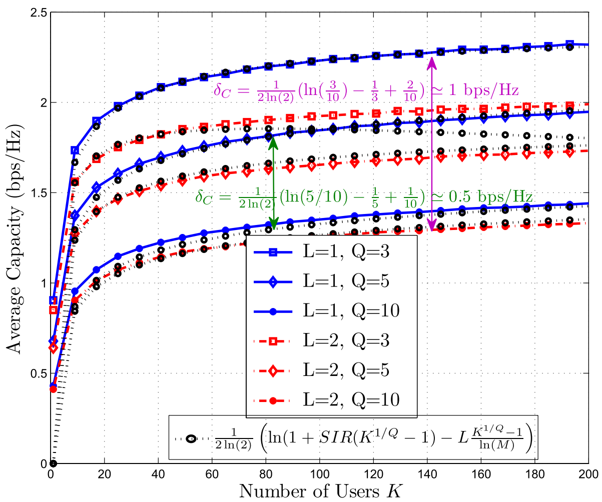


Fig. 6. Average capacity vs. K for different values L and Q of the numbers of interferers at the relay and destinations, respectively, with $M = 1000$ and $SIR = 10$ dB.

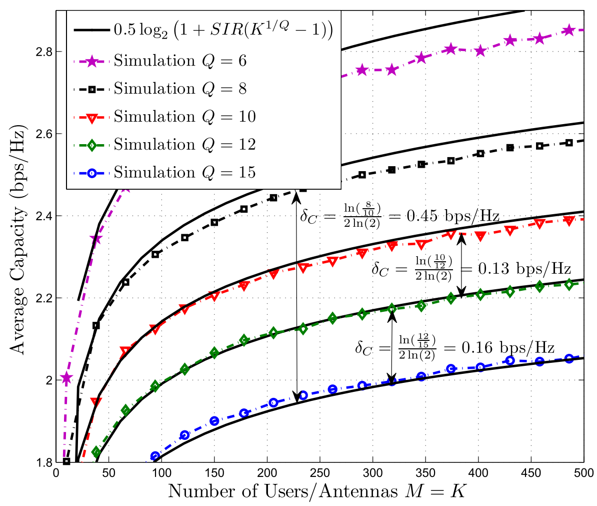


Fig. 7. Average capacity vs. $M = K$ for different values of the number of interferers Q at the destinations with $L = 1$ and $SIR = 15$ dB.

to the increase of Q corroborates the analytical loss obtained using (45) that neglects the term $\frac{1}{Q_1} - \frac{1}{Q_2}$ when Q is large. Notice, however, that the tightness of the scaling law is poor when Q is in the vicinity of $\frac{\ln(K)}{\ln\ln(M)}$. As stated below (44), the capacity scaling law is in this case is predicted more accurately using (19).

VII. Conclusion

In this work, we introduced the CMGF integral transform as a tool to compute the average capacity of two-hop AF MU-MIMO relay networks in interference-limited environments. We presented a large-scale analysis of network capacity with transmit antenna selection (TAS) at the source and interference-aware (IA) user scheduling when the number of antennas and users grow large. The derived scaling laws revealed that capacity grows faster with SIR-optimal (or IA) scheduling compared to interference-oblivious (IO) scheduling in TAS. However, due to the AF protocol, capacity regions run either by IA or IO are determined using decision rules that include the number of antennas and users and the number of interferers pertaining to each hop. Capitalizing on these novel scaling laws, we have been able to derive new closed-form expressions for capacity losses due to intercell interference at the relay and all users. The merits of the proposed analysis were unambiguously illustrated both analytically and numerically.

