An Effective transmit Weight Design for DPC with Maximum Beam in Multi-user MIMO Downlink

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***Abstract*—A novel transmit scheme is proposed for the cancelation of Inter-User Interference (IUI) and the improvement of achievable sum-rate of system in Multi-User Multiple-Input Multiple Output (MU-MIMO) downlinks. Particle Swarm Optimization (PSO) algorithm is employed to solve the constrained nonlinear optimization problem for obtaining the optimal transmit weights. Compared with the conventional Dirty Paper Coding (DPC) having single receive antenna, the proposed scheme applies the principle of DPC to cancel the IUI in MU-MIMO downlinks, where the Mobile Station (MS) users are equipped with multiple receive antennas. With the Channel State Information (CSI) known at the Base Station (BS) and the MS, the eigenvalues for all user channels are calculated first and then the user with the maximum eigenvalue is selected as the 1-st user. For the remaining users, the users are sequentially processed and the transmit weights are generated from the previously selected users by using the Particle Swarm Optimization (PSO) algorithm, which makes the transmit gain for each user as large as possible. The analysis of computa-tional load and simulation results verify the effectiveness of the proposed scheme.**

Keywords-Multi-user MIMO downlink, Capacity, Dirty Paper Coding (DPC), Particle Swarm Optimization (PSO).

I. INTRODUCTION

Recently, MU-MIMO schemes have attracted consider-able interests toward the next generation wireless communication systems MU-MIMO because of its potential for increasing capacity [1]-[5]. In scenario of MU-MIMO downlink, the base station transmits spatially multiplexed signals to multiple users simultaneously, and attempts to transmit independent signal streams to all users over the same frequency. However, it suffers from the Inter-User Interference (IUI) in the received signal at each user. To mitigate the IUI, many linear precoding techniques have been employed to eliminate the IUI, such as the channel inversion [4] and Block Diagonalization (BD) schemes [5]. The Channel Inversion (CI) method pre-processes the transmit signals with the channel pseudo-inverse to suppress the IUI. In the case of highly independent channels, Zero Forcing (ZF) transmit weight can completely remove the IUI, but it leads to the noise enhancement at the receiver and reduces of achievable rate. Though the transmit weight with Minimum Mean-Squared Error (MMSE) criterion, can achieve the throughput increase, however it results in vestigial level of IUI. BD scheme is a well-known linear precoding technique, which decomposes MU-MIMO channels into multiple parallel SU-MIMO channels to completely cancel the IUI by using orthogonal space. However, these schemes impose a restriction on the system configuration in respect of the number of receive antennas, that is, only the number of transmit antennas at BS is larger than the sum of receive antennas of all users, BS can provided enough degrees of freedom to force the IUI to zero at each MS. In addition, the correlation among users also degrades the system performance. Thus we should take care to avoid the spatial multiplexed users with highly correlated channel.

DPC technique not only approaches the capacity more closely, but also suppresses the IUI completely [6]-[8]. However, the conventional DPC based on QR decomposition is restricted to the case of single receive antenna at each MS. The Maximum Beam (MB) transmit scheme in [9] utilizes the eigenvector corresponding to the maximum eigenvalue of desired user channel as the transmit weight, but the IUI among users is the serious problem. To assure the independence among users, especially in the case of many users, the author gave an imperfect block diagonalization method to reduce the IUI by employing Gram-Schmidt orthonormalization on transmit weights. But this method needs to keep the balance between IUI and transmit gain. In [10] a jointly design of a transmit scheme is proposed, where the near-orthogonal effective channels are success-sively obtained from 1-th user to the last user by subtracting the interference components from the preceding users. However, the interference among users cannot be cancelled completely because of near orthogonality.

