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Research Article

Beamforming Optimization for Information Enhancement Transmission in MISO SWIPT with NOMA System

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This paper mainly considers a communication network with multiple-input single-output (MISO), in which nonorthogonal multiple access (NOMA) decoding technology is adopted, and wireless power-carrying technology is used to enhance the transmission quality of user information in the communication network. Through joint optimization of power splitting ratio and beamforming vector, we aim at minimizing transmission power (base station transmit power and secondary transmit power) while satisfying the quality-of-service requirement of all users and minimum power for secondary transmission. The problem is a nonconvex optimization program, and it is difficult to get the optimal value directly. First, in order to solve the problem for two-user case, the original problem is transformed into a semidefinite programming (SDP) problem, and then, the iterative updating algorithm is used to approximate the optimal value. When the number of users is greater than two, the original problem is transformed into a second-order cone problem, in which we deal with a sequence of second-order cone programming (SOCP). Results verify that the optimal value of the sequence of SOCPs is not increasing and converges to a local optimal value. Detailed simulation experiments indicate that the algorithm improves the performance of NOMA downlink beamforming under the condition of enhancing information and eliminating network interference.

1. Introduction

In order to achieve good system throughput and have features of improvement of spectral efficiency, nonorthogonal multiple access (NOMA) beamforming has received great attention in multiuser systems. NOMA beamforming permits the base station (BS) to apply spatially free overlay coding. Currently, NOMA beamforming has become an important wireless access technology for the 5G wireless networks [1, 2]. In 5G wireless networks, increasing the spectral efficiency of the downlink is an important factor [3–12]. Maximizing energy efficiency is another key objective of 5G networks besides improving the spectrum efficiency. In order to explore more energy networks, simultaneous wireless information and power transfer (SWIPT) technology was first mentioned in [5]. It has caught much attention for years. In [5], it is shown that radio frequency signals could carry information as well as energy at the same time. Motivated by the issue, the authors in [6] studied two kinds of receiving protocols, namely the time switch receiving protocol and the power split receiving protocol. Furthermore, the transmitter design in a multiple-input single-output (MISO) interference channel to increase the energy efficiency of the communication system is considered in [7]. Recent research on SWIPT has concentrated on cooperative transmission protocol [8, 9] in communication systems.

Motivated by the advantages of NOMA and SWIPT as well as the requirements of 5G, researchers propose NOMA cooperation strategies [13–16] that can improve the communication performance of users at the edge of the communication network. Due to the energy storage limitation of relay equipment in the communication network, there is a tradeoff between users decoding their own information directly and forwarding information to other users. SWIPT has been used in the NOMA to reduce the energy constraints, and users who are close to the base station can be used as relays to provide information enhancement for those who have long distance. Furthermore, many scholars have done studies on optimization problems of NOMA with multiple users [17–19]. In [17], considering that the signal-to-interference-plus-noise ratio (SINR) thresholds of the users are equal, a user admission approach is proposed which is optimal with respect to both the sum rate and the maximum number of admitted users. In [18], a joint design of beamforming and power allocation is proposed, which is designed to maximize the sum rate of the users in one group while ensuring the minimum required target rates of the users in the other group. In [19], two beamforming schemes are proposed, and the corresponding optimal power allocation is developed to maximize the sum rate of the downlink system.

In this work, considering cooperative MISO SWIPT with the NOMA system, we do studies on a MISO communication optimization problem with information enhancement (EN) and internetwork interference elimination in the setting of a MISO multiuser downlink transmission system. We mainly consider a total power minimization problem constrained by base station power and user SINR and secondary transmission power constraint under the NOMA scheme. Correspondingly, we propose iterative algorithms based on semidefinite programming (SDP) approximation and second-order cone programming (SOCP) approximation. First, for the case of two users, we use the SDP approximation to deal with. For the multiuser problem with the enhancement of adjacent user information, we use the internetwork interference cancellation technology to eliminate the interference and solve the problem through SOCP approximation.

2. System Model and Problem Formulation

As shown in Figure 1, a downlink MISO transmission system is considered, where the base station of this system has K antennas to transmit information to M users. In other words, a user nearest the base station is a single antenna receiving multiple antenna transmissions, and the other $M-1$ users are a single-antenna user. Under general circumstances, we assume that M users in the communication network have different channel conditions, among which the user m with a shorter distance has better channel conditions than the user $m-1$ with a longer distance. In this paper, we divide M users into two groups: group 1 is the central user, and group 2 is the edge user. To ensure the quality-of-service requirements of group 2, group 1 is used as an energy harvesting relay to help users in group 2. In this communication system, we use NOMA to improve the efficiency of the spectrum, assuming that the channel is perfect, and the channel state is known.

In this paper, the SWIPT NOMA transmission mainly includes two stages. In the first stage, the base station transmits information to all users. The information received by group 1 is divided into two parts: one part is used to decode information, and the other part is collected by SWIPT. In the second stage, group 1 enhances the information of users in group 2 with the collected energy, and users in group 2 combined the information collected in the two stages to enhance the information.

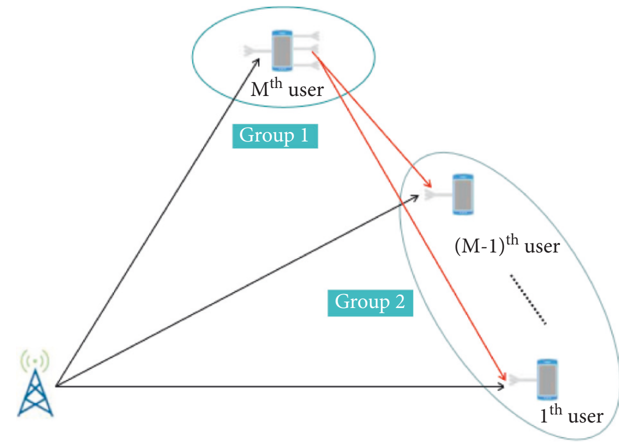


Figure 1: A downlink MISO transmission system.

2.1. Direct Transmission Stage. For the communication network system in this paper, the base station with K antennas transmits signals for M single-antenna users, and the signal transmitted by the base station can be expressed as follows:

$$x = \sum_{m=1}^{M} s_m w_m, \tag{1}$$

where w_m is the beamforming vector for user m, and s_m is the information symbol. The received signal of user m can be expressed as follows:

$$y_m = h_m^H x + n_m, \tag{2}$$

where h_m is the channel vector, n_m and is the complex Gaussian white noise with mean 0 and variance σ_m^2.

To conduct successive interference cancellation at the users, a decoding sequence should be built. It depends on the users' power level. Thus, we assume that h_m, $m = 1, \ldots, M$, follow the model of the Rician channel model [11, 20].

$$h_m = \sqrt{\beta_m}\left(\sqrt{\frac{\zeta}{1+\zeta}}a(\theta_m) + \sqrt{\frac{1}{1+\zeta}}u_m\right), \tag{3}$$

where u_m is a Gaussian random vector with mean 0 and covariance $(1/K)I$ and $a(\theta) = 1/\sqrt{K}[1; e^{-j2\pi(d/\lambda)\sin\theta}; \ldots; e^{-j(K-1)2\pi(d/\lambda)\sin\theta}]$ is "the steering vector for a uniform linear array of half-wavelength spacing" [20]. Here, θ_m is the angle of departure to user m, and β_m is calculated by $1/(d_m)^{\eta}$ [20], where d_m is the distance from the base station to the user m, and η is the path loss exponent [20], which is a nonnegative number.