Appendix A

A. Derivation of $M^{(c)}_{\Gamma^{(M)}}$ for Arbitrary M

Recall that $\Gamma^{(M)} = \frac{\max_{n=1,\ldots,M} \upsilon_n}{\sum_{j=1}^{L} \mu_j |\mathbf{w}_{i^*}^{\dagger}\mathbf{h}_j|^2}$, where υ_n, $n = 1, \ldots, M$ are i.i.d $\rho\chi(2N)$ random variables. The PDF of $\max_{n=1,\ldots,M} \upsilon_n$ is given by

$$f_{\upsilon}(x) = \frac{M x^{N-1} e^{-\frac{x}{\rho}}}{\rho^N \Gamma(N)} \left(1 - \frac{\Gamma(N, \frac{x}{\rho})}{\Gamma(N)}\right)^{M-1} \stackrel{(a)}{=} \frac{M}{\rho^N \Gamma(N)} \sum_{n=0}^{M-1} \sum_{\Omega(n,N)} \frac{(-1)^n \binom{M-1}{n} n!}{\prod_{k=1}^{N} n_k!} \times \frac{\prod_{p=0}^{N-1} \left(\frac{1}{p!}\right)^{n_{p+1}} x^{N+\delta_n-1} e^{-\frac{x(n+1)}{\rho}}}{\rho^{\delta_n}}, \quad (46)$$

where (a) follows form using the binomial expansion [18, eq. (1.111.1)]. Note in (46) that we denote $\Omega(n, N) = \{(n_1, \ldots, n_N) : n_k \geq 0; \sum_{k=1}^{N} n_k = n\}$; and $\delta_n = \sum_{l=0}^{N-1} l n_{l+1}$. Moreover, the CDF of υ_n is obtained after some manipulations using [18, eq. (3.351.2)] as

$$F_{\upsilon}^{(c)}(x) = \sum_{n=0}^{M-1} \sum_{\Omega(n,N)} \binom{M-1}{n} \frac{\Theta_n M \Gamma\left(N + \delta_n, \frac{x(n+1)}{\rho}\right)}{(n+1)^{N+\delta_n} \Gamma(N)}, \quad (47)$$

where

$$\Theta_n = \frac{(-1)^n n! \prod_{p=0}^{N-1} \left(\frac{1}{p!}\right)^{n_{p+1}}}{\prod_{k=1}^{N} n_k!}. \quad (48)$$

Since in general the relay undergoes non i.i.d interference, then according to [24], $\sum_{j=1}^{L} |\mathbf{w}_{i^*}^{\dagger}\mathbf{h}_j|^2$ follows an hyper-exponential distribution with PDF

$$f_{\sum_{j=1}^{L} \mu_j |\mathbf{w}_{i^*}^{\dagger}\mathbf{h}_j|^2}(x) = \sum_{i=1}^{\rho(\mathbf{D})} \sum_{j=1}^{\tau_i(\mathbf{D})} \zeta_{i,j}(\mathbf{D}) \frac{\mu_{\langle i \rangle}^{-j} x^{j-1}}{(j-1)!} e^{-\frac{x}{\mu_{\langle i \rangle}}}, \quad (49)$$

where $\mathbf{D} = \mathrm{diag}(\mu_1, \mu_2, \ldots, \mu_L)$, $\rho(\mathbf{D})$ is the number of distinct diagonal elements of $\mathbf{D}$, $\mu_{\langle 1 \rangle} > \mu_{\langle 2 \rangle} > \ldots > \mu_{\langle L \rangle}$ are the distinct diagonal elements in decreasing order, $\tau_{\mathbf{i}}(\mathbf{D})$ is the multiplicity of $\mu_{\langle i \rangle}$, and $\zeta_{i,j}(\mathbf{D})$ is the (i, j)-th characteristic coefficient of $\mathbf{D}$ [24]. For instance, when non-equal-power interferers are considered, we have $\tau_i(\mathbf{D}) = 1$ and $\zeta_{i,1}(\mathbf{D}) = \prod_{k=1,k\neq i}^{\rho(\mathbf{D})} 1/\left(1 - \frac{\mu_{\langle k \rangle}}{\mu_{\langle i \rangle}}\right)$. The CCDF of $\Gamma^{(M)}$ is therefore obtained as