Particle Swarm Optimization (PSO), first proposed by Kennedy and Eberhart in 1995 [11], is developed from the swarm intelligence and based on the research of flock movement behaviour of birds flock finding foods [12]-[15]. PSO is employed in many optimization problems, especially, in the optimization of continue space, it shows the better computational efficiency than the other algorithm, such as Genetic Algorithm (GA). Recently, the optimal algorithms PSO have been considerable interest in Multi-user MIMO. A PSO aided optimal Multi-user MIMO linear precoding scheme is proposed in [14], where PSO is used to search the optimal transmit weight which make SINR maximum at each MS. Though the IUI can be completely moved by multiplying decoder matrix, it leads noise enhancement and large computational load. In this paper, we proposed a novel MU-MIMO downlinks transmit scheme not only to obtain the optimal transmit weights for each user but also to eliminate the IUI completely. We first select the user with the maximum eigenvalue as the 1-st user by calculating eigenvalues of all users. Then we obtain the possible transmit weight for the next user by using the PSO algorithm, which makes sure that the selected user has an

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optimal accessible SNR. The remaining transmit weights are generated by the same method as the previous users. In the proposed scheme, we introduced the DPC principle to remove the IUI at the BS.

This paper is organized as follows. In Section II, we will present the system model of MU-MIMO. In Section III, we propose the optimal transmit weight based on the PSO algorithm for each user. The simulation results are given in Section IV, in which the proposed scheme shows the excellent BER performance compared with the conventional schemes. Finally the conclusions will be made in Section V. We illustrate some of the notations as follows; vectors and matrixes are expressed by bold letters, we use $E[\bullet]$, $[\bullet]^T$ and $[\bullet]^H$ as the expectation, transpose and conjugate transpose of matrix, respectively.

II. SYSTEM MODEL

We consider the downlink multi-user MIMO system with N_T transmit antennas and $n_R^{(k)}$ receive antennas at the k-th user, as shown in Fig. 1, where N_u is the number of multiple antenna users. In this paper, we focus on the flat Rayleigh (i.i.d.) fading channel model, because the wideband scheme, such as the OFDM, can be accommodated at each frequency index. We assume that the MIMO channel matrix $\boldsymbol{H}_k \subset \boldsymbol{C}^{n_R^{(k)} \times N_T}\ (k = 1, 2, \cdots, N_u)$ is available at BS and MS.

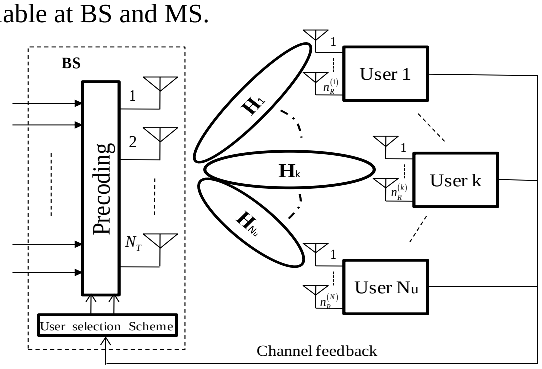

Fig. 1 Downlinks of multi-user MIMO

The $n_R^k \times 1$ received signal at the k-th user is written as

$$\boldsymbol{y}_k = \boldsymbol{H}_k \boldsymbol{M}_k \boldsymbol{x}_k + \sum_{k=1, j \neq k}^{N_u} \boldsymbol{H}_k \boldsymbol{M}_j \boldsymbol{x}_j + \boldsymbol{n}_k \qquad (1)$$

where $\boldsymbol{x}_k$ and $\boldsymbol{n}_k$ are transmit signal vector additive Gaussian noise and $\boldsymbol{M}_k$ is transmit weight at the k-th user. In this paper, we only focus on one transmit stream for each user and assume that

$$E(\boldsymbol{x}_k \boldsymbol{x}_k^H) = \boldsymbol{I},\ E(\boldsymbol{n}_k \boldsymbol{n}_k^H) = \sigma_{\boldsymbol{n}}^2 \boldsymbol{I},\ E(\boldsymbol{x}_k \boldsymbol{n}_k^H) = \boldsymbol{0} \qquad (2)$$

III. PPROPOSED OPTIMAL TRANSMIT WEIGHTS BASED ON PARTICLE SWARM OPTIMIZATION

The principle of conventional DPC based on QR decomposition indicates that the sufficient condition of the feasibility of DPC is the existence of lower or upper triangular matrix derived from the channel matrix. Since the IUI cannot be removed at the receiver in the case of MB, we carefully design the transmit weight for each user to transform the effective channels to the lower or upper triangular matrices. Then we can use DPC to remove the IUI completely. However, how to obtain the optimal transmit weight becomes a problem, referred to as the problem of optimal transmit weight design.