In the paper, we used $S = \{u_1, u_2, \ldots, u_m\}$ to denote the user set, which is an ordered set [12, 20]. The shorter the distance between the base station and the user, the stronger the channel condition the user (with a bigger index) has. Thus, under the condition of $n \le m$, u_m is able to decode the information for u_n, under quality-of-service conditions [20].

$$\min_{n \le m < M} \{\mathrm{SINR}_m^n\} \ge \gamma_n, \quad 1 \le n < M, \tag{4}$$

where SINR_m^n is expressed as

$$\mathrm{SINR}_m^n = \frac{\left|h_m^H w_n\right|^2}{\sum_{i=n+1}^{M}\left|h_m^H w_i\right|^2 + \sigma_m^2}, \quad n \le m, \tag{5}$$

and γ_n is given by

$$\gamma_n = 2^{R_n} - 1, \tag{6}$$

where R_n is the target rate for user u_n.

For user M, it acts as an energy harvesting relay to help users in group 2. As shown in Figure 2, information decoding and energy harvesting are carried out in the architecture. Then, the SINR of user M can be described as

$$\mathrm{SINR}_M^n = \frac{(1-\beta)\left|h_M^H w_n\right|^2}{\sum_{i=n+1}^{M}(1-\beta)\left|h_M^H w_i\right|^2 + \sigma_M^2}, \quad n \le M. \tag{7}$$

The energy that is harvested by group 1 can be modeled as [21]

$$E = \beta \sum_{i=1}^{M} \left|h_M^H w_i\right|^2 \Gamma, \tag{8}$$

where Γ denotes the transfer time fraction of the first stage. Suppose that the transfer time of the two stages is the same, that is, $\Gamma = 1/2$. Suppose that all the energy collected by user M is forwarded to user information, and the energy for signal processing, circuit consumption, is ignored. Therefore, the transmitted power of group 1 is shown as

$$P_M = \frac{E}{1-\Gamma} = \beta \sum_{i=1}^{M} \left|h_M^H w_i\right|^2. \tag{9}$$

2.2. Cooperative Transmission Stage. In the second stage, the signal transmitted by user M is given by

$$y = \sum_{m=1}^{M-1} s_m v_m, \tag{10}$$

where $v_m \in \mathscr{C}^K$ is the beamforming vector of group 1, and s_m is the information transmitted to user m. The received signal by user m of group 2 is expressed as

$$Z_m = g_m^H y + n_m, \tag{11}$$

and we get

$$Z_m = g_m^H v_m s_m + \sum_{i=1, i \ne m}^{M-1} g_m^H v_i s_i + n_m, \tag{12}$$

where g_m is the channel vector between user M and user $m (m \in \{1 \ldots (M-1)\})$, and n_m is the complex Gaussian white

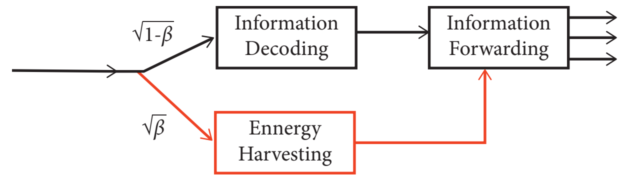


Figure 2: The power splitting structure of group 1.

noise with mean 0 and variance σ_m^2. For user m of group 2, the received SINR can be described as

$$\mathrm{SINR}_m^{(2)} = \frac{\left|g_m^H v_n\right|^2}{\sum_{i=1+i\ne m}^{M-1}\left|g_m^H v_i\right|^2 + \sigma_m^2}. \tag{13}$$

At the end of the second stage, group 1 decodes the message $\{s_1, s_2, \ldots, s_{M-1}\}$ jointly based on the signals received from the base station and the information received in the first stage. Therefore, the signal-to-noise ratio (SINR) of user m can be written as

$$\begin{aligned}\mathrm{SINR}_m &= \mathrm{SINR}_m^m + \mathrm{SINR}_m^{(2)} \\ &= \frac{\left|h_m^H w_m\right|^2}{\sum_{i=m+1}^{M}\left|h_m^H w_i\right|^2 + \sigma_m^2} + \frac{\left|g_m^H v_m\right|^2}{\sum_{i=1, i\ne m}^{M-1}\left|g_m^H v_i\right|^2 + \sigma_m^2}.\end{aligned} \tag{14}$$

In order to enhance the information of user m, we design a special beam vector matrix to ensure that user m is not disturbed by other users. Here, a new $K \times (M-2)$ matrix $G^m = [g_1, \ldots, g_{m-1}, g_{m+1}, \ldots, g_{M-1}]$ is defined, where G^m contains the channel vectors from the user M to all the weaker users in the second stage except for those from the user M to user m of group 2. We decompose the beamforming vector v_m as $v_m = U_m q_m$, where U_m is normalized and lies in the null space of G^m. Based on the definition of U_m and using the singular value decomposition, we decompose G^m as

$$\bar{G}^m = \left[A_m^{M-2}, A_m^{K-M+2}\right] D_m B_m^H, \tag{15}$$

where A_m^{M-2} is the first $M-2$ left eigenvectors of $\bar{G}^m$, which form an orthogonal basis of $\bar{G}^m$, and A_m^{K-M+2} corresponding the zero eigenvalues represents the last $K-M+2$ left eigenvectors of $\bar{G}^m$, which form an orthogonal basis of the null space of $\bar{G}^m$. Thus, U_m is given by $U_m = A_m^{K-M+2}$.

Suppose that successive interference cancellation technology is employed for user m to eliminate the interference of other users' information. Therefore, user m can be decoded, and the information received by user m can be expressed as

$$Z_m = g_m^H U_m q_m s_m + n_m. \tag{16}$$

For user m of group 2, the SNR can be described as

$$\mathrm{SNR}_m^{(2)} = \frac{\left|g_m^H U_m q_m\right|^2}{\sigma_m^2}. \tag{17}$$

Therefore, the equivalent SINR at user m can be expressed as

$$\mathrm{SINR}_m = \mathrm{SINR}_m^m + \mathrm{SNR}_m^{(2)} = \frac{\left|h_m^H w_m\right|^2}{\sum_{i=m+1}^{M}\left|h_m^H w_i\right|^2 + \sigma_m^2} + \frac{\left|g_m^H U_m q_m\right|^2}{\sigma_m^2}. \quad (18)$$

In order to work normally for M users, the received power needs to be greater than or equal to the transmitted power

$$P_M \geq \sum_{i=1}^{M-1}\left|U_i q_i\right|^2. \quad (19)$$

The system design aims to minimize the total power of base and M user and, meanwhile, guarantee the quality-of-service requirement of all users and decoding requirements of NOMA and constraints on user M ability to work properly in the two stages. Then, problem (P1) can be formulated as

$$\underset{\{w_m,q_m\},\beta}{\text{minimize}} \sum_{m=1}^{M} w_m^H w_m + \sum_{m=1}^{M-1}\left(U_m q_m\right)^H U_m q_m, \quad (20a)$$

$$\text{subject to} \frac{\left|h_m^H w_n\right|^2}{\sum_{i=n+1}^{M}\left|h_m^H w_i\right|^2 + \sigma_m^2} \geq \gamma_n, \quad n \leq m < M, \quad (20b)$$

$$\frac{(1-\beta)\left|h_M^H w_n\right|^2}{\sum_{i=n+1}^{M}(1-\beta)\left|h_M^H w_i\right|^2 + \sigma_M^2} \geq \gamma_n, \quad n \leq M, \quad (20c)$$

$$\beta\sum_{i=1}^{M}\left|h_M^H w_i\right|^2 \geq \sum_{i=1}^{M-1}\left|U_i q_i\right|^2, \quad (20d)$$

$$\frac{\left|h_m^H w_m\right|^2}{\sum_{i=m+1}^{M}\left|h_m^H w_i\right| + \sigma_m^2} + \frac{\left|g_m^H U_m q_m\right|^2}{\sigma_m^2} \geq \gamma_m, \quad 1 \leq m < M, \quad (20e)$$

$$0 \leq \beta \leq 1. \quad (20f)$$

In problem (P1), the objective (20a) is to minimize the total power of the base station and M user in the two stages. Constraints (20b) and (20c) are traditional NOMA constraints. Constraints (20b) and (20c) indicate that the received SINR to decode s_n needs to be no less than the target SINR γ_n. Constraint (20d) is guaranteed to transmission normally for the second stage. Constraint (20e) is the sum of the information received by user m of group 2 in the first stage plus the information received in the second stage, which should be greater than the information decoding threshold γ_m. Constraint (20f) indicates the power splitting ratio.

