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# Power Allocation for Sum Rate Maximization of Uplink Massive MIMO System with Maximum Ratio Combining


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**Abstract.** This paper investigates the sum rate optimization of uplink massive multiple-input multiple-output (MIMO) system with imperfect channel state information (CSI) and maximum ratio combining (MRC) under the constraints of maximum power and minimum rate, and power allocation (PA) schemes are developed to improve the rate. With the help of concave-convex procedure (CCCP) method, a near-optimal PA scheme is proposed to transform the no-concave maximization problem into a concave one. Considering that both small-scale and large-scale fading information are required in near-optimal PA scheme, which will result in high complexity, a suboptimal PA scheme under the case of large number of receive antennas is presented, which only needs large-scale fading information without real-time estimation and frequent feedback. Moreover, it has the rate close to that of near-optimal scheme but with lower complexity. Simulation results show that the sum rate obtained by the near-optimal PA scheme can match that offered by the benchmark scheme well, and the suboptimal scheme can obtain the rate close to that of near-optimal scheme, especially for large number of receive antennas, which verifies the effectiveness of the proposed schemes.



**Keywords:** Massive MIMO · Power allocation · Sum rate · Imperfect CSI · Maximum ratio combining


## 1 Introduction

The use of multiple-input multiple-output (MIMO) systems can improve the system capacity without increasing the bandwidth and antenna transmission power. Especially for massive MIMO systems where the base station (BS) is equipped with a large number of antennas, the improvement of system capacity is more obvious [1–3]. It has been shown that the interference among the users can be eliminated for massive MIMO system. Similarly, irrelevant noise can also be eliminated, and the small-scale fading effects are averaged out [4]. Meanwhile, linear detectors on uplink transmission, such as



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maximum ratio combining (MRC) detectors and zero-forcing (ZF) detectors, have near-optimal performance in massive MIMO systems. Due to the above advantages, massive MIMO systems are widely studied for fifth generation mobile communication [5].

As an important performance metric in massive MIMO system, sum rate has been widely studied. Reference [6] derived the lower bounds of achievable uplink rate with Jensen's inequality for the massive MIMO system using three linear detection methods. In [7], a power control scheme is developed to maximize the ergodic rate of massive MIMO system with MRC method. The authors of [11] considered the sum rate maximization problem for cell-free massive MIMO system with ZF method, which subjected to the constraints of transmit power and quality of service requirements, e.g., minimum rate requirements. Furthermore, a downlink sum rate maximization problem for co-located massive MIMO system with perfect channel state information (CSI) was considered in [8]. In [9], a power allocation (PA) scheme with the constraints of training duration and the data signal power was formulated to maximize multicell MIMO system rate with MRC receivers. Motivated by the above-mentioned literature, we consider the uplink sum rate maximization problem of co-located massive MIMO under both maximum power and minimum rate constraints in this paper. The major contributions are listed as follows:

- With imperfect CSI and MRC method, we formulate a sum rate maximization problem of uplink massive MIMO system under both maximum power and minimum rate constraints. With the help of concave-convex procedure (CCCP) method, a near-optimal PA scheme is developed to solve the optimization problem, which can obtain the almost same sum rate by using CVX software but with lower complexity.
- Considering that both small-scale and large-scale fading information are required in near-optimal PA scheme, a low-complexity suboptimal PA scheme is proposed in terms of the characteristics of massive MIMO system (large BS antenna number). This scheme needs large-scale information only, and thus it has lower complexity since timely estimation and frequent feedback of CSI are avoided. Moreover, it has the rate close to that of near-optimal scheme, especially for large receive antenna.

## 2 System Model

### 2.1 Uplink Transmission

Here, an uplink single cell massive MIMO system with BS equipped with $N$ antennas is considered. Meanwhile, $K$ single antenna users are uniformly distributed in the cell. The $N \times 1$ received signal vector at BS is

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

where $\mathbf{G}$ is a $N \times K$ channel matrix with the channel coefficient $g_{nk} = [\mathbf{G}]_{nk}$ between the $n$-th antenna of BS and the $k$-th user; $\mathbf{P} = diag\left\{p_1, ..., p_K\right\}$ is a transmission power matrix, whose $k$-th diagonal element represents the $k$-th user's transmission power. In addition, $\mathbf{x} = \left[x_1, x_2, ..., x_K\right]^T$ represents the signal vector transmitted by the $K$ users; $\mathbf{z} \sim \mathcal{CN}\left(0, \sigma_z^2\mathbf{I}_N\right)$ is a $N \times 1$ noise vector, where $\mathcal{CN}\left(0, \mathbf{R}\right)$ denotes the complex

