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Energy Efficiency Optimization for Uplink Multiuser MIMO Systems

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Abstract

To satisfy green communication needs, energy efficiency is regraded as one of the most important indicators to evaluate the effectiveness of a communication system. In this paper, we establish the energy efficiency optimization framework for uplink multiuser mutliple-input multiple-output system. Taking the circuit power, the antenna link power and signal processing power into consideration, an analytical expression of the achieveable energy efficiency is firstly established, which can better model the practical communication process. Furthermore, we simplify the objective function under some mild conditions. After demonstrating the existence of a unique golbally optimal energy efficiency, an adaptive water-filling power allocation algorithm is proposed to further improve the energey efficiency of the system. Finally some simulation results are given to verify the performance of our scheme. Our work can provide a fundamental principles for uplink mutiluser multiple-input multiple-output systems design.

Keywords*: energy efficiency, multiuser MIMO, user selection, adaptive power allocation*

1. Introduction

Green wireless communications have drawn increasing attention these days. This is not only because of the exponential traffic growth with the popularity of smart phones but also the limited energy supply with ever higher prices. Energy efficiency (EE), defined as the ratio of achievable capacity to power, is becoming an increasingly critical indicator for wireless systems. How to maximize the bits-per-Joule energy efficiency (EE) is one of the major topics in the research of green wireless communications [1-4].

Multiuser Multiple-input multiple-output (MU-MIMO) systems have a great potential for improving system capacity without any increase in bandwidth or transmission power, and have attracted great attentions. According to information theory [5-6], with the increasing of serving mobile users, the system can obtain a higher multiplex gain at the cost of diversity gain. In order to exploit the channel capacity, there exists an optimal user number to make a tradeoff between the diversity gain and multiplexing gain. When it comes to energy efficiency, more factors should be taken into consideration, like circuit consumption power, radio link consumption and signal processing power consumption [7].

In order to achieve the most energy efficiency usage for wireless communication systems, adaptive techniques is a key technology. Under the constraint of total transmission power, adaptive algorithm has been proposed based on convex optimization techniques to compute the achievable EE of MU-MIMO [8]. In [9], it addresses the energy-efficient design of uplink (UL) MU-MIMO in a single cell environment and provides a one-dimensional adaptive iterative algorithm to optimize the EE. Adaptive switching between MIMO and single-input and multiple-output (SIMO) is adopted to save energy at mobile terminals in [10-11]. In [11], the author further optimizes the power allocation for a given transmission mode. Meanwhile, the design and analysis of very

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large MU-MIMO system is a fairly new subject that is attracting substantial interest [12]-[13]. An important advantage of large MIMO systems is that they enable us to reduce the transmitted power and the adaptive techniques can improve EE. On the uplink, reducing the transmit power of the terminals will drain their batteries slower.

However, the operation of adaptive schemes relies on the instantaneous channel state information (CSI), and thus requires a base station (BS) to schedule huge instantaneous CSI feedback from multiple users. In this paper, we discuss the EE based on the ergodic throughput. Compared with [11], we complement the work and our contributions are summarized as follows:

1) We establish the energy efficiency optimization framework for uplink MU-MIMO system using zero-forcing(ZF) detector. The circuit power, the antenna link power and signal processing power are taken into consideration.

2) We derive an analytical expression of the achievable ergodic throughput firstly which are more generality for the MU-MIMO system. After this step, we simplify the objective function under some mild conditions.

3) We demonstrate the existence of a unique globally optimal energy efficiency and propose an water-filling algorithm to solve the optimization problem. Compared with average power allocation algorithm, water-filling algorithm can improve system performance significantly. We discover that there exist an optimal number of users to maximize EE.

The remainder of this paper is organized as follows. Section II describes the system model. Section III optimizes EE under mild condition and proposes power allocation scheme. Section IV provides numerical results. Concluding remarks are drawn in Section V.