As for the optimization problem (P1), we can know that it is a nonconvex problem. It is difficult to find the optimal solution directly mainly because the constraint conditions in the optimization problem have quadratic terms. We start with the simple two-user communication network and use SDP and SDR technology to solve the optimization problem and use successive convex approximation iterative approach to gradually approximate the optimal value. Then, we extended to general multiusers, where SOCP techniques are used to solve optimization problems. The iterative algorithm is used to gradually approximate optimal values.

3. An Approximate SDP Algorithm for Two Users

In this part, we consider the two-user case, and the whole problem (P2) can be written as

$$\underset{\{w_1,w_2,v_1\},\beta}{\text{minimize}}\, w_1^H w_1 + w_2^H w_2, \quad (21a)$$

$$\text{subject to} \frac{(1-\beta)\left|h_2^H w_1\right|^2}{(1-\beta)\left|h_2^H w_2\right|^2 + \sigma_2^2} \geq \gamma_1, \quad (21b)$$

$$\frac{(1-\beta)\left|h_2^H w_2\right|^2}{\sigma_2^2} \geq \gamma_2, \quad (21c)$$

$$\beta\left(\left|h_2^H w_2\right|^2 + \left|h_2^H w_1\right|^2\right) \geq \left|v_1\right|^2, \quad (21d)$$

$$\frac{\left|h_1^H w_1\right|^2}{\left|h_1^H w_2\right| + \sigma_1^2} + \frac{\left|g_1^H v_1\right|^2}{\sigma_1^2} \geq \gamma_1, \quad (21e)$$

$$0 \leq \beta \leq 1. \quad (21f)$$

The above optimization problem (P2) is nonconvex, and we can use SDP and SDR technology to transform the problem (P2) into an equivalent optimization problem [22]. Thus, a successive convex approximation iterative algorithm is used to gradually approach the optimal solution of the optimization problem. We set W_1, W_2, and V as positive semidefinite matrices

$$\begin{aligned} V &= v_1 v_1^H, \\ W_i &= w_i w_i^H, \quad i = 1, 2. \end{aligned} \quad (22)$$

Through adopting the SDR technology, problem (P2) can be relaxed as

$$\underset{\{W_1,W_2,V_1\},\beta}{\text{minimize}}\, tr\left(W_1 + W_2\right), \quad (23a)$$

$$\text{subject to}\, tr\left(h_2 h_2^H\left(W_1 - \gamma_1 W_2\right)\right) \geq \frac{\gamma_1\sigma_2^2}{1-\beta}, \quad (23b)$$

$$tr\left(h_2 h_2^H W_2\right) \geq \frac{\gamma_2\sigma_2^2}{1-\beta}, \quad (23c)$$

$$tr\left(h_2 h_2^H W_2 + h_2 h_2^H W_1\right) \geq \frac{tr\left(V_1\right)}{\beta}, \quad (23d)$$

$$\frac{tr\left(h_1h_1^HW_1\right)}{tr\left(h_1h_1^HW_2\right)+\sigma_1^2}+\frac{tr\left(g_1g_1^HV_1\right)}{\sigma_1^2}\geq\gamma_1, \tag{23e}$$

$$0\leq\beta\leq 1, \tag{23f}$$

$$W_1\succeq 0, W_2\succeq 0, V_1\succeq 0. \tag{23g}$$

In problem (P2), tr(·) denotes the trace of the square matrix argument. The curled inequality symbol $\succeq$ (and its strict form $\succ$) denotes generalized inequality. $A\succeq B$ means that A – B is a Hermitian positive semidefinite matrix ($A\succ B$ for positive definiteness).

Proposition 3.1. *Assume that* (W_1^*, W_2^*, V_1^*) *is optimal for (23a)–(23g). Then, there always exist* $W_1^*=w_1^*w_1^{*H}, W_2^*=w_2^*w_2^{*H}, V_1^*=v_1^*v_1^{*H}$, *and* (w_1^*, w_2^*, v_1^*) *is the optimal solution of (21a)–(21f).*

Proof. See Appendix A.

Note that since the rank-one constraints are removed in problem (P2), the equivalence of optimization problem (P1) and optimization problem (P2) is not able to be guaranteed, so we should prove that the two optimization problems are equivalent. In problem (P2), because the objective function and constraints (23d) and (23e) are nonlinear, it cannot be directly proved the rank-one optimality. By introducing an auxiliary variable y for constraint (23d), we observe that

$$tr(V_1)\leq y\beta, \tag{24a}$$

$$tr\left(h_2h_2^HW_2+h_2h_2^HW_1\right)\geq y. \tag{24b}$$

We utilize the constrained concave-convex procedure to transform (24a) into a tractable approximation. It is observed that $tr(V_1)\leq 1/4(y+\beta)^2-1/4(y-\beta)^2$; we again observed that $f(y,\beta,\tilde{y},\tilde{\beta})=1/4(\tilde{y}+\tilde{\beta})^2+1/2\ (\tilde{y}+\tilde{\beta})^2(y+\beta-\tilde{y}-\tilde{\beta})$ as the first-order Taylor expansion of the second quadratic term $1/4(y+\beta)^2$ around a given point $\{\tilde{y},\tilde{\beta}\}$. Thus, (24a) can be approximated as

$$\begin{aligned}4tr(V_1)&=(\tilde{y}+\tilde{\beta})^2+2(\tilde{y}+\tilde{\beta})\\&\quad\cdot(y+\beta-\tilde{y}-\tilde{\beta})-(y-\beta)^2.\end{aligned} \tag{25}$$

By introducing an auxiliary variable $x\geq 0$ into (23e), then constraint (23e) can be equivalently rewritten as

$$x+tr\left(g_1g_1^HV_1\right)\geq\gamma_1, \tag{26a}$$

$$tr\left(h_1h_1^HW_1\right)\geq xtr\left(h_1h_1^HW_2\right)+x\sigma_1^2. \tag{26b}$$

For constraint (26b), the arithmetic-geometric mean inequality can be used to produce an approximately equivalent constraint. For nonnegative variables x, y, z, the arithmetic-geometric mean inequality based approximation of expression can be expressed as

$$2xy\leq(ax)^2+\left(\frac{y}{a}\right)^2\leq 2z, \tag{27}$$

so for condition (27), we can see that when $a=\sqrt{y/x}$, the first equality can be obtained. So constraint (26b) can be approximately given by

$$\left(a^{(n)}x\right)^2+\left(\frac{tr\left(h_1h_1^HW_2\right)}{a^{(n)}}\right)^2\leq 2tr\left(h_1h_1^HW_1\right)-2x\sigma_1^2, \tag{28}$$

where $a^{(n)}$ is the value of a at the *n-th* iteration, and it can be determined by

$$a^{(n)}=\sqrt{\frac{\left(tr\left(h_1h_1^HW_2\right)\right)^{(n-1)}}{x^{(n-1)}}}. \tag{29}$$