Gaussian distribution with zero-mean and covariance matrix $\mathbf{R}$. Then,the channel coefficient $g_{nk}$ is defined as

$$g_{nk} = \sqrt{\beta_k} h_{nk} \tag{2}$$

where $h_{nk}$ is zero-mean and unit variance Gaussian random variable representing the small-scale fading and $\beta_k$ represents large-scale fading. As a result, the channel matrix $\mathbf{G}$ is written as

$$\mathbf{G} = \mathbf{H}\mathbf{D}^{1/2}, \tag{3}$$

where $\mathbf{H}$ is the $N \times K$ fast fading matrix and $\mathbf{D} = diag\left\{\beta_1, ..., \beta_K\right\}$ is the $K \times K$ large-scale fading matrix.

## 2.2 Uplink Training

In practice, the uplink training is used to obtain the CSI. We assume that this paper has the same uplink training process as [8]. The received signal vector is

$$\mathbf{Y}_p = \sqrt{\tau}\mathbf{G}\mathbf{\Phi}^T + \mathbf{Z}, \tag{4}$$

where $\mathbf{\Phi}$ denotes the pilot sequences matrix, $\tau$ is a coefficient related to the length of the pilot sequences and the pilot transmit power and $\mathbf{Z} \sim \mathcal{CN}(0, \sigma_z^2 \mathbf{I}_N)$. After minimum mean-square error (MMSE) estimation at BS, the estimation of channel is shown as

$$\hat{\mathbf{G}} = \left(\mathbf{G} + \frac{1}{\sqrt{\tau}}\mathbf{Z}\mathbf{\Phi}^*\right)\left(\frac{\sigma_z^2}{\tau}\mathbf{D}^{-1} + \mathbf{I}_K\right)^{-1}, \tag{5}$$

Let $\mathbf{E} = [\mathbf{e}_1, \cdots, \mathbf{e}_K]$ be the channel estimation error. Then we have

$$\hat{\mathbf{G}} = \mathbf{G} + \mathbf{E}, \tag{6}$$

As we know, $\mathbf{E}$ is independent of $\hat{\mathbf{G}}$ after MMSE estimation. In addition, we assume $\hat{\mathbf{g}}_k$ and $\mathbf{e}_k$ are the $k$-th column of $\hat{\mathbf{G}}$ and $\mathbf{E}$, respectively. Thus we have $\mathbf{e}_k \sim \mathcal{CN}\left(0, {\varepsilon_k}^2 \mathbf{I}_N\right)$ and $\hat{\mathbf{g}}_k \sim \mathcal{CN}\left(0, \delta_k^2 \mathbf{I}_N\right)$, where ${\varepsilon_k}^2 = \sigma_z^2 \beta_k / \left(\tau\beta_k + \sigma_z^2\right)$ and $\delta_k^2 = \tau\beta_k^2 / \left(\tau\beta_k + \sigma_z^2\right)$.

## 2.3 Achievable Uplink Rate with MRC

According to MRC method, the received signal of $k$-th user is given by

$$r_k = \hat{\mathbf{g}}_k^H \hat{\mathbf{g}}_k p_k^{1/2} x_k + \hat{\mathbf{g}}_k^H \sum_{i=1, i\neq k}^{K} \hat{\mathbf{g}}_i p_i^{1/2} x_i - \hat{\mathbf{g}}_k^H \sum_{i=1}^{K} \mathbf{e}_i p_i^{1/2} x_i + \hat{\mathbf{g}}_k^H \mathbf{z}, \tag{7}$$

With (7), the $k$-th user's effective SINR is derived as

$$\rho_k = \frac{p_k \left\|\hat{\mathbf{g}}_k\right\|^4}{\sum\limits_{i=1, i\neq k}^{K} p_i \left|\hat{\mathbf{g}}_k^H \hat{\mathbf{g}}_i\right|^2 + \left\|\hat{\mathbf{g}}_k^H\right\|^2 \sum\limits_{i=1}^{K} p_i \varepsilon_i^2 + \left\|\hat{\mathbf{g}}_k^H\right\|^2 \sigma_z^2}, \tag{8}$$