A. Transmit scheme for eliminating IUI

We design the transmit weights for each user as the following steps. First, we employ Singular Value Decomposition (SVD) for on user channels.

$$\boldsymbol{H}_k = \boldsymbol{U}_k \boldsymbol{\Lambda}_k [\boldsymbol{v}_k^1, \boldsymbol{v}_k^2, \cdots, \boldsymbol{v}_k^{N_T}]^H, (k = 1, 2, \cdots, N_u) \qquad (3)$$

To achieve the optimal transmit weight for the 1-st user, we perform the following algorithm.

$$\boldsymbol{H}_k, \boldsymbol{v}_k^1 = \arg\max_{\boldsymbol{H}_k} (\|\boldsymbol{H}_k \boldsymbol{v}_k^1\|), k \in [1, N_u] \qquad (4)$$

Then, the transmit weight for the 1-st user is given by

$$\boldsymbol{M}_1 = \boldsymbol{v}_k^1,\ o(1) = k \qquad (5)$$

where $o(1)$ denotes the number of the selected user in (4). Then the channel matrix of the selected user is arranged on the first layer of the system channel matrix.

$$\boldsymbol{H} = \begin{bmatrix} \boldsymbol{H}_{o(1)}^T & \boldsymbol{H}_2^T & \cdots & \boldsymbol{H}_{N_u}^T \end{bmatrix}^T \qquad (6)$$

In this way, we ensure that the 1-st user uses the MB. For the 2-nd user, in order to use the DPC for eliminating the IUI, we have to transform the effective channel matrix to triangular matrix, and the following operation is performed.

$$\left(\boldsymbol{H}_{o(1)} \boldsymbol{M}_1\right)^H \boldsymbol{H}_{o(1)} \overset{\text{SVD}}{=} \boldsymbol{U\Lambda}[\boldsymbol{v}^1, \underbrace{\boldsymbol{v}^2, \cdots, \boldsymbol{v}^{N_T}}_{\text{Null space}}]^H \qquad (7)$$

We can obtain the transmit weight for the 2-nd user from the null space in (7). However, we have to notice that all of these vectors in null space can meet the condition of the availability of DPC. The optimal transmit weight for the 2-nd user can be expressed as follows.

$$\boldsymbol{M}_2 = \sum_{l=1}^{N_u - 1} \alpha_l \boldsymbol{v}^{l+1} \Big/ \left\| \sum_{l=1}^{N_u - 1} \alpha_i \boldsymbol{v}^{l+1} \right\| \qquad (8)$$

where $\alpha_l\ (l = 1, 2, \cdots N_u)$ is real coefficient. Then we estimate the channel of the 2-nd user corresponding to $\boldsymbol{M}_2$ in (8). It can be obtained by the following algorithm.

$$\boldsymbol{H}_k = \arg\max_{\boldsymbol{H}_k} (\|\boldsymbol{H}_k \boldsymbol{M}_2\|);\ k \in [1, N_u],\ k \neq o(1) \qquad (9)$$

by letting $o(2) = k$, the 2-nd user is determined. Similarly, the channel matrix corresponding to the selected user in (9) is arranged on the second layer of channel matrix in (6).