Therefore, the problem in the *n-th* iteration can be given by problem (P3)

$$\underset{\{W_1,W_2,V_1\},x,y,\beta}{\text{minimize}}\ tr(W_1+W_2+V_1), \tag{30a}$$

$$\begin{aligned}&\text{subject to (23b), (23c), (23f), (24b), (25), (26a),}\\&\text{(28) satisfied,}\end{aligned} \tag{30b}$$

$$W_1\succeq 0, W_2\succeq 0, V_1\succeq 0, x\geq 0, y\geq 0. \tag{30c}$$

It is assumed that the problem (P3) is feasible, and accordingly, it is dual feasible. Based on Theorem 3.2 in [23, 24], it can be deduced that problem (P3) always has an optimal solution (W_1^*, W_2^*, V_1^*) and satisfies

$$\text{rank}^2(W_1^*)+\text{rank}^2(W_2^*)+\text{rank}^2(V_1^*)\leq 4. \tag{31}$$

Since the variables satisfy the condition (31), the equivalence of optimization problem (P1) and optimization problem (P2) can be guaranteed. Therefore, the rank-one constraints of problem (P2) can be dropped, and the two optimization problems are equivalent. Here, we propose an approximate constraint algorithm based on SDP technology. Algorithm 1 is shown as follows. □

4. An Approximate SOCP Algorithm for Multiusers

In this part, we establish a second-order cone program-based approximate algorithm for (20a)–(20f). Observe that the optimization problem (20a)–(20f) can be rewritten as a separable quadratic constrained quadratic programming [20]. And the SDP technology for the optimization problem (20a)–(20f) is not tight. Therefore, a new method should be established instead of SDP relaxation. By introducing auxiliary variables $\{t_{mn}, t_{Mn}\}$, (20a)–(20f) can be rewritten as

$$\underset{\{w_m,q_m\},\beta}{\text{minimize}}\sum_{m=1}^{M}w_m^Hw_m+\sum_{m=1}^{M-1}(U_mq_m)^HU_mq_m. \tag{32a}$$

$$\text{subject to (20d), (20e), (20f) satisfied,} \tag{32b}$$

$$\left|h_m^Hw_n\right|\geq t_{mn}, \tag{32c}$$

Require: $\{h_m\}, \{g_m\}, \{\sigma_m\}, \{\gamma_n\}, K, \zeta, \eta, \xi, y^0, \beta^0, x^0$;
Ensure: A solution $\{w_1^*\}, \{w_2^*\}$ and$\{v_1^*\}$ for problem (21a)–(21f);
(1) Suppose that $\{W_1^0, W_2^0, V_1^0\}$ is an initial point; set $l = 0$ and $r_0 = tr(W_1 + W_2 + V_1)$ (a large number);
(2) do;
(3) solve SDP (30a)–(30c), obtaining optimal solution $\{W_m^{l+1}, V_1^{l+1}, \beta^{l+1}, x^{l+1}, y^{l+1}\}$ and optimal value r_{l+1};
(4) solve(29), obtaining solution a^{l+1};
(5) $l: = l + 1$;
(6) UNTIL $r_{l-1} - r_l \le \xi$;
(7) **return** $\mathbf{w}^*, v^*$.

Algorithm 1: Approximate SDP algorithm for (21a)–(21f).

$$\left|h_M^H w_n\right| \ge t_{Mn}, \tag{32d}$$

$$t_{mn} \ge \sqrt{\gamma_n \sum_{i=n+1}^{M} \left|h_m^H w_i\right|^2 + \gamma_n \sigma_m^2}, \quad n \le m < M, \tag{32e}$$

$$t_{Mn} \ge \sqrt{\gamma_n \sum_{i=n+1}^{M} \left|h_M^H w_i\right|^2 + \frac{\gamma_n \sigma_M^2}{1-\beta}}. \tag{32f}$$

It is nonconvex for (32c) and (32d) because of the absolute value, we propose a method of approximation [20] as follows:

$$\left|h_m^H w_n\right| \ge t_{mn}, \quad n \le m \le M, 1 \le n \le M. \tag{33}$$

In order to design an algorithm for solving (20a)–(20f), we assume that $\{w_1^0, \ldots, w_m^0\}$ is an iteration starting point. Observe that

$$\left|h_m^H w_n\right| \ge \frac{\left|w_n^H h_m h_m^H w_n^0\right|}{\left|h_m^H w_n^0\right|} \ge \frac{\Re\left(w_n^H h_m h_m^H w_n^0\right)}{\left|h_m^H w_n^0\right|}. \tag{34}$$

It concludes that if

$$\frac{\Re\left(w_n^H h_m h_m^H w_n^0\right)}{\left|h_m^H w_n^0\right|} \ge t_{mn}, \tag{35}$$

then one has

$$\left|h_m^H w_n\right| \ge t_{mn}. \tag{36}$$

Therefore, consider the second-order cone programming problem as follows:

$$\underset{\{w_m, q_m\}, \beta, t_{mn}}{\text{minimize}} \sum_{m=1}^{M} w_m^H w_m + \sum_{m=1}^{M-1} \left(U_m q_m\right)^H U_m q_m, \tag{37a}$$

$$\text{subject to (20d), (20e), (20f), (32e), (32f) satisfied,} \tag{37b}$$

$$\frac{\Re\left(w_n^H h_m h_m^H w_n^0\right)}{\left|h_m^H w_n^0\right|} \ge t_{mn}, \quad 1 \le n \le M, n \le m \le M. \tag{37c}$$

For the following analysis, let $l: = 1$. Solve SOCP problem (37a)–(37c), finding a solution $(w_1^l, \ldots, w_M^l; \{t_{mn}^l\})$. Observe that $|h_m^H w_n| \ge |w_n^H h_m h_m^H w_n^l| / |h_m^H w_n^l| \ge \Re(w_n^H h_m h_m^H w_n^l) / |h_m^H w_n^l|$, and that

$$\frac{\Re\left(w_n^H h_m h_m^H w_n^l\right)}{\left|h_m^H w_n^l\right|} \ge t_{mn} \text{ implies } \left|h_m^H w_n\right| \ge t_{mn}. \tag{38}$$

Then, construct another convex restriction of (20a)–(20f) in a similar way based on $(w_1^l, \ldots, w_M^l)$

$$\underset{\{w_m\}, \{t_{mn}\}}{\text{minimize}} \sum_{m=1}^{M} w_m^H w_m + \sum_{m=1}^{M-1} \left(U_m q_m\right)^H U_m q_m, \tag{39a}$$

$$\text{subject to (20d), (20e), (20f), (32e), (32f) satisfied,} \tag{39b}$$

$$\frac{\Re\left(w_n^H h_m h_m^H w_n^l\right)}{\left|h_m^H w_n^l\right|} \ge t_{mn}, \quad 1 \le n \le M, n \le m \le M. \tag{39c}$$

Solve problem (39a)–(39c) to get $(w_1^l, \ldots, w_M^l; \{t_{mn}^l\})$. Set $l: = l+1$ and again deal with (39a)–(39c), and an iterative process is formulated in the way. Let

$$v_l = \sum_{m=1}^{M} \left\|w_m^l\right\|^2, \quad l = 1, \ldots \tag{40}$$

be the optimal values. The property about to be demonstrated is that $\{v_l\}$ is a nonincreasing sequence.