2. System Model

Considering the uplink MU-MIMO system, a base station (BS) is equipped with an array of N antennas which service K single-antenna users. Users transmit their data in the same time-frequency resource. In a quasi-static Rayleigh flat-fading propagation environment, the channel matrix between users and BS is denoted as $\mathbf{H} \in C^{N\times K}$, and the elements of $\mathbf{H}$ is assumed to be zero mean independent and identically distributed(i.i.d.) complex Gaussian distributed with unit variance. The transmitted signal is $\mathbf{x} = [x_1, x_2, ..., x_K]^T$, and $\mathbf{E[xx^+] = I}_K$. Then, the received signal $\mathbf{y} = [y_1, y_2, ..., y_N]^T$ can be expressed as

$$\mathbf{y} = \mathbf{H}\mathbf{G}^{1/2}\mathbf{P}^{1/2}\mathbf{x} + \mathbf{n} \tag{1}$$

Where $\mathbf{G} = diag\{G1, G2, ..., G_K\}$ denotes the large-scale fading matrix. $\mathbf{P}$ is the power allocation matrix, which is a diagonal matrix , *i.e.*, $diag\{P_1, P_2, ..., P_K\}$. $\mathbf{n}$ is the $N\times 1$ noise vector, which is Gaussian distributed with zero mean and covariance matrix $\mathbf{E[nn}^H] = \mathbf{I}_N \sigma^2$.

With the perfect knowledge of channel state information at BS, the post-processing signal to noise ratio(SNR) for the k-th user γ_k using conventional linear detector zero-forcing detector [11]can be written as

$$\gamma_k = \underbrace{P_k G_k / \sigma^2}_{\delta_k} \underbrace{\frac{1}{[\mathbf{WW}^H]_{kk}}}_{x_k} \tag{2}$$

where $\mathbf{W} = (\mathbf{H}^H\mathbf{H})^{-1}\mathbf{H}^H$ is the zero-forcing weighted matrix at the BS. Note that the restriction on $K \le N$ is needed for the existence of the ZF receiver. Then, the ergodic throughput for k-th user can be defined as

$$\mathrm{R}_k = \mathrm{E}[\log_2(1+\gamma_k)] \tag{3}$$

x_k is a chi-square variable with $2(N-K+1)$ degrees of freedom as it is defined in [14]-[16], *i.e.*, $x_k \sim \chi^2(2(N-K+1))$. Therefore, the ergodic throughput for k-th user can be further derived as

$$\begin{aligned} \mathrm{R}_k &= \mathrm{E}[\log_2(1+\frac{P_k G_k}{\sigma^2[\mathbf{W}\mathbf{W}^H]_{kk}})] \\ &= \sum_{n=0}^{M} \log_2(e)(\sum_{i=1}^{M-n}(-\frac{1}{\delta_k})^{i-1}\frac{(M-n-i)!}{(M-n)!}) + \sum_{n=0}^{M}\frac{\log_2(e)}{(M-n)!}(-\frac{1}{\delta_k})^{M-n} e^{\frac{1}{\delta_k}} E_1(\frac{1}{\delta_k}) \end{aligned} \quad (4)$$

where $E_1(.)$ is the first order exponential function. M is the difference between N and K, *i.e.*, $M = N - K$.

Proof: See Appendix A

The power radiated to the environment for signal transmission is only a portion of system power consumption. Apart from the transmission power, there is some circuit power consumption from digital signal processing and analog filter used for RF and baseband. The total power consumption is defined as

$$P^{total} = P_t + \sum_{k=1}^{K} b_k P_c + NP_b \quad (5)$$

where $P_t = \sum_{k=1}^{K} P_k$ is the transmission power. P_c denotes the circuit power of each user. P_b is the circuit power of each receiver antenna. The binary value b_k denotes whether a user is active or not, *i.e.* $P_k = 0, b_k = 0$, the user is active; $P_k > 0, b_k = 1$, the user is not active.