We consider the k-th user and its transmit weight, the same operations as the above are performed to the matrix corresponding to these $k-1$ selected users.

$$\begin{bmatrix} \left(\boldsymbol{H}_{o(1)} \boldsymbol{M}_1\right)^H \boldsymbol{H}_{o(1)} \\ \left(\boldsymbol{H}_{o(2)} \boldsymbol{M}_2\right)^H \boldsymbol{H}_{o(2)} \\ \vdots \\ \left(\boldsymbol{H}_{o(k-1)} \boldsymbol{M}_{k-1}\right)^H \boldsymbol{H}_{o(k-1)} \end{bmatrix} \overset{\text{SVD}}{=} \boldsymbol{U\Lambda}[\boldsymbol{v}^1, \cdots \boldsymbol{v}^{k-1}, \underbrace{\boldsymbol{v}^k, \cdots, \boldsymbol{v}^{N_u}}_{\text{Null space}}]^H \qquad (10)$$

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from the null space in (10), the transmit weight for k-th user can be given by

$$\boldsymbol{M}_k = \sum_{l=1}^{N_u-k+1} \alpha_l \boldsymbol{v}^{k+l-1} \Big/ \left\| \sum_{l=1}^{N_u-k+1} \alpha_l \boldsymbol{v}^{k+l-1} \right\| \tag{11}$$

$$\boldsymbol{H}_k = \arg\max_{\boldsymbol{H}_k} (\|\boldsymbol{H}_k \boldsymbol{M}_k\|); k \in [1, N_u], k \neq o(1), o(2), \cdots o(k-1) \tag{12}$$

Similarly, the user channel obtained in (12) is arranged on the k-th layer of the system channel.

Consequently, we obtain the transmit weights for all users, and the transmit signal vector can be rewritten as

$$\boldsymbol{X} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N_u} \end{pmatrix} = \begin{pmatrix} s_1 \\ s_2 - \frac{1}{\|\boldsymbol{H}_2 \boldsymbol{M}_2\|} \sum_{j<2} \|\boldsymbol{H}_2 \boldsymbol{M}_1\| x_1 \\ \vdots \\ s_{N_u} - \frac{1}{\|\boldsymbol{H}_{N_u} \boldsymbol{M}_{N_u}\|} \sum_{j<N_u} \|\boldsymbol{H}_{N_u} \boldsymbol{M}_j\| x_j \end{pmatrix} \tag{13}$$

where s_k is the transmitted information for the k-th user. To avoid the power enhancement problem, the same modulo device as in [8] is used in this paper.

Then we discuss the Signal to Noise Ratio (SNR) at each user terminal. If the Maximum Radio Combining (MRC) is used to detect the receive signal, the SNR at each MS is given by

$$\langle SNR \rangle_k = \|\boldsymbol{H}_k \boldsymbol{M}_k\|^2 \bullet \|s_k\|^2 / N_k \tag{14}$$

where $\|\boldsymbol{H}_k \boldsymbol{M}_k\|$ can be considered as the transmit gain of the k-th user. If $\|\boldsymbol{v}_k^{\max} \boldsymbol{M}_k\| = 1$, $\boldsymbol{M}_k$ is considered as the ideal transmit weight which enables the k-th user to get the largest transmit gain $\lambda_k^{\max^2}$, and $\boldsymbol{v}_k^{\max}$ is the vector corresponding to the maximum eigenvalue of $\boldsymbol{H}_k$. However, in fact, $\|\boldsymbol{v}_k^{\max} \boldsymbol{M}_k\|$ lies in between 0 and 1, and it depends on the coefficients α_i for combining $\boldsymbol{M}_k$, where $\alpha_i \in R$ lies in a certain lattice. In order to obtain the optimal transmit gain, it is crucial to search the optimal combination coefficients which makes $\boldsymbol{M}_k$ parallel to $\boldsymbol{v}_k^{\max}$. We solve the nonlinear optimization problem by employing PSO algorithm to obtain the optimal transmit weights. In this case, if we use the DPC principle to cancel the IUI, the achievable rate can reach optimal. The capacity of proposed scheme can be expressed as