Proposition 4.1. *It holds that $v_l \ge v_{l+1}$ for $l \ge 1$.*

Proof. The optimal solution $(w_1^l, \ldots, w_M^l; \{t_{mn}^l\})$ for problem (37a)–(37c) with w_n^0 replaced by w_n^{l-1} is feasible for problem (39a)–(39c). In that case, the optimal solution $(w_1^{l+1}, \ldots, w_M^{l+1}; \{t_{mn}^{l+1}\})$ for (39a)–(39c) has the following property:

$$v_l = \sum_{m=1}^{M} \left(w_m^l\right)^H w_m^l \ge \sum_{m=1}^{M} \left(w_m^{l+1}\right)^H w_m^{l+1} = v_{l+1}. \tag{41}$$

We have an immediate check whether it is feasible for problem (39a)–(39c). Since replacing w_n^0 with w_n^{l-1} is the optimal solution of (37a)–(37c), it is also feasible, so (37c) satisfies

$$\frac{\Re\left(\left(w_n^l\right)^H h_m h_m^H w_n^{l-1}\right)}{\left|h_m^H w_n^{l-1}\right|} \geq t_{mn}^l, \tag{42}$$

which imply that

$$\left|h_m^H w_n^l\right| \geq t_{mn}^l. \tag{43}$$

So we have

$$\frac{\Re\left(\left(w_n^l\right)^H h_m h_m^H w_n^l\right)}{\left|h_m^H w_n^l\right|} = \left|h_m^H w_n^l\right| \geq t_{mn}^l, \tag{44}$$

and (39a) is also fulfilled

$$t_{mn}^l \geq \sqrt{\gamma_n \sum_{i=n+1}^{M} \left|h_m^H w_i^l\right|^2 + \gamma_n \sigma_m^2}, \tag{45}$$

for $1 \leq n \leq M, n \leq m \leq M$. It follows from (44), (45) that $(w_1^l, \ldots, w_M^l; \{t_{mn}^l\})$ is feasible for (39a).

For problem (39a)–(39c), the optimal value of each iteration is not increasing. So with the increase in the number of iterations, the optimal value will converge to a local minimum point.

Note that we can equivalently rewrite (39a)–(39c) as

$$\underset{\{w_m\}}{\text{minimize}} \sum_{m=1}^{M} w_m^H w_m + \sum_{m=1}^{M-1} \left(U_m q_m\right)^H U_m q_m, \tag{46a}$$

$$\text{subject to (20d), (20e), (20f) satisfied,} \tag{46b}$$

$$\frac{\Re\left(w_n^H h_m h_m^H w_n^l\right)}{\left|h_m^H w_n^l\right|} \geq \sqrt{\gamma_n \sum_{i=n+1}^{M} \left|h_m^H w_i\right|^2 + \gamma_n \sigma_m^2}, \quad n < m < M, 1 < n < M, \tag{46c}$$

$$\frac{\Re\left(w_n^H h_M h_M^H w_n^l\right)}{\left|h_m^H w_n^l\right|} \geq \sqrt{\gamma_n \sum_{i=n+1}^{M} \left|h_M^H w_i\right|^2 + \frac{\gamma_n \sigma_m^2}{1-\beta}}. \tag{46d}$$

For problem (46a)–(46d), by introducing an auxiliary variable ∂ to the constraint (20d), thus, (20d) can be rewritten as

$$\beta \partial \geq \sum_{i=1}^{M-1} \left|U_i q_i\right|^2, \tag{47}$$

$$\sum_{i=1}^{M} \left|h_M^H w_i\right|^2 \geq \partial. \tag{48}$$

So for formula (47), we deal with it in the same way as (24a)

$$4 \sum_{i=1}^{M-1} tr\left(\left|U_i q_i\right|^2\right) \leq (\widetilde{\partial} + \widetilde{\beta})^2 + 2(\widetilde{\partial} + \widetilde{\beta})(\partial + \beta - \widetilde{\partial} - \widetilde{\beta}) - (\partial - \beta)^2. \tag{49}$$

To approximate the quadratic matrix inequality (48), we assume that an initial point $(\{w_n^0\}, q_n^0)$ is given, and that

$$\left(w_n - w_n^0\right)\left(w_n - w_n^0\right)^H \approx 0, \tag{50}$$

for $n = 1, \ldots M$, and

$$\left(q_n - q_n^0\right)\left(q_n - q_n^0\right)^H \approx 0. \tag{51}$$

This means that w_n^0 is sufficiently close to w_n for each n and q_n^0 is sufficiently close to q_n. Then, we have

$$w_n w_n^H \approx w_n w_n^{0H} + w_n^0 w_n^H - w_n^0 w_n^{0H}, \forall n, \tag{52}$$

$$q_n q_n^H \approx q_n q_n^{0H} + q_n^0 q_n^H - q_n^0 q_n^{0H}, \tag{53}$$

and by this approximation, we can get

$$\sum_{n=1}^{M} h_M^H \left(w_n w_n^{0H} + w_n^0 w_n^H - w_n^0 w_n^{0H}\right) h_M \geq \partial. \tag{54}$$

For problem (46a)–(46d), we can introduce an auxiliary variable x_m, so the constraint (20e) can be written as

$$x_m + \frac{\left|g_m^H U_m q_m\right|^2}{\sigma_m^2} \geq \gamma_m, \quad 1 \leq m < M, \tag{55}$$

$$\frac{\left|h_m^H w_m\right|^2}{\sum_{i=m+1}^{M} \left|h_m^H w_i\right|^2 + \sigma_m^2} \geq x_m, \quad 1 \leq m < M. \tag{56}$$

So for formula (55), we deal with it in the same way as (48)

$$x_m + g_m^H U_m \left(q_n q_n^{0H} + q_n^0 q_n^H - q_n^0 q_n^{0H}\right) g_m U_m^H \geq \gamma_m, \quad 1 \leq m < M. \tag{57}$$

In order to approximate the inequality (56), by constructing a perfect plane, we can get

$$\begin{gathered}\left(\frac{|u|}{\sqrt{v}} - \frac{(u_0)}{v_0}\sqrt{v}\right)^2 \geq 0, \\ \frac{|u|^2}{v} \geq 2\frac{\Re\left(u_0 u\right)}{v_0} - \frac{\left(u_0^2\right)}{v_0^2} v.\end{gathered} \tag{58}$$

For formula (56), it can be approximated by the perfect plane method, which can be obtained

$$\frac{2\Re\left(h_m^H w_m^l w_m^H h_m\right)}{x_m^l} - \frac{h_m^H w_m^l \left(w_m^l\right)^H h_m}{\left(x_m^l\right)^2} x_m \geq \sum_{i=m+1}^{M} \left|h_m^H w_i\right|^2 + \sigma_m^2, \quad 1 \leq m < M. \tag{59}$$

Therefore, problem (20a)–(20f) is solved by solving the following optimization problem:

Require: $\{h_m\}, \{\sigma_m\}, \{\gamma_n\}, \{P_k\}, M, K, w_m^0, q_m^0, \tilde{\partial}, \tilde{\beta}, \xi$
Ensure: A solution $\{w_m^*\}, \{q_m^*\}$ for problem (20a)–(20f);
(1) Suppose that $\{w_m^0, q_m^0\}$ is an initial point; set $l = 0$ and $v_l = \sum_{m=1}^{M} w_m^H w_m + \sum_{m=1}^{M-1} (U_m q_m)^H U_m q_m$ (a large number);
(2) **repeat**;
(3) solve SOCP (60a)–(60b), obtaining optimal solution $\{w_m^{l+1}, q_m^{l+1}\}$;
(4) $\partial = \partial, \beta = \beta, l: = l + 1$;
(6) **until** $v_{l-1} - v_l \le \xi$.

Algorithm 2: An Approximate SOCP algorithm for (20a)–(20f).

$$\underset{\{w_m, q_m\}, x_m, \beta, \partial}{\text{minimize}} \sum_{m=1}^{M} w_m^H w_m + \sum_{m=1}^{M-1} (U_m q_m)^H U_m q_m, \tag{60a}$$

$$\text{subject to (46c), (46d), (49), (54), (57), (59), (20f) satisfied.} \tag{60b}$$

Thus, an approximate SOCP algorithm is formulated as in Algorithm 2. □

5. Simulations Results

In this part, simulation results are presented to verify the performance of the proposed approximate algorithms for dealing with beamforming optimization problems of the NOMA system with information enhancement and inter-network interference elimination. For the NOMA downlink system, let the number of antennas in the base station be the same as that in user M, and the receiver noise power $\sigma_m^2 = 1$ Watt for all m.