$$F^{(c)}_{\Gamma^{(M)}}(x) = \mathbb{E}_{\sum_{j=1}^{L}\mu_j|\mathbf{w}^\dagger_{i*}\mathbf{h}_j|^2}\left[F^{(c)}_{v}(xy),\, y=\sum_{j=1}^{L}\mu_j|\mathbf{w}^\dagger_{i*}\mathbf{h}_j|^2\right]$$
$$\overset{(a)}{=} \sum_{n=0}^{M-1}\sum_{\Omega(n,N)}\sum_{i=1}^{\rho(\mathbf{D})}\sum_{j=1}^{\tau_i(\mathbf{D})}\sum_{k=0}^{N+\delta_n-1}\frac{\Theta_n\zeta_{i,j}(\mathbf{D})\Gamma(k+j)}{\mu^j_{\langle i\rangle}(j-1)!}\times\frac{M\rho^{-k}(N+\delta_n-1)!}{(n+1)^{N+\delta_n-k}\Gamma(N)k!}\frac{x^k}{\frac{x(n+1)}{\rho}+\frac{1}{\mu_{\langle i\rangle}}}, \quad (50)$$

where (a) follows from applying [18, eq. (3.381.8)] and [18, eq. (3.381.4)]. The CMGF of $M^{(c)}_{\Gamma^{(M)}}(s) = \mathcal{L}_{F^{(c)}_{\Gamma^{(M)}}}(s)$ is obtained after some manipulations as

$$M^{(c)}_{\Gamma^{(M)}}(s) = \sum_{n=0}^{M-1}\sum_{\Omega(n,N)}\sum_{i=1}^{\rho(\mathbf{D})}\sum_{j=1}^{\tau_i(\mathbf{D})}\sum_{k=0}^{N+\delta_n-1}\frac{\Theta_n\zeta_{i,j}(\mathbf{D})\Gamma(k+j)\rho}{(j-1)!\mu_{\langle i\rangle}\Gamma(N)}\times\frac{M(N+\delta_n-1)!}{(n+1)^{N+\delta_n+1}}\Psi\left(k+1,2-j,s\frac{\rho}{\mu_{\langle i\rangle}(n+1)}\right). \quad (51)$$

B. Derivation of $M^{(c)}_{\Gamma^{(K)}}$ for Arbitrary K

Let $\Gamma^{(K)} = \max_{j=1,\dots,K} w_j$ where $w_j = \frac{|\mathbf{h}_{j,r}|^2}{\sum_{v=1}^{Q}|h_{v,j}|^2}$, $j=1,\dots,K$ denote the normalized SIR at user U_k. Recall that $w_j \overset{d}{=} \frac{\chi(2N)}{\chi(2Q)}$ with PDF

$$f_W(x) = \frac{x^{N-1}}{xB(N,Q)}(x+1)^{-(N+Q)}, \quad (52)$$

and CDF

$$F_W(x) = \frac{x^N{}_2\mathrm{F}_1(N+Q,N,1+N,-x)}{NB(N,Q)} \overset{(a)}{=} \frac{(1+x)^{1-Q-N}}{NB(N,Q)}\sum_{k=0}^{Q-1}\frac{(1-Q)_k(-1)^k}{(1+N)_k}\left(\frac{x}{x+1}\right)^{k+N}, \quad (53)$$

where (a) follows from substituting the Gauss hypergeometric function by its finite series expansion [18]. Assuming a homogeneous network with i.i.d SIRs, we calculate the CCDF of $\Gamma^{(K)} = \frac{\lambda}{\nu}\max_{j=1,\dots,K} w_j$ as