$$\begin{aligned} C &= \max_{\boldsymbol{M}_k, \boldsymbol{H}_k \boldsymbol{M}_j = 0, k>j} \log \left| \boldsymbol{I} + \frac{1}{\sigma_n^2} \boldsymbol{H} \boldsymbol{M} \boldsymbol{M}^H \boldsymbol{H}^H \right| \\ &= \max_{\boldsymbol{H}_k \boldsymbol{M}_j = 0, k>j} \sum_{k=1}^{N_u} \log \left| \boldsymbol{I} + \frac{1}{\sigma_n^2} \boldsymbol{H}_k \boldsymbol{M}_k \boldsymbol{M}_k^H \boldsymbol{H}_k^H \right| \end{aligned} \tag{15}$$

The water filling can be used to distribute transmit power. We define the achievable sum-rate of system with users equipped with single receive antenna as

$$C = \sum_{k=1}^{N_u} \left[\log_2 \mu \|\boldsymbol{H}_k \boldsymbol{M}_k\|^2 \right]_+$$

and μ solves

$$\sum_{k=1}^{N_u} \left[\mu - 1 / \|\boldsymbol{H}_k \boldsymbol{M}_k\|^2 \right]_+ = P_T \tag{16}$$

where P_T is the total transmitting power.

B. Particle Swarm Optimization aided optimal transmit weights

The PSO algorithm, based on the research of flock movement behaviour of birds flock finding foods, where the random flying bird flock are referred to as particles, which represent potential solutions initialized over the whole search space randomly. An objective function is used to evaluate the goodness of positions of particles. Each particle has a fitness value which is evaluated by the objective function to be optimized, and the fitness value is evaluated at each iteration search.

For k-th user, we assume that the size of swarm and the dimension of search space are Ω_k and D_k, respectively. The position and velocity of particle $i\ (i = 1, 2, \cdots \Omega_k)$ are denoted as $\boldsymbol{\chi}_{i,k} = [\chi_{i1}\ \chi_{i2}\ \cdots\ \chi_{iD_k}]^T$ and $\boldsymbol{\zeta}_{i,k} = [\zeta_{i1}\ \zeta_{i2}\ \cdots\ \zeta_{iD_k}]^T$. In the course of searching optimal solution, the particle i knows its best position $\boldsymbol{P}_{i,k} = [p_{i1}\ p_{i2}\ \cdots\ p_{iD_k}]^T$, which provides the best information, and the best position so far among the entire particles, is denoted as $\boldsymbol{P}_{g,k} = [p_{g1}\ p_{g2}\ \cdots\ p_{gD_k}]^T$, which provides the global best location. $\boldsymbol{P}_{i,k}$ and $\boldsymbol{P}_{g,k}$ are updated at each iteration by the objective function. Each particle has its own velocity to direct its flying, which relies on its previous speed $\zeta_{id_k}\ (d_k = 1, 2, \cdots, D_k)$ as well as its p_{id_k} and p_{id_k} information. At each iteration, the velocity and position of particle i are updated based on the following equations.

$$\begin{aligned} \zeta_{id_k}^{t+1} &= w\zeta_{id_k}^t + c_1\varphi_1(p_{id_k}^t - \chi_{id_k}^t) + c_2\varphi_2(p_{gd_k}^t - \chi_{id_k}^t) \\ \chi_{id_k}^{t+1} &= \chi_{id_k}^t + \zeta_{id_k}^{t+1} \end{aligned} \tag{17}$$

where t is the current iteration number, $\zeta_{id_k}^t$ and $\chi_{id_k}^t$ denote the velocity and location of the particle i in d_k dimensional space, respectively. $p_{id_k}^t$ is the individual best location that the particle i has achieved so far, and $p_{gd_k}^t$ is the global best location that all particles have achieved so far at the i-th iteration. w is the inertia weight which determines to what extent the particle remains along its original course unaffected by the influence of $p_{id_k}^t$ and $p_{gd_k}^t$, it is usually set between 0 and 1. c_1 and c_2 are acceleration constants which are set to 2. φ_1 and φ_2 are uniformly distributed random number in [0,1]. This iterative search process will be repeated up to the maximal iteration number or till the termination criterion is satisfied.