Different from the definition of energy efficiency (EE) in [11], here, the EE of the communication system is measured in bits/Joule and equals the ratio between the average achievable sum information rate and the total average power consumption. Taking both electronic circuit and transmission power consumption into consideration, the average energy efficiency (EE) is written as

$$EE = \frac{\sum_{k=1}^{K} R_k}{P^{total}} \quad (6)$$

3. Optimal EE under Mild Condition

The achievable rate for k-th user can be obtained as:

$$\mathrm{R}_k = \sum_{n=0}^{M}\frac{\log_2(e)}{(M-n)!}(\sum_{i=1}^{M-n}(-\frac{1}{\delta_k})^{i-1}(M-n-i)!) + \sum_{n=0}^{M}\frac{\log_2(e)}{(M-n)!}(-\frac{1}{\delta_k})^{M-n} e^{\frac{1}{\delta_k}} E_1(\frac{1}{\delta_k}) \quad (7)$$

We have the following two properties.

Lemma1: When the signal to noise ratio δ_k is large enough, δ_k^{-1} will be small. Because $\delta_k^{-1} > \delta_k^{-2} > ... > \delta_k^{-(N-K)}$, $\delta_k^{-2}, \delta_k^{-3} ... \delta_k^{-(N-K)}$ can be omitted in (7).

Lemma2: When integer variable M is large enough, $\frac{(M-n-i)!}{(M-n)!}$ and $\frac{1}{(M-n)!}$ will be very small.

Based on the Lemma1, we need to simplify expression (7) at first and then optimize EE under power constraints. In the following, we consider two different cases.

3.2. The Case of $\mathrm{N}=\mathrm{K}$

Consider a MU-MIMO system where the number of transmitted antenna is equal to the number of received antenna. When $\mathrm{N}=\mathrm{K}$, the first term in (7) is equal to zero. Then the expression (7) can be rewritten as

$$\mathrm{R}_k = \log_2(e)e^{\frac{1}{\delta_k}} E_1(\frac{1}{\delta_k}) \tag{8}$$

It is interesting to find that our result is accordance to the numerator of (6) in [17]. If the SNR is large or the antenna number at BS is large, the (8) can be simplified based on the Lemma1, and the approximate ergodic throughput for k-th user can be expressed as:

$$R_k = \frac{1}{\ln 2}(\ln \delta_k + \frac{1.42}{\delta_k} - 0.58) + \mathrm{o}(\delta_k^{-2}) \tag{9}$$

Correspondingly, the overall approximation ergodic throughput is

$$\tilde{R} = \frac{1}{\ln 2}\sum_{k=1}^{K}(\ln(\frac{P_k G_k}{\sigma^2}) + \frac{1.42\sigma^2}{P_k G_k} - 0.58) \tag{10}$$

From (5) and (10), the MU-MIMO system EE optimization problem can be established as a function of $\mathbf{P}$:

$$\begin{aligned}\max_{\mathbf{P}}\ \mathrm{EE}(\mathbf{P}) &= \max_{\mathbf{P}} \frac{\sum_{k=1}^{K}\tilde{R}_k}{P^{total}} \\ &= \max_{P_k \geq 0} \frac{\frac{1}{\ln 2}\sum_{k=1}^{K}(\ln(\frac{P_k G_k}{\sigma^2}) + \frac{1.42\sigma^2}{P_k G_k} - 0.58)}{\sum_{k=1}^{K}P_k + \sum_{k=1}^{K}b_k P_c + NP_b}\end{aligned} \tag{11}$$

Since the numerator and denominator in (11) are concave and affine respectively as well as differential. (11) is a concave-convex fractional program with a pseudo-concave objective, which is complicate to calculate (11) directly. So it is better to separate numerator and denominator with the help of parameter λ to solve the problem [8]. Here we assume that λ is a nonnegative, and define the parametric problem as

$$\mathrm{F}(\lambda) = \frac{1}{\ln 2}\sum_{k=1}^{K}(\ln(\frac{P_k G_k}{\sigma^2}) + \frac{1.42\sigma^2}{P_k G_k} - 0.58) - \lambda(\sum_{k=1}^{K}P_k + \sum_{k=1}^{K}b_k P_c + P_b) \tag{12}$$