Example 1. Assume that the base station serves $M = 2$ users (as in problem (21a)–(21f)). There are two channel models, namely channel 1 and channel 2. And for channel 1, suppose that the Rayleigh fading channel h_m follows $\mathrm{N}(0, 1/(2(d_m)^\eta K)I)$ (i.e., (3) with $\zeta = 0$; similarly, suppose that g_m also follows $\mathrm{N}(0, 1/(2(d_m)^\eta K)I)$; for channel 2, suppose that h_m follows $\mathrm{N}(0, 1/(2(d_m)^\eta K)I + 1/(2(d_m)^\eta)a(\theta_m^M)I)$ (i.e., (3) with $\zeta = 1$); similarly, suppose that g_m also follows $\mathrm{N}(0, 1/(2(d_m)^\eta K)I + 1/(2(d_m)^\eta)a(\theta_m^M)I)$, where d_m is the distance from the base station to user m, d_m^M is the distance from the user M to user m, θ_m is the angle of departure (AoD) between the base station and user m, θ_m^M is the angle of departure between the user M and user m, and η denotes the path loss exponent. In the simulation, we set $d_M = d_2 = 0.8$ m (meter), $d_1 = 1.6$ m, $d_1^2 = 1.2$ m, and $\eta = 1$, and the AoDs in (3) are $(\theta_1, \theta_2, \theta_1^2) = (30^0, 70^0, 90^0)$. The SINR targets $\gamma_2 = 1, \gamma_1 = 1$.

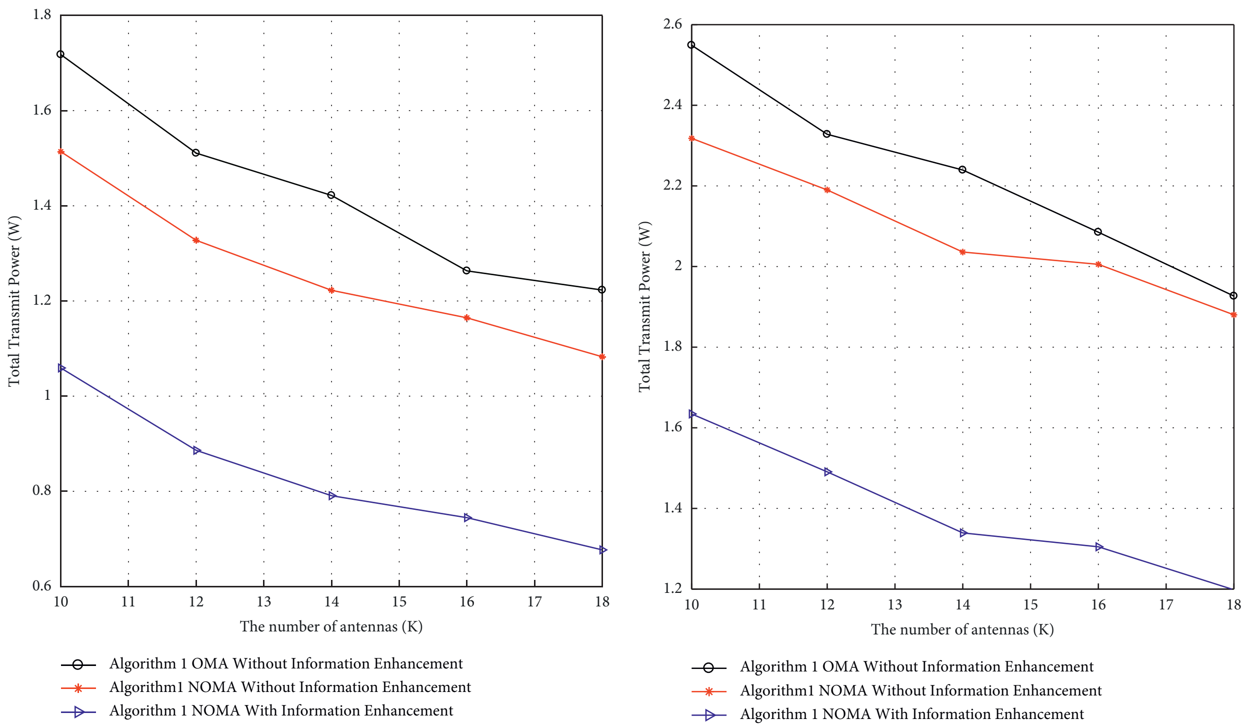
In Figure 3, we have plotted the minimum base station total power of OMA without information enhancement (OMA-No-En), NOMA without information enhancement (NOMA-No-En), and NOMA with information enhancement (NOMA-En) schemes versus the number of antennas as shown in Figure 3(a) and Figure 3(b) for a set of 100 channel realizations. All three models are solved based on Algorithm 1. As shown in Figure 3(a), the power of the three communication models decreases as the number of antennas increases. The reason is that as the antennas grow larger, the beamforming is more flexible to allocate information, thus reducing the total power. The total power of NOMA-No-En is less than that of OMA-No-En under the same parameters. For NOMA-En (as in problem (21a)–(21f)) and NOMA-No-En (as in problem (21a)–(21f)) without information enhances this part of the constraint, the constraint is enhanced by adding part of enhanced information in NOMA-En, which means that the constraint set of the whole optimization problem becomes larger, and the value of the objective function becomes smaller. Therefore, under the same parameters, the total power of NOMA-En is less than that of NOMA-No-En. It also proves that the method we proposed is effective. Figure 3(a) and Figure 3(b) are different in that their channel models and the other parameters are the same.

Example 2. Assume that the base station serves $M = 2$ users. It is assumed that channel 1 is used for all channels. Number of antennas in the base station $K = 16$. Other settings follow Example 1.

In Figure 4, we have plotted the minimum base station total power of OMA-No-En, NOMA-No-En, and NOMA-En schemes versus the distance between the center user and the edge user in Figure 4 for a set of 100 channel realizations. In OMA-No-En and NOMA-No-En, their optimization problem and the distance between the center user and the edge user are not unrelated, so the total power of their base stations does not change with the increase of the distance between the center user and the edge user. For NOMA-En, as the distance between the center user and the edge user increases, the channel g_1^2 becomes worse, and the information enhancement becomes smaller. For problem (21a)–(21f), its constraint set becomes smaller, causing the objective function to become larger. As this distance gets bigger, the constraint on the problem gets smaller, the target function gets bigger, and NOMA-En becomes closer to NOMA-No-En.

Example 3. Consider a scenario in which up to 4 users are served (as in problem (60a)–(60b)). Suppose that h_m and g_m follow the channel model (3) with $\zeta = 0$, and the SINR thresholds are the same, that is, $\gamma_m = \gamma = 1, \forall m$. The distances between the base station and user m are (d_1, d_2, d_3, d_4)=(1.6, 0.8, 0.6, 0.4), and the distances between user M and user m are $(d_1^4, d_2^4, d_3^4) = (1.4, 0.9, 0.5)$.

Figure 5 tests the differences in optimal values acquired by approximation SOCP. The figure displays the total



(a) (b)

FIGURE 3: The optimal total transmission power versus the number of transmit antennas, with $\gamma = 1$ and $\eta = 1$.