With the above analysis, we can obtain the $k$-th user's rate as follows

$$R_k = \log_2\left(1+\frac{p_k\|\hat{\mathbf{g}}_k\|^4}{\sum\limits_{i=1,i\neq k}^{K} p_i\left|\hat{\mathbf{g}}_k^H\hat{\mathbf{g}}_i\right|^2+\|\hat{\mathbf{g}}_k\|^2\sum\limits_{i=1}^{K} p_i\varepsilon_i^2+\|\hat{\mathbf{g}}_k\|^2\sigma_z^2}\right), \quad (9)$$

## 3 Problem Formulation

In this section, we will introduce two effective PA schemes in term of solving the uplink sum rate maximization problem of massive MIMO. From the above analysis, we have a sum rate maximization problem subject to the constraints of maximum power and minimum rate as follows

$$\begin{aligned}&\max_{\mathbf{p}} \eta_{SE}(\mathbf{p}) = \sum_{k=1}^{K}\log_2\left(1+\frac{p_k\|\hat{\mathbf{g}}_k\|^4}{\sum\limits_{i=1,i\neq k}^{K} p_i\left|\hat{\mathbf{g}}_k^H\hat{\mathbf{g}}_i\right|^2+\|\hat{\mathbf{g}}_k\|^2\sum\limits_{i=1}^{K} p_i\varepsilon_i^2+\|\hat{\mathbf{g}}_k\|^2\sigma_z^2}\right)\\ &s.t.\, 0\le p_k\le P_{\max}, R_k\ge R_{\min}, \forall k\in\{1,2,...,K\},\end{aligned} \quad (10)$$

To begin with, we transform the minimum rate constraints $R_k \geq R_{\min}, \forall k \in \{1, 2, ..., K\}$ into

$$p_k \ge \frac{\left(2^{R_{\min}}-1\right)\left[\sum\limits_{i=1,i\neq k}^{K} p_i\left(\left|\hat{\mathbf{g}}_k^H\hat{\mathbf{g}}_i\right|^2+\|\hat{\mathbf{g}}_k\|^2\varepsilon_i^2\right)+\|\hat{\mathbf{g}}_k\|^2\sigma_z^2\right]}{\|\hat{\mathbf{g}}_k\|^4-\left(2^{R_{\min}}-1\right)\|\hat{\mathbf{g}}_k\|^2\varepsilon_k^2} \quad (11)$$

where $\|\hat{\mathbf{g}}_k\|^2 - \left(2^{R_{\min}}-1\right)\varepsilon_k^2 > 0$ will be satisfied. When $y \neq k$, $R_y \geq R_{\min}$ can be transformed into

$$p_k \le \frac{p_y\|\hat{\mathbf{g}}_y\|^4-\left(2^{R_{\min}}-1\right)\left(\sum\limits_{i=1,i\neq y,i\neq k}^{K} p_i\left|\hat{\mathbf{g}}_y^H\hat{\mathbf{g}}_i\right|^2+\|\hat{\mathbf{g}}_y\|^2\sum\limits_{i=1,i\neq k}^{K} p_i\varepsilon_i^2+\|\hat{\mathbf{g}}_y\|^2\sigma_z^2\right)}{\left(2^{R_{\min}}-1\right)\left(\left|\hat{\mathbf{g}}_y^H\hat{\mathbf{g}}_k\right|^2+\|\hat{\mathbf{g}}_y\|^2\varepsilon_k^2\right)} \quad (12)$$