$$F^{(c)}_{\Gamma^{(K)}}(x) = 1-\left[\left(\frac{\frac{x\nu}{\lambda}}{1+\frac{x\nu}{\lambda}}\right)^{Q+N-1}+\frac{\left(\frac{x\nu}{\lambda}\right)^N}{NB(N,Q)}\left(1+\frac{x\nu}{\lambda}\right)^{1-Q-N}\times\sum_{k=0}^{Q-2}\frac{(1-Q)_k(-1)^k}{(1+N)_k}\left(\frac{x\nu}{\lambda}\right)^k\right]^K$$
$$\overset{(a)}{=}\sum_{i=0}^{K(Q+N-1)-1}\binom{K(Q+N-1)}{i}\left(\frac{x\nu}{\lambda}\right)^i\left(1+\frac{x\nu}{\lambda}\right)^{-K(Q+N-1)} -\sum_{n=1}^{K}\sum_{\Omega(n,Q-1)}\frac{\binom{K}{n}n!\prod_{p=0}^{Q-2}\left(\frac{(1-Q)_p(-1)^p}{(1+N)_p}\right)^{n_{p+1}}}{(NB(N,Q))^n\prod_{k=1}^{Q-1}n_k!}\times\left(\frac{x\nu}{\lambda}\right)^{\delta_n+K(Q+N-1)+n(1-Q)}\left(1+\frac{x\nu}{\lambda}\right)^{-K(Q+N-1)}, \quad (54)$$

where (a) follows from applying the multinomial expansion [18, eq. (1.111.1)]. The Laplace transform of $F^{(c)}_{\Gamma^{(K)}}$ yields its CMGF expression given by

$$M^{(c)}_{\Gamma^{(K)}}(s) = \sum_{i=0}^{K(Q+N-1)-1}\binom{K(Q+N-1)}{i}\frac{\lambda\Gamma(i+1)}{\nu}\times\Psi\left(i+1,i+2-K(Q+N-1),\frac{\lambda s}{\nu}\right)-\sum_{j=1}^{K}\sum_{\Omega(j,Q-1)}\binom{K}{j}\times\frac{\lambda\alpha_j}{\nu}\Gamma\Big(\delta_j+K(Q+N-1)+j(1-Q)+1\Big)\Psi\times\left(\delta_j+2-j(Q-1),\delta_j+K(Q+N-1)+j(1-Q)+1,\frac{\lambda s}{\nu}\right), \quad (55)$$

where

$$\alpha_j = \frac{j!\prod_{p=0}^{Q-2}\left(\frac{(1-Q)_p(-1)^p}{(1+N)_p}\right)^{n_{p+1}}}{N^jB(N,Q)^j\prod_{k=1}^{Q-1}n_k!}. \quad (56)$$

C. Derivation of C in Corollary 1

Plugging (51) and (55) into (10) reveals that the computation of C requires the resolution of integrals of the form

$$I = \int_0^\infty xe^{-x}\Psi(a_1,b_1,c_1;zx)\,\Psi(a_2,b_2,c_2,yx)\,dx. \quad (57)$$

By resorting to the following identity

$$\Psi(a,b,c,z) = \frac{1}{\Gamma(a)\Gamma(a-b+1)}G^{2,1}_{1,2}\left(z\,\middle|\,\begin{matrix}1-a\\0,1-b\end{matrix}\right), \quad (58)$$

integrals like in (57) can be evaluated by means of the generalized Meijer's G-function of two variables, as can be seen from a more general integral formula due to [19, eq. (3.2)], thereby leading to (15) after some manipulations.

APPENDIX B

A. Derivation of $M^{(c)}_{\Gamma^{(M)}}$ for Large M

1) Definition 1: Let X_i denote an i.i.d. random process with CDF given by F_X and PDF f_X. Let's define the growth function as $g_X(x) = (1-F_X(x))/f_X(x)$. Then if g_X is such that $\lim_{x\longrightarrow\infty} g_X(x) = c > 0$, for some constant c, then

$$\lim_{M\to\infty}\Pr\left\{\max_{i=1,\dots,M}X_i - b_M < t\right\} = e^{-e^{-t/c}}, \quad t>0, \quad (59)$$

where $b_M = F_X^{-1}\left(1-\frac{1}{M}\right)$ [26].