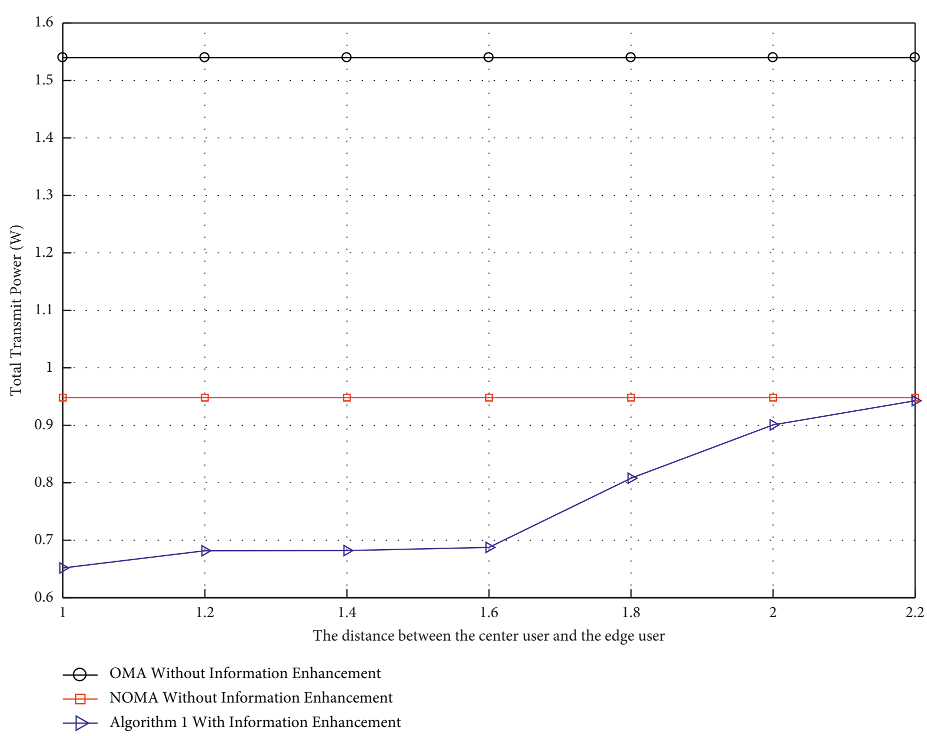


FIGURE 4: The optimal total transmission power versus the distance between the center user and the edge user, with $\gamma = 1, \eta = 0$ and $K = 16$.

transmission power of OMA without information enhancement and interference elimination (OMA-No-En-No-IF), NOMA without information enhancement and interference elimination (NOMA-No-En-No-IF), NOMA with information enhancement and without interference elimination (NOMA-En-No-IF), and NOMA with information enhancement and interference elimination (NOMA-En-IF) schemes versus the number of transmit antennas K. In

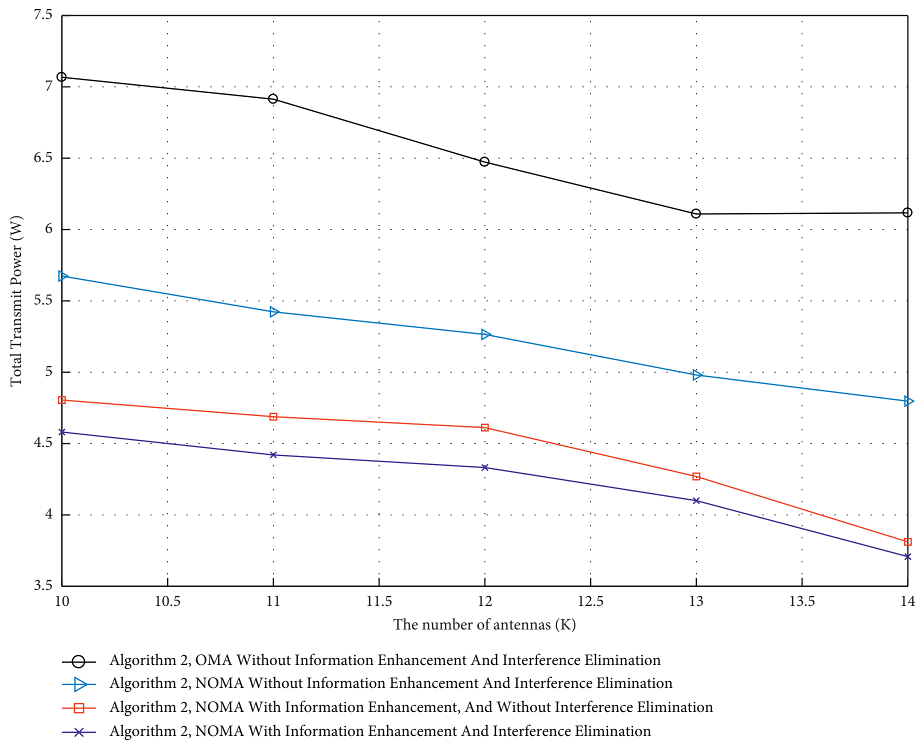


Figure 5: The optimal total transmission power versus the number of transmit antennas, with $\gamma = 1$ and $\zeta = 0$.

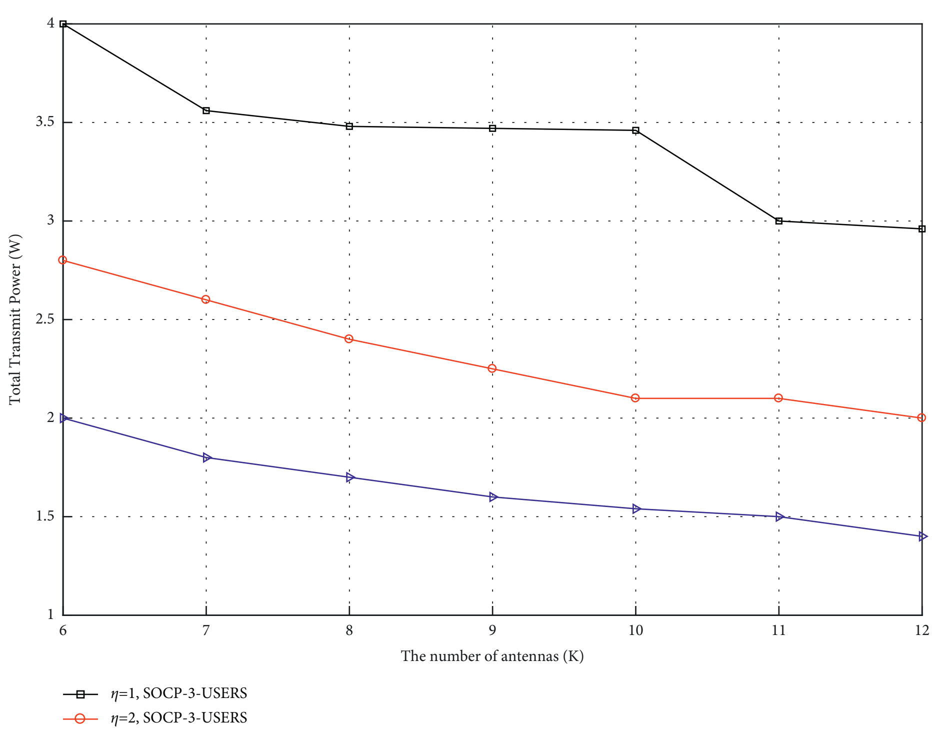


Figure 6: The optimal total transmission power versus the number of transmit antennas, with $\gamma = 1$ and $\zeta = 0$.