According to the analysis above, with (11) and (12), we define $LB_k$ and $UB_k$ to be the lower and upper bounds of $p_k$ derived from the rate constraints, respectively. Thus, the maximum power and minimum rate constraints in (10) can be changed into

$$LB_k^{near-op} \le p_k \le UB_k^{near-op}, \forall k \in \{1,2,...,K\} \quad (13)$$

where $UB_k^{near-op} = \min\left(\{x\,|x = UB_k, \forall y \in \{1,2,...,K\}\setminus k\}, P_{\max}\right)$ and $LB_k^{near-op} = LB_k$. Next, we will introduce a near-optimal PA algorithm with the help of CCCP method to solve the maximization problem (10). Namely, the transformation of objective function in (10) with CCCP method is derived as

$$\begin{aligned} f\left(\mathbf{p}\right) &= \sum_{k=1}^{K} \log_2\left(\sum_{i=1,i\neq k}^{K} p_i\left|\hat{\mathbf{g}}_k^H\hat{\mathbf{g}}_i\right|^2 + \left\|\hat{\mathbf{g}}_k\right\|^2\sum_{i=1}^{K} p_i\varepsilon_i^2 + \left\|\hat{\mathbf{g}}_k\right\|^2\sigma_z^2 + p_k\left\|\hat{\mathbf{g}}_k\right\|^4\right) \\ &\quad - \sum_{k=1}^{K} \log_2\left(\sum_{i=1,i\neq k}^{K} p_i\left|\hat{\mathbf{g}}_k^H\hat{\mathbf{g}}_i\right|^2 + \left\|\hat{\mathbf{g}}_k\right\|^2\sum_{i=1}^{K} p_i\varepsilon_i^2 + \left\|\hat{\mathbf{g}}_k\right\|^2\sigma_z^2\right) \\ &= f_1\left(\mathbf{p}\right) - f_2\left(\mathbf{p}\right) \end{aligned} \tag{14}$$

Based on the first-order Taylor expansion $f_2\left(\mathbf{p}\right) \simeq f_2\left(\mathbf{p}_0\right) + \left(\mathbf{p}-\mathbf{p}_0\right)^T\nabla f_2\left(\mathbf{p}_0\right)$, where the gradient of $f_2\left(\mathbf{p}\right)$ at initial value $\mathbf{p}_0$ is defined as $\nabla f_2\left(\mathbf{p}_0\right)$ and and $\mathbf{p}_0$ is initial value, we transform the objective function (14) into a concave one. Therefore, the maximization problem (10) can be transformed into

$$\begin{aligned} \max_{\mathbf{P}} \quad & J_1 = f_1\left(\mathbf{p}\right) - f_2\left(\mathbf{p}_0\right) - \left(\mathbf{p}-\mathbf{p}_0\right)^T\nabla f_2\left(\mathbf{p}_0\right) \\ s.t. \quad & LB_k^{near-op} \le p_k \le UB_k^{near-op}, \forall k \in \{1,2,...,K\} \end{aligned} \tag{15}$$

With the above analysis, CVX software can be used to get the optimal value of sum rate [12]. However, there is a particularly high cost of complexity because of low computational efficiency. Therefore, we use the block-coordinate decent (BCD) method [10] to replace the CVX method. The derivative of $J_1$ with respect to (w.r.t.) $p_k$ is

$$\begin{aligned} \frac{\partial J_1}{\partial p_k} &= \frac{\|\hat{\mathbf{g}}_k\|^2\varepsilon_m^2 + \|\hat{\mathbf{g}}_k\|^4}{\ln 2\left(p_k\|\hat{\mathbf{g}}_k\|^4 + \sum\limits_{i=1,i\neq k}^{K} p_i\left|\hat{\mathbf{g}}_k^H\hat{\mathbf{g}}_i\right|^2 + \|\hat{\mathbf{g}}_k\|^2\sum\limits_{i=1}^{K} p_i\varepsilon_i^2 + \|\hat{\mathbf{g}}_k\|^2\sigma_z^2\right)} \\ &+ \sum_{s=1,s\neq k}^{K} \frac{\left|\hat{\mathbf{g}}_s^H\hat{\mathbf{g}}_k\right|^2 + \|\hat{\mathbf{g}}_s\|^2\varepsilon_k^2}{\ln 2\left(p_s\|\hat{\mathbf{g}}_s\|^4 + \sum\limits_{i=1,i\neq s}^{K} p_i|\hat{\mathbf{g}}_s^H\hat{\mathbf{g}}_i|^2 + \|\hat{\mathbf{g}}_s\|^2\sum\limits_{i=1}^{K} p_i\varepsilon_i^2 + \|\hat{\mathbf{g}}_s\|^2\sigma_z^2\right)} \\ &- \frac{\|\hat{\mathbf{g}}_k\|^2\varepsilon_k^2}{\ln 2\left(\sum\limits_{i=1,i\neq k}^{K} p_{0,i}|\hat{\mathbf{g}}_m^H\hat{\mathbf{g}}_i|^2 + \|\hat{\mathbf{g}}_k\|^2\sum\limits_{i=1}^{K} p_{0,i}\varepsilon_i^2 + \|\hat{\mathbf{g}}_k\|^2\sigma_z^2\right)} \\ &- \sum_{s=1,s\neq k}^{K} \frac{\left|\hat{\mathbf{g}}_s^H\hat{\mathbf{g}}_k\right|^2 + \|\hat{\mathbf{g}}_s\|^2\varepsilon_k^2}{\ln 2\left(\sum\limits_{i=1,i\neq s}^{K} p_{0,i}|\hat{\mathbf{g}}_s^H\hat{\mathbf{g}}_i|^2 + \|\hat{\mathbf{g}}_s\|^2\sum\limits_{i=1}^{K} p_{0,i}\varepsilon_i^2 + \|\hat{\mathbf{g}}_s\|^2\sigma_z^2\right)} \end{aligned} \tag{16}$$