Based on Lemma 3.2[8], we need to optimize (12) at first under given λ to obtain $\mathrm{F}(\lambda)$ and then solve the equation $\mathrm{F}(\lambda)=0$ to get the unique λ^*. In the following, we will optimize (12) under a given λ at first. As the objective function of (12) is concave in P_k, problem (12) can be solved by solving the KKT optimality conditions, and the solution can be denoted as

$$P_k^* = [\frac{2\times 1.42\sigma^2}{\ln 2G_k}.\frac{1}{\frac{1}{\ln 2} \pm \sqrt{(\frac{1}{\ln 2})^2 - 4\lambda\frac{1.42\sigma^2}{\ln 2G_k}}}]^+ \qquad k = 1, 2, ..., K \tag{13}$$

where $[x]^+ = \max(x, 0)$. Because we study the EE problem at high SNR regimes. Then we must be sure that the SNR is large enough. That is to say, $\frac{P_k^* G_k}{\sigma^2}$ is large enough. So we

$$P_k^* = [\frac{2\times 1.42\sigma^2}{\ln 2G_k}.\frac{1}{\frac{1}{\ln 2}-\sqrt{(\frac{1}{\ln 2})^2-4\lambda\frac{1.42\sigma^2}{\ln 2G_k}}}]^+$$

choose the as the optimal value under a given λ

Next, we need to find the unique λ^* fulfilling $F(\lambda^*)=0$. So we have that

$$\frac{1}{\ln 2}\sum_{k=1}^{K}(\ln(\frac{P_k^* G_k}{\sigma^2})+\frac{1.42\sigma^2}{P_k G_k}-0.58)-\lambda^*\times(\sum_{k=1}^{K}P_k^*+\sum_{k=1}^{K}b_k P_c+P_b)=0 \tag{14}$$

After obtaining λ^* by solving (14), the optimal solution of (11) can be derived as

$$P_k^* = [\frac{2\times 1.42\sigma^2}{\ln 2G_k}.\frac{1}{\frac{1}{\ln 2}-\sqrt{(\frac{1}{\ln 2})^2-4\lambda^*\frac{1.42\sigma^2}{\ln 2G_k}}}]^+ \qquad k=1,2,...,K \tag{15}$$

Now we consider the problem under some power constraints. Then the EE maximization problem can be formulated as follows:

$$\max_{\{\mathbf{P}\}} \ \mathrm{EE}(\mathbf{P}) \tag{16}$$

$$s.t. \ \sum_{k=1}^{K}P_k = \bar{P} \tag{17}$$

$$\gamma_k \ge \beta_k \tag{18}$$

Constraint (17) is the total transmission power constraint. Constraint(18) ensure a basic quality of service (QoS) of each serving user communication.

By the method of fractional optimization and the Lagrange multiplier, the optimal solution for the EE maximization problem in (16)-(18) can be expressed by

$$P_k^* = \frac{2\times 1.42\sigma^2}{\ln 2G_k}.\frac{1}{\frac{1}{\ln 2}-\sqrt{(\frac{1}{\ln 2})^2-4(\lambda^*+\alpha^*)\frac{1.42\sigma^2}{\ln 2G_k}}} \tag{19}$$

where $\lambda^* \ge 0$ and α^* is the optimal Lagrange multiplier.