Applying the above definition to $v_n \overset{d}{=} \rho\chi(2N)$ with the PDF and CDF given, respectively, by $f_V(x) = \frac{(\frac{x}{\rho})^{N-1}}{N!}e^{-\frac{x}{\rho}}$ and $F_V(x) = 1-\frac{\Gamma(N,\frac{x}{\rho})}{\Gamma(N)}$, then it holds that

$$\frac{1-F_V(x)}{f_V(x)} = \frac{\Gamma(N,\frac{x}{\rho})}{(\frac{x}{\rho})^{N-1}e^{-\frac{x}{\rho}}} \underset{x\to\infty}{\longrightarrow} \rho > 0. \quad (60)$$

Moreover, it is easy to find that

$$b_M \underset{M\to\infty}{\overset{(a)}{\approx}} \rho\ln(M)+\rho(N-1)\ln\ln(M), \quad (61)$$

where (a) follows form the fact that $\Gamma(\alpha, x) \underset{\alpha\to\infty}{\approx} x^{\alpha-1}e^{-x}$. Since we focus on massive antenna selection at the source, we assume for tractability, that the relay is subject to L i.i.d interferers with mean power μ. Accordingly, using the asymptotic CDF of $\max_{n=1,\dots,M} v_n$, we calculate the CCDF of the first-hop SIR $\Gamma^{(M)} = \frac{\max_{n=1,\dots,M} v_n}{\mu \sum_{j=1}^{L} |\mathbf{w}_{i*}^{\dagger}\mathbf{h}_j|^2}$ as

$$\begin{aligned} F^{(c)}_{\Gamma^{(M)}}(x) &= \int_0^\infty F^{(c)}_{\max_{n=1,\dots,M} v_n}(xy) f_{\mu \sum_{j=1}^{L} |\mathbf{w}_{i*}^{\dagger}\mathbf{h}_j|^2}(y)dy \\ &= \frac{\mu^{-L}}{\Gamma(L)}\int_0^\infty y^{L-1}e^{-\frac{y}{\mu}}\left(1-e^{-e^{-\frac{yx-b_M}{\rho}}}\right)dy \\ &\overset{(a)}{=} \frac{(-1)^{L-1}\left(\frac{\rho}{\mu x}\right)^L}{\Gamma(L)}\left(\int_0^{\frac{4}{\zeta}} \ln(t)^{L-1} t^{\frac{\rho}{\mu x}-1}\left(1-e^{-\zeta t}\right)dt \right. \\ &\quad \left. + \int_{\frac{4}{\zeta}}^1 \ln(t)^{L-1} t^{\frac{\rho}{\mu x}-1} dt\right), \end{aligned} \tag{62}$$

where (a) follows from letting $t = e^{-\frac{yx}{\rho}}$ and defining $\zeta = e^{\frac{b_M}{\rho}}$. From (61), we can easily see that the limit of the first term on the R.H.S. of (62) becomes vanishingly small as $\lim_{M\longrightarrow\infty} \frac{4}{\zeta} \approx \frac{4}{M} = 0$. Furthermore, the limit of the second term can be simplified using [18, eq. (3.381.1)] as

$$F^{(c)}_{\Gamma^{(M)}}(x) \overset{(a)}{\simeq} 1 - \frac{\Gamma\left(L, \frac{\beta_M^2}{x}\right)}{\Gamma(L)}, \tag{63}$$

where $\beta_M = \sqrt{\frac{b_M - \rho\ln(4)}{\mu}}$. Consequently, the CMGF of $\Gamma^{(M)}$ can be given after applying (11) as

$$\begin{aligned} M^{(c)}_{\Gamma^{(M)}}(s) &= \int_0^\infty e^{-sx}\left(1 - \frac{\Gamma\left(L, \frac{\beta_M^2}{x}\right)}{\Gamma(L)}\right)dx \\ &\overset{(a)}{=} \frac{1}{s} - 2\sum_{n=0}^{L-1} \frac{\beta_M^{n+1}}{n!} s^{\frac{n-1}{2}} K_{n-1}\left(2\beta_M\sqrt{s}\right), \end{aligned} \tag{64}$$

where (a) is obtained by resorting to [18, eq. (8.352.2)] and [18, eq. (3.471.9)].