Then we have to consider two important issues, one is the particle modelling, and the other is the selection of objective function. Considering the SNR in equation (14), we search the optimal transmit weight $\boldsymbol{M}_k$, which infinitely close to the ideal transmit weight $\boldsymbol{v}_k^{\max}$ for the k-th user, $\boldsymbol{v}_k^{\max}$ where $\boldsymbol{v}_k^{\max}$ denotes the desired point lying in the best location. So we define the angle between $\boldsymbol{v}_k^{\max}$ and $\boldsymbol{M}_k$ as $\theta_{\boldsymbol{v}_k^{\max},\boldsymbol{M}_k}$ and consider the sine function as the objective function for k -th user at the t -th iteration.

$$\begin{cases} \alpha_l = \chi_{il}^t \\ \boldsymbol{M}_k = \sum_{l=1}^{N_u-k+1} \alpha_l \boldsymbol{v}^{k+l-1} / \left\| \sum_{l=1}^{N_u-k+1} \alpha_l \boldsymbol{v}^{k+l-1} \right\| \\ f_{i,k}^t = function(\boldsymbol{v}_k^{\max}, \boldsymbol{M}_k) \\ \quad = \sin(\theta_{\boldsymbol{v}_k^{\max},\boldsymbol{M}_k}) = \sqrt{1-\cos^2(\theta_{\boldsymbol{v}_k^{\max},\boldsymbol{M}_k})} \\ \quad = \sqrt{1-\left\| \left(\boldsymbol{v}_k^{\max}\right)^H \boldsymbol{M}_k \right\|^2} \end{cases} \tag{18}$$

Here, we use the sine value of angle between the ideal weight $\boldsymbol{v}_k^{\max}$ and the tentative weight $\boldsymbol{M}_k$ to measure the degree of approach. During the process of search, the sine value becomes small when the tentative weight gets close to the desired weight, and the search speed and accuracy are conditioned on the size of swarm, iteration number and search dimension. In this paper, the proposed optimal transmit weights based on PSO algorithm is obtained by the following steps.

(a). BS obtains the information of the channels by the feedback from MS and computes the maximum eigenvalues $\lambda_k^{\max}$ of each user and determines the order of user. By eq. (10), the dimension of search space of PSO is determined for the next user, and then the swarm size Ω_k and the maximum iteration number $I_{\max}^k$ are set for each user.

(b). PSO algorithm is employed to search the optimal transmit weight for each user. For the k -th user in Ω_k, we initialize the velocity and location for each particle as $\boldsymbol{\zeta}_{i,k}^1 = [\zeta_{i,1}^1, \cdots, \zeta_{i,l}^1, \cdots \zeta_{i,D_k}^1]^T$ and $\boldsymbol{\chi}_{i,k}^1 = [\chi_{i,1}^1, \chi_{i,2}^1, \cdots \chi_{i,D_k}^1]^T$, where the initial velocity $\boldsymbol{\zeta}_{i,k}^1$ can be set as a random vector, such as $\zeta_{i,l}^1 \in [-10,10]$, and the initial location is set as $\boldsymbol{\chi}_{i,k}^1 = [1,1,\cdots,1] / \sqrt{N_u - k}$.

*(c).*Taking $\boldsymbol{\zeta}_{i,k}^1$ and $\boldsymbol{\chi}_{i,k}^1$ as starting point, PSO is implemented to search the optimal transmit weights. In each iteration, the temporary best locations will be measured and updated by the objective function in (18) and all the particles achieve the next optimal directions for the search. For example, in the t -th iteration, all particles use the given best global locations to update the velocity and location by using (17), then compare the location obtained in (17) with the last best location $p_{id_k}^{t-1}$ and obtain the $p_{id_k}^t$,and then the $p_{id_k}^t$ of each particle will be exchanged to get the global beat location $p_{gd_k}^t$. Ultimately, all of the particles update their location by the $p_{gd_k}^t$. In this paper, $\boldsymbol{\chi}_{i,k}^t$ is normalized after the update in each iteration.