With (13) and (16), the optimal PA of user $k$ is obtained by

$$p_{near-op,k} = \begin{cases} LB_k^{near-op}, & \left.\frac{\partial J_1}{\partial p_k}\right|_{p_k = LB_k^{near-op}} \le 0 \\ UB_k^{near-op}, & \left.\frac{\partial J_1}{\partial p_k}\right|_{p_k = UB_k^{near-op}} \ge 0 \\ p_{near-op,k}^*, otherwise & \end{cases}, \tag{17}$$

where $p_{near-op,k}^*$ is the zero point of $\partial J_1/\partial p_k = 0$ obtained with the bisection method.

The proposed sum rate optimization scheme is shown as Algorithm 1.

**Algorithm 1.** Near-optimal PA Algorithm

**Initialize** tolerances $\nu > 0$, iterative index $l = 0$ and initial point $\mathbf{p}_0^{(l)}$
**repeat**
  $l = l + 1$
  **Initialize** tolerances $\eta > 0$, iterative index $\mu = 0$ and iterative point $\mathbf{p}^{(\mu)}$
  **repeat**
    $\mu = \mu + 1$
    Compute $\mathbf{p}^{(\mu)} = \mathbf{p}_{near-op}$ via (17)
  **until** $\left\| \mathbf{p}^{(\mu)} - \mathbf{p}^{(\mu-1)} \right\| \leq \eta$
  Update $\mathbf{p}_0^{(l)} = \mathbf{p}^{(\mu)}$
**until** $\left\| \mathbf{p}_0^{(l)} - \mathbf{p}_0^{(l-1)} \right\| \leq \nu$

Meanwhile, we get the initial value point that satisfies the BCD algorithm by solving a minimum rate maximization problem. Although the near-optimal PA scheme has less complexity compared with the CVX scheme, it is related to small-scale and large-scale fading information, which requires CSI feedback frequently. Therefore, a suboptimal PA scheme only depending on the large-scale fading information is developed. The difference from the near-optimal scheme is that the latter doesn't require frequent CSI feedback, which means the lower complexity of suboptimal scheme.

We consider the case of $N$ is very large for uplink massive MIMO, an approximate expression of the objective function in problem (10) is shows as

$$\tilde{\eta}_{SE} = \sum_{k=1}^{K} \log_2 \left( 1 + \frac{N p_k \delta_k^2}{\sum\limits_{i=1}^{K} p_i \varepsilon_i^2 + \sigma_z^2} \right) \tag{18}$$

With the similar CCCP transformation process, we get the approximate sum rate optimization problem as follows

$$\begin{array}{ll} \max\limits_{\mathbf{P}} & J_2 = g_1(\mathbf{p}) - g_2(\mathbf{p}_0) - (\mathbf{p} - \mathbf{p}_0)^T \nabla g_2(\mathbf{p}_0) \\ s.t. & LB_k^{sub-op} \leq p_k \leq UB_k^{sub-op}, \forall k \in \{1, 2, ..., K\} \end{array} \tag{19}$$