B. Derivation of $M^{(c)}_{\Gamma^{(K)}}$ for Large K

Definition 2: Let Y_j, $j = 1, \dots, K$ be an i.i.d random process with CDF $F_Y(x)$. Then Y_j has regularly varying distribution of Frechet type [27] with exponent β if and only if

$$\frac{1 - F_Y(x)}{1 - F_Y(tx)} \to t^{-\beta}, \quad \text{when } x \to \infty \tag{65}$$

and

$$\lim_{K\to\infty} \Pr\left\{\max_{j=1,\dots,K} Y_j < a_K t\right\} = e^{-x^{-\beta}}, \quad x > 0, \tag{66}$$

where $a_K = F_Y^{-1}(1 - \frac{1}{K})$.

In the sequel, we show how the definition above applies to our situation. Let $w_j = \frac{|\mathbf{h}_{j,r}|^2}{\sum_{v=1}^{Q} |h_{v,j}|^2}$, $j = 1, \dots, K$, with CDF $F_W(x)$ given in (17), then we have

$$\begin{aligned} \lim_{x\to\infty} \frac{1 - F_W(x)}{1 - F_W(tx)} &= \lim_{x\to\infty} \frac{t^{-N}(1+tx)^{N+Q}}{(1+x)^{N+Q}} && (67) \\ &= t^Q, && (68) \end{aligned}$$

after substituting the hypergeometric function by its equivalent ${}_2\mathrm{F}_1(a, b; b+1; z) = bz^{-b}B_z(b, 1-a)$ where $B_z(c, d)$ is the Beta function [18, eq. (8.380.1)] and using the Hospital rule to get from (67) to (68). In order to find a_K while keeping the analytical complexity tractable, we focus on the cases: (i) $Q = 1, \forall\, N$, and (ii) $N = 1, \forall\, Q$. The arbitrary N, Q case can be handled using bounding techniques but thwarts the paper goal of exact capacity analysis. In case (i), by exploiting the ${}_2\mathrm{F}_1$ reduction formulas ${}_2\mathrm{F}_1(b, a; a; z) = (1-z)^{-b+1}$, we show that a_K satisfies

$$a_K \underset{K\to\infty}{\approx} NK. \tag{69}$$

In case (ii), we have $N = 1$ thereby enabling the simplification of $F_Z(x)$ relying on the fact that ${}_2\mathrm{F}_1(1, b; 2; z) = \frac{(1-z)^{-b+1}-1}{(b-1)z}$. The parameter a_K is therefore obtained as follows

$$a_K \underset{K\to\infty}{\approx} K^{1/Q} - 1. \tag{70}$$

Capitalizing on *Definition 2*, we obtain the CDF of the second hop SIR $\Gamma^{(K)} = \max_{j=1,\dots,K} w_j$ when $K \to \infty$ as

$$F_{\Gamma^{(K)}}(x) = \begin{cases} e^{-\frac{NK\lambda}{vx}}, & Q = 1, \forall\, N, \\ e^{-\left(\frac{(K^{1/Q}-1)\lambda}{vx}\right)^Q}, & N = 1, \ \forall\, Q. \end{cases} \tag{71}$$

The Laplace transform of the CCDF of $\Gamma^{(K)}$ yields its CMGF given by

$$M^{(c)}_{\Gamma^{(K)}}(s) \overset{(a)}{\approx} \begin{cases} \frac{1}{s}\left(1 - e^{-\frac{NK\lambda}{4v}s}\right), & Q = 1, \ \forall\, N, \\ \frac{1}{s}\left(1 - e^{-\frac{\lambda}{v}\left(\frac{K^{\frac{1}{Q}}-1}{4^{\frac{1}{Q}}}\right)s}\right), & N = 1, \ \forall\, Q, \end{cases} \tag{72}$$

where (a) follows from using the fact that $1 - e^{-x} \underset{x\geq 4}{\approx} 1$ along with some manipulations.

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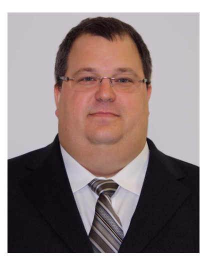

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