3.3. The Case of $N > K$

Considering that the number of received antenna is greater than the number of transmitted antenna. When the SNR is very large, the expression (7) based on the Lemma1 can be simplified to

$$R_k = \frac{1}{\ln 2}(\ln(\delta_k)+\frac{1}{M}\frac{1}{\delta_k})+\frac{1}{\ln 2}(\sum_{n=0}^{M-1}\frac{1}{(M-n)}-0.58)+o(\delta^{-2}) \tag{20}$$

Correspondingly, the approximate expression of overall ergodic throughput is

$$\tilde{R} = \frac{1}{\ln 2}\sum_{k=1}^{K}(\ln(\frac{P_k G_k}{\sigma^2})+\frac{1}{M}\frac{\sigma^2}{P_k G_k})+\frac{K}{\ln 2}(\sum_{n=0}^{M-1}\frac{1}{(M-n)}-0.58) \tag{21}$$

From (5) and (21), the MU-MIMO system EE as a function of $\mathbf{P}$ can be defined as

$$\max_{\mathbf{P}} \ \mathrm{EE}(\mathbf{P}) = \max_{\mathbf{P}}\frac{\sum_{k=1}^{K}\tilde{R}_k}{P^{total}}$$
$$= \max_{P_k \ge 0}\frac{\frac{1}{\ln 2}\sum_{k=1}^{K}(\ln(\frac{P_k G_k}{\sigma^2})+\frac{1}{M}\frac{\sigma^2}{P_k G_k})+\frac{K}{\ln 2}(\sum_{n=0}^{M-1}\frac{1}{(M-n)}-0.58)}{\sum_{k=1}^{K}P_k+\sum_{k=1}^{K}b_k P_c+NP_b} \tag{22}$$

Similar to the method (12), the optimal value can be obtained as:

$$P_k^* = \frac{2\sigma^2}{\ln 2(N-K)G_k} \cdot \frac{1}{\frac{1}{\ln 2} - \sqrt{(\frac{1}{\ln 2})^2 - \frac{4\lambda^*\sigma^2}{\ln 2(N-K)G_k}}} \tag{23}$$

In the following we study the EE maximization problem under power constraints. The problem can be formulated as follows:

$$\max_{\{\mathbf{P}\}} \ \mathrm{EE}(\mathbf{P}) \tag{24}$$

$$s.t. \ \sum_{k=1}^{K} P_k = \bar{P} \tag{25}$$

$$\gamma_k \geq \beta_k \tag{26}$$

By the method of fractional optimization and the Lagrange multiplier, the optimal power for the k-th user is

$$P_k^* = \frac{2\sigma^2}{\ln 2(N-K)G_k} \cdot \frac{1}{\frac{1}{\ln 2} - \sqrt{(\frac{1}{\ln 2})^2 - \frac{4(\lambda^* + \alpha^*)\sigma^2}{\ln 2(N-K)G_k}}} \tag{27}$$

where $\lambda^* > 0$ and α^* is the optimal Lagrange multiplier.

4. Simulation Results

In this section, we present several numerical results and analytical results to verify the performance of the proposed scheme. The detailed simulation parameters are listed in Table 1.

Table 1. Simulation Parameter

Channel estimation	Perfect
Traffic model	Full buffer
Circuit power of base station antenna P_b	0.1w
Circuit power of each user P_c	0.1w
signal to noise ratio(SNR) β_k	5dB
Noise power σ^2	1