Importantly, the approximation is close to the original problem (10) only when $N$ is very large. Therefore, there will be obvious performance gap of sum rate between the two proposed PA schemes when $N$ is not large enough, but similar sum rate for very large $N$. According to (19), the derivative of $J_2$ w.r.t. $y_k$ is

$$\begin{aligned} \frac{\partial J_2}{\partial p_k} = & \frac{1}{\ln 2} \frac{N\delta_k^2 + \varepsilon_k^2}{N p_k \delta_k^2 + \left(\sigma_z^2 + \sum_{i=1}^{K} p_i \varepsilon_i^2\right)} \\ & + \frac{1}{\ln 2} \sum\nolimits_{i=1, i \neq k}^{K} \frac{\varepsilon_k^2}{N p_i \delta_i^2 + \left(\sigma_z^2 + \sum_{m=1}^{K} p_m \varepsilon_m^2\right)} \\ & - \frac{1}{\ln 2} \frac{K \varepsilon_k^2}{\sigma_z^2 + \sum_{i=1}^{K} p_{0,i} \varepsilon_i^2} \end{aligned} \tag{20}$$

Based on BCD method, the suboptimal PA of the $k$-th user for the problem (10) is shown as

$$p_{sub-op,k} = \begin{cases} LB_k^{sub-op}, & \left.\frac{\partial J_2}{\partial p_k}\right|_{p_k=LB_k^{sub-op}} \leq 0 \\ UB_k^{sub-op}, & \left.\frac{\partial J_2}{\partial p_k}\right|_{p_k=UB_k^{sub-op}} \geq 0 \\ p^*_{sub-op,k}, otherwise \end{cases}, \tag{21}$$

where $p^*_{sub-op,k}$ is the zero point of $\partial J_2/\partial p_k = 0$ obtained with the bisection method. Similarly, the optimal solution of suboptimal PA scheme can be obtained by Algorithm 1.

## 4 Simulation Results

In this section, the simulation for the proposed PA schemes of the uplink massive MIMO systems with MRC method and imperfect CSI is provided. In order to verify the accuracy of the two schemes, we use the CVX method as a benchmark. This paper considers the case of circle cellular with a radius of 1000 m and $K = 5$ uniformly distributed users. We assume that the reference distance is $d_h = 100$ m and define $\beta_k = s_k/(d_k/d_h)^v$ as the large-scale fading, where $s_k$ is modeled as log-normal RV with a standard deviation $\sigma = 8$ dB, $d_k$ denotes the distance between the $k$-th user and the BS and $v = 3.8$ represents the path lose exponent. In the following simulation results, the noise power $\sigma_z^2$ is set as $-104$ dBm.