(d). PSO algorithm is repeated till the maximum iteration number of $I_{\max}^k$.

The above operations are separately implemented at all users and the different user has the different search dimension. In other words, from the 1-st to the N_u -th user, the search dimension becomes small, which leads to low SNR at each MS. Thus for those "bad" users, we can enlarge the swarm size or increase the iteration number to obtain the optimal weights. Certainly, the solution of the above is usually achieved by the water filling.

C. *Computational load analysis*

Under the same simulation conditions we compare the computational complexity between the proposed scheme and other schemes in [10] and [14]. The comparison is limited in searching the transmit weights for all user. Generally, a SVD has a complexity with order of max $(p^2 q, pq^2, q^3)$ in the case of k -th user, where $p = N_T$ and $q = k-1$ [16]. We assume a complex multiplication equal to 4 real multiplications and 2 real additions. In the proposed scheme in this paper and the scheme in [14], $\Omega_k = 10$ and $I_{\max}^k = 20$ are set. If the particles denote real number, PSO algorithm has at least a real computation of $\left\{\Omega_k \left[10 + \Phi_f\right] + \Omega_k - 1\right\} \times I_{\max}^k$, where Φ_f denotes the computation of objective function. The total numbers of real products and additions required for detecting one transmit symbol are derived as follows.

TABLE 1. COMPUTATIONAL COMPLEXITY/SYMBOL

	$N_T = 4$, $N_u = 4$, $n_R^{(k)} = 1$	$N_T = 4$, $N_u = 4$, $n_R^{(k)} = 2$
Φ_L	8126	11648
Φ_{OW-L}	52400	52400
Φ_{OW-DPC}	15688	16288

Φ_L : Computational complexity of linear scheme in [10].
Φ_{OW-L} :Computational complexity of linear scheme with PSO in [14].
Φ_{OW-DPC} : Computational complexity of the proposed scheme in this paper.

Table 1. shows the PSO algorithm consume the largest computational work in [14] because of continuous complex vector space. However, in this paper, we search the optimal coefficient in real vector space to greatly reduce computational load. Though the scheme in [10] has the least computational load, when the number of receive antennas at MS is increased, the quantity difference becomes small between Φ_{OW-DPC} and Φ_{OW-L}. Moreover, the demerits of increment of noise in [14] and residual IUI in [10] lead to loss of achievable rate to a certain degree. Taken together, the proposed scheme in this paper is feasible.

IV. COMPUTER SIMULATION

In this Section, we present simulation results demonstrating the performance of the proposed scheme. To verify the performance of it, first, we compare the achievable sum-rate between the proposed scheme and the other schemes, such as, conventional DPC, Channel Inversion (CI) and BD, with the water filling algorithm. Then we compare the average BER performance of each user and demonstrate the feasibility of the proposed scheme.

We consider the case of 4×(1,1,1,1) in MU-MIMO, where the average achievable rate of system is determined for the total 1000 realizations of $\boldsymbol{H}$. The particle number of

$\Omega_k = 10$ and the iteration number of $I_{\max}^k = 20$ are set for the PSO algorithm. Fig. 2 shows that the channel inversion scheme obtains a close average capacity to BD scheme by employing the water filling, but both of those two methods are inferior to the conventional DPC, which approaches the multiuser capacity more closely. The simulations results show that the proposed scheme obtains the best capacity because of the optimal transmit weights and user order with PSO. In the conventional DPC, the transmit weight for each user in the precoding matrix $\boldsymbol{Q}$ is obtained by Gram-Schmidt orthogonalization without sorting.