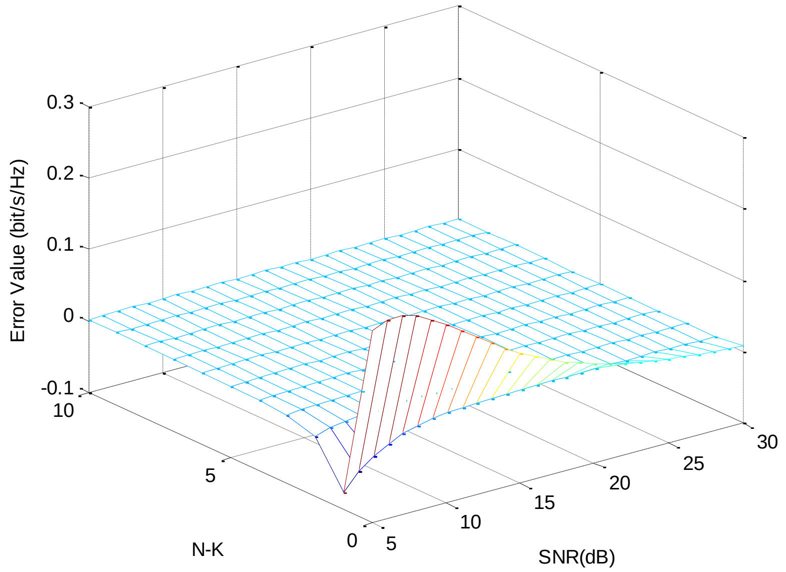

Figure 1. Error of Ergodic Capacity

Figure.1 investigates the error of ergodic capacity between the actual value and the approximate value for each active user. As expected, the error is rather small at high SNR regime. When the SNR is 5dB and the number of transmitted antenna is equal to the number of received antenna, the maximum estimated error 0.18bit/s which accounted 15% of the actual value 1.2bit/s can be acquired. Besides, when the number of received antenna is far more than the number of transmitted antenna, the error value can also be omitted. That is to say, our work can be extended to future massive MIMO system, which is a potential communication scheme for 5G communication. It can be shown that the simplified expression is also valid to approximate the real EE of the system even at low SNR regime if the number of BS station antenna is large enough.

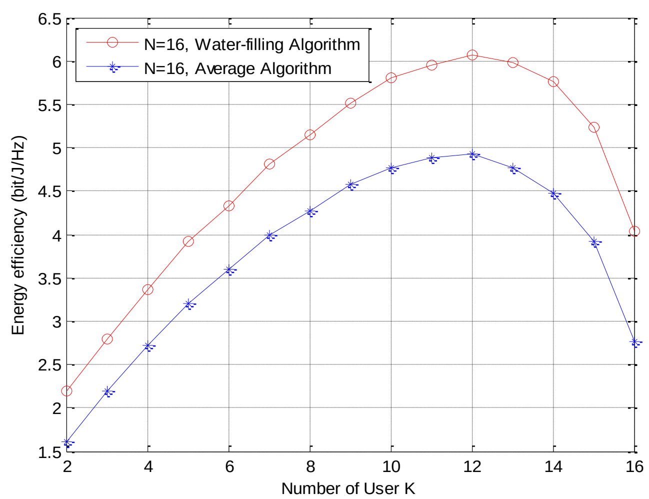

Figure 2. EE versus the Number of User

As shown in Figure. 2, we can see that there exists an optimal number of user when the number of base station antenna and the total power are given, *i.e.*, $N = 16$, $\bar{P} = 10$ W. The

EE performance increases from K=2 to K=12, peaking at K=12 with 6 bit/J/Hz and 4.9 bit/J/Hz for water-filling algorithm and average algorithm respectively. However, the performance degrade sharply when the user number increasing, with only 4bit/J/Hz for water-filling algorithm and 2.7 bit/J/HZ at K=16 for water-filling algorithm and average algorithm respectively. The reason for this phenomenon is straightforward, with the number of user increasing, the multiplexing gain outweigh the diversity gain and the achieving capacity over-ride the increasing energy consumption of the system, and thus the EE performance rise rapidly. With the increasing of served users, the energy consumption dominate the EE performance, as a result, the performance degrade. In addition, it should be noted that compared with average algorithm scheme, water-filling algorithm scheme have a better performance due to its adaptive power allocation.