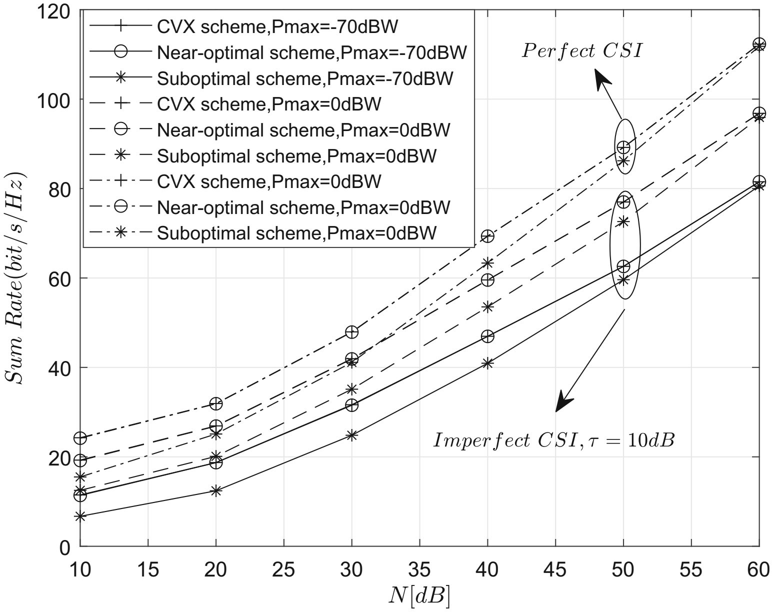


**Fig. 1.** Sum rate for different $\tau$ and $P_{\max}$.

Figure 1 shows the sum rate comparison of the system with different uplink training coefficients $\tau$ and maximum power $P_{\max}$ for $R_{\min} = 2$ bit/s/Hz. It can be seen that the sum rate obtained by near-optimal PA scheme always perfectly match that offered by benchmark scheme as $N$ increases. Meanwhile, the sum rate gap between near-optimal scheme and suboptimal scheme gradually decreases as $N$ increases and the two schemes have similar performance of $N = 60\,\text{dB}$, which is consistent with the analysis in Sect. 3. In addition, the sum rate of $\tau = 10\,\text{dB}$ is lower than that of perfect CSI when $P_{\max} = 0\,\text{dBW}$. As $\tau$ increases, the error variances gradually decreases, which leads to the higher sum rate. As shown in Fig. 1, the sum rate of $P_{\max} = -70\,\text{dBW}$ is lower than that of $P_{\max} = 0\,\text{dBW}$ when $\tau = 10\,\text{dB}$. The above results verify the feasibility of the two proposed PA schemes.

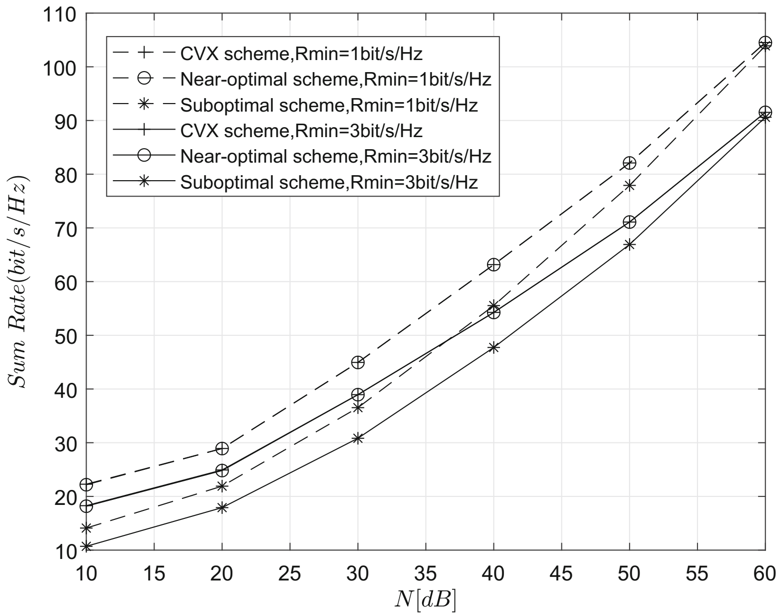


**Fig. 2.** Sum rate for different $R_{\min}$

Figure 2 presents the sum rate comparison of the system with different rate constraints $R_{\min}$, where $\tau = 10\,\text{dB}$ and $P_{\max} = 0\,\text{dBW}$. From Fig. 2, the results similar to Fig. 1 is found. Namely, the near-optimal scheme has almost the same rate as the benchmark scheme, and the suboptimal scheme also obtain the rate near to that of near-optimal scheme with the increase of $N$. Besides, the sum rate under the constraint of $R_{\min}$ = 3 bit/s/Hz is lower than that of $R_{\min}$ = 1 bit/s/Hz, as expected. This is because when rate constraint is large, the possibility of the system meeting the rate requirement will be greatly decreased. Correspondingly, the system communication will be suspended. As a result, the sum rate will become smaller.

## 5 Conclusion

We have investigated the sum rate of uplink massive MIMO with MRC and imperfect CSI. Under the constraints of minimum rate and maximum transmit power, we formulate a non-convex maximization problem of sum rate. Then, using the CCCP method, a near-optimal PA scheme is proposed to tackle the problem, and resultant sum rate is almost the same as that offered by the benchmark scheme. Considering that this scheme needs both small-scale and large-scale fading information, a low-complexity suboptimal scheme is developed based on the asymptotic analysis under large $N$. This suboptimal scheme only requires large-scale information, which avoids frequent feedback and real-time estimation of small-scale information. Thus, the suboptimal scheme has lower complexity. Simulation results show that the proposed schemes are valid, and have the rate close to the benchmark scheme. Moreover, the suboptimal scheme can also obtain similar sum rate to that of near-optimal PA scheme for very large $N$.

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