Figure 5, we observe that the total transmission power of NOMA-No-En-No-IF is greater than the total transmission power of NOMA-No-En-IF, and the total transmission power of NOMA-No-En-IF is greater than the total transmission power of NOMA-En-IF, it is because that the set of constraints in NOMA-No-En-No-IF is less than the set of

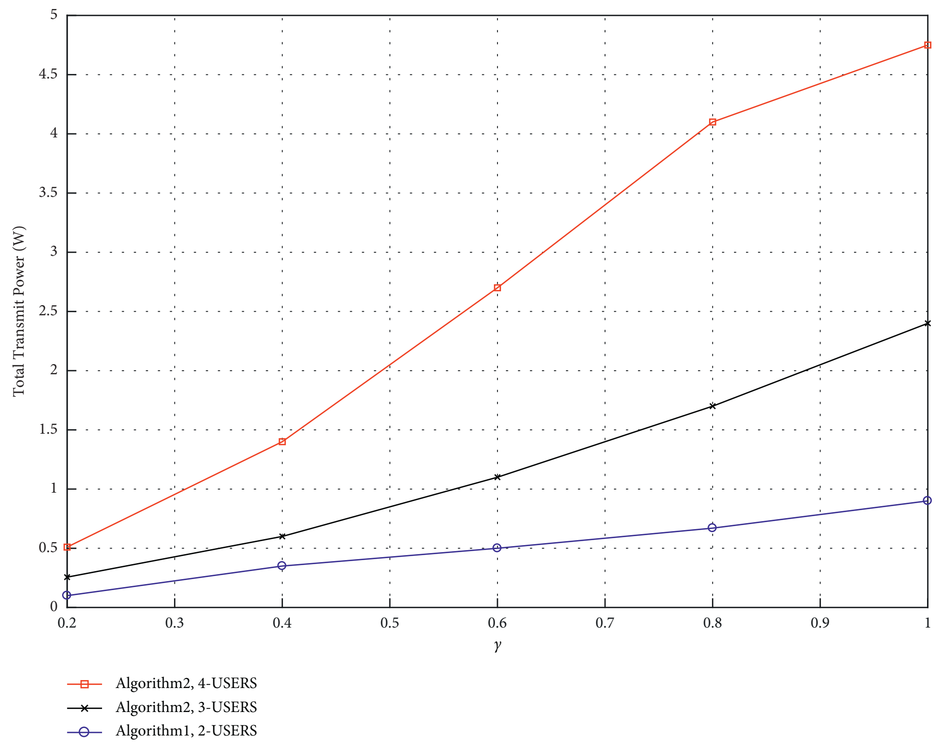


Figure 7: The optimal total transmission power versus the value of SINR, with $\gamma = 1$, $K = 20$, and $\eta = 1$.

constraints in NOMA-No-En-IF, and the set of constraints in NOMA-No-En-IF is less than the set of constraints in NOMA-En-IF.

Example 4. Consider a scenario in which up to 3 users are served (as in problem (60)). Suppose that h_{m} and g_m follow the channel model (3) with $\zeta = 0$, and the SINR thresholds are the same, that is, $\gamma_m = \gamma = 1, \forall m$. The distances between the base station and user m are $(d_1, d_2, d_3) = (1.6, 0.8, 0.6)$, the distances between the user M and user m are $(d_1^3, d_2^3) = (1.4, 0.9)$, and the angle of departures (AoDs) in (3) are $(\theta_1, \theta_2, \theta_3, \theta_1^3, \theta_2^3) = (30^0, 70^0, 80^0, 80^0, 90^0)$.

Figure 6 demonstrates the optimal total transmission power versus the number of transmit antennas under different path loss exponents. As can be seen, when the path loss exponent increases, the total power of the base station decreases.

Example 5. Suppose that the base station serves a set of four users u_1, u_2, u_3, u_4, which is an ordered set representing the decoding sequence with bigger index user having stronger channel. Number of antennas in the base station $K = 20$. Assume that h_m follows the channel model (3) with $\zeta = 1$. The distances between the base station and user m are $(d_1, d_2, d_3, d_4) = (1.6, 0.8, 0.6, 0.4)$, the distances between the user M and user m are $(d_1^4, d_2^4, d_3^4) = (1.4, 0.9, 0.5)$, and the angle of departures in (3) are $(\theta_1, \theta_2, \theta_3, \theta_4, \theta_1^4, \theta_2^4, \theta_3^4) = (30^0, 70^0, 70^0, 70^0, 70^0, 70^0, 70^0)$. The path loss exponent $\eta = 1$. In addition, we assume that $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_6 = \gamma$. When we say that the base station serves three (two) users, it refers to the users $(u_1, u_2, u_3)((u_1, u_2))$.

In Figure 7, the relationship between the optimal total transmitted power and SINR is given. As can be seen, more transmission power is required when the base station has more value of the SINR. In order to satisfy the larger signal-to-noise ratio, the system needs larger transmission power. Furthermore, more transmission power is needed when the number of users is increasing. This is also sound since more transmission power is required in order to serve additional users.

6. Conclusion

Beamforming optimization problems in MISO NOMA communication network with information enhancement and internetwork interference elimination have been studied in this paper. First, for the two-user case in the communication system, we propose an iterative approximation algorithm based on SDP and SDR technology for the NOMA downlink beamforming optimization problem. Then, we propose an iterative approximation algorithm based on SOCP for the general multiusers case. Results verify that the optimal value of the sequence of SOCPs is not increasing and converges to a local optimal value. Finally, the performance of the proposed algorithms has been demonstrated by simulation results.

APPENDIX

A. Proof of Proposition 3.1

In order to present the proof of Proposition 3.1, let us first show the following lemma.

Lemma 7.1 (see [25]). *Suppose that $\boldsymbol{X}$ is a $N\times N$ complex Hermitian positive semidefinite matrix of rank R, and A, $\boldsymbol{B}$ are two $N\times N$ given Hermitian matrices. Then, there is a rank-one decomposition $X = \sum_{r=1}^{R} x_r x_r^H$ such that $x_r^H A x_r = X \cdot A/R$ and $x_r^H B x_r = X \cdot B/Rr = 1, \ldots, R$.*

At this point, we are ready to prove Proposition 3.1.

Proof. Assume that

$$tr\left(W_1^*\right) = a_0, \tag{A.1}$$

$$tr\left(H_1 W_1^*\right) = a_1, \tag{A.2}$$

$$tr\left(H_2 W_1^*\right) = a_2, \tag{A.3}$$

which a_0, a_1, a_2 are nonzero real numbers. Then, we have

$$tr\left(W_1^*\left(H_1 - \frac{a_1}{a_0} I\right)\right) = 0, \tag{A.4}$$

$$tr\left(W_1^*\left(H_2 - \frac{a_2}{a_0} I\right)\right) = 0. \tag{A.5}$$

Considering Lemma 7.1, the optimal solution satisfies (A.4) (A.5), which means that

$$w_1^{*\,H}\left(H_1 - \frac{a_1}{a_0} I\right) w_1^* = 0, \tag{A.6}$$

$$w_1^{*\,H}\left(H_2 - \frac{a_2}{a_0} I\right) w_1^* = 0. \tag{A.7}$$

It follows that

$$w_1^{*\,H} H_1 w_1^* = \frac{a_1}{a_0} w_1^{*\,H} w_1^*, \tag{A.8}$$

$$w_1^{*\,H} H_2 w_1^* = \frac{a_2}{a_0} w_1^{*\,H} w_1^*. \tag{A.9}$$

Suppose that $w_1^{*\,H} w_1^* = \lambda$. To satisfy condition (A.1), we have to renew the solution of rank-one decomposition w_1^* as

$$w_1^* \coloneqq \sqrt{\frac{a_0}{\lambda}} w_1^*. \tag{A.10}$$

It follows that

$$w_1^{*\,H} w_1^* = a_0, \tag{A.11}$$

$$w_1^{*\,H} H_1 w_1^* = a_1, \tag{A.12}$$

$$w_1^{*\,H} H_2 w_1^* = a_2. \tag{A.13}$$

Similarly, $W_2^* = w_2^* w_2^{*\,H}$, $V_1^* = v_1^* v_1^{*\,H}$ have also rank-one decomposition by Lemma 7.1.

Therefore, the proof is complete. □

Data Availability

The data in this paper used to support the findings are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the work reported in this paper.

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