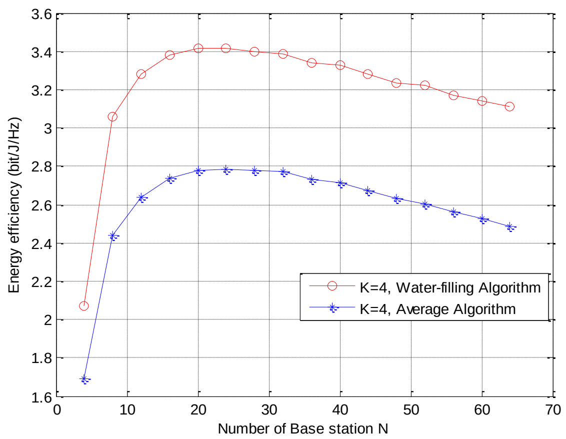

Figure 3. EE versus the Number of Base Station Antennas

Figure 3 illustrates the impact of the number of base station antennas on the EE. Assuming $K=4$, $\bar{P}=10$ W, it can be seen that, for both power allocation algorithm, the system EE goes up rapidly with the number of base station antenna increasing from N=5 to N=20, as a benefit of increasing diversity gain and multiplexing gain. The EE reaches its highest point at N=20, with around 2.8bit/J/Hz and 3.4bit/J/Hz respectively. After that, the EE performance declined gradually with the increasing of base station antenna number. Through the whole line graph, the proposed adaptive algorithm and average algorithm have a similar tendency, and the adaptive water-filling algorithm performance can enjoy a better EE performance than the average algorithm similar to Figure 2.

5. Conclusions

In this paper, taking both electronic circuit and transmission power consumption into consideration, we firstly establish a general theory analytical framework to evaluate the EE of uplink MU-MIMO systems using ZF detector. Also, an accurate closed-form expression of EE for uplink MU-MIMO system is derived and simplified under some mild conditions. The system EE is further improved by utilizing an adaptive power allocation algorithm. From our work, it can be concluded that the user number, the BS antenna number, transmission power are key to system EE, which can be provide a basic design principles for MU-MIMO network.

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7. Appendix A

From (3), we have

$$\mathrm{R}_k = \mathrm{E}[\log_2(1+\frac{P_k G_k}{\sigma^2[\mathbf{W}\mathbf{W}^H]_{kk}})]$$

Assume $\frac{P_k G_k}{\sigma^2}=\delta_k$, $N-K=M$, $x=\frac{1}{[\mathbf{W}\mathbf{W}^H]_{kk}}$. Where M is the difference between N and K. δ_k is the SNR. Since $x \sim \chi^2(2(N-K+1))$, the probability density function is

$$f(x)=\frac{1}{(N-K)!}\times x^{N-K}\times e^{-x}$$

Therefore

$$\begin{aligned}
\mathrm{R}_k &= \frac{1}{M!}\int_0^{\infty}\log_2(1+\delta_k \mathrm{x})\times x^M \times e^{-x}dx \\
&= \sum_{\mathrm{n}=0}^{M}\frac{\log_2 e}{(M-n)!}\int_0^{\infty}\frac{\delta_k}{1+\delta_k x}\times x^{M-n}\times e^{-x}dx \\
&= \sum_{\mathrm{n}=0}^{M}\frac{\log_2(e)}{(M-n)!}\int_0^{\infty}e^{-x}\sum_{i=1}^{M-n}(-1)^{i-1}(\frac{1}{\delta_k})^{i-1}x^{M-n-i}dx+\sum_{\mathrm{n}=0}^{M}\frac{\log_2(e)}{(M-n)!}\int_0^{\infty}e^{-x}\frac{(-1)^{M-n}(\frac{1}{\delta_k})^{M-n}}{x+\frac{1}{\delta_k}}dx \\
&= \sum_{\mathrm{n}=0}^{M}\log_2(e)(\sum_{i=1}^{M-n}(-\frac{1}{\delta_k})^{i-1}\frac{(M-n-i)!}{(M-n)!})+\sum_{\mathrm{n}=0}^{M}\frac{\log_2(e)}{(M-n)!}(-\frac{1}{\delta_k})^{M-n}e^{\frac{1}{\delta_k}}E_1(\frac{1}{\delta_k})
\end{aligned}$$

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