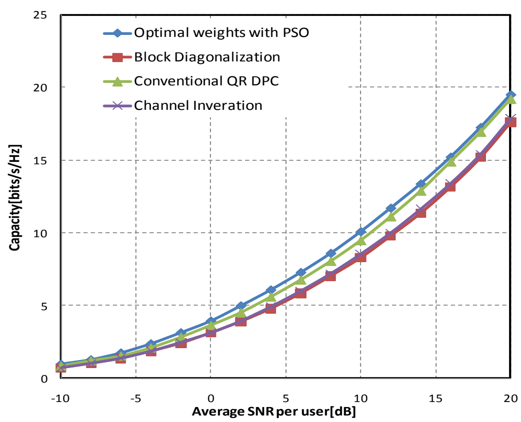

Fig. 2 Capacity comparison among the proposed PSO-DPC with optimal weights DPC and the BD, Channel inversion, Conventional DPC

Next we show the BER performance of proposed transmit scheme and compare it with the BD, channel inversion and conventional DPC schemes. Here we only consider the uniform assignment of transmit power to all users.

Fig. 3 shows the case of $4 \times (1,1,1,1)$ in MU-MIMO downlink. The particle number of $\Omega_k = 10$ and the iteration number of $I_{\max}^k = 20$ are set in the PSO algorithm and QPSK is used to modulate the transmit signal. Without regard to the power distribution on each user, both BD and Channel Inversion with ZF can completely eliminate the IUI on i.i.d Rayleigh fading channels and these two methods show the same performance as SISO in i.i.d Rayleigh fading channel. As shown in Fig. 3, though the channel inversion with MMSE can not exactly cancel the IUI caused by the spatially multiplexed channel and results in some vestigial IUI, it can reduce the effect of noise enhancement between 0 and 12dB. The DPC, referred to as the interference dependent nonlinear precoding, can obtain the better performance compared with the linear BD and channel inversion schemes. In the case of conventional DPC, the QR decomposition only aims to cancel the IUI, but does not involve the optimality of transmit weights in the matrix Q. Our proposed transmit scheme with optimal weights by PSO, not only suppresses the IUI completely, but also searches the optimal transmit weights achieving the SNR as large as possible at each MS. Fig. 3 shows the proposed scheme has obtained the better BER performance by about 4 dB than the conventional DPC at BER=10^{-3}.

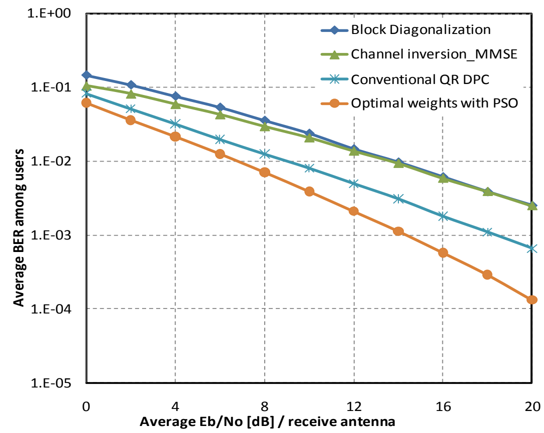

Fig. 3 Comparison of BER characteristics among proposed PSO-DPC with optimal weights, BD, Channel inversion (ZF&MMSE) and Conventional DPC.

Fig. 4 shows the BER performance of proposed scheme with multiple receives antennas and it is compared with the conventional DPC. Similarly, the values of $\Omega_k = 10$ and $I_{\max}^k = 20$ are set in the PSO algorithm and QPSK is employed. The conventional DPC based on QR decomposition is restricted to the users with single receive antenna, because in the case of users with multiple receive antennas, if we use the QR decomposition on $\boldsymbol{H}$, some of the users have no throughput. However, the proposed scheme can ensures the throughput for each user and improves the receive SNR by increasing the number of receive antennas. In addition, based on the channel condition and the Qos requirement of users, the PSO search algorithm works with different swarm size of Ω_k and the iteration number of $I_{\max}^k$ to improve the transmit gains. As shown in Fig. 4, with the increase of receive antenna number, the system performance can be greatly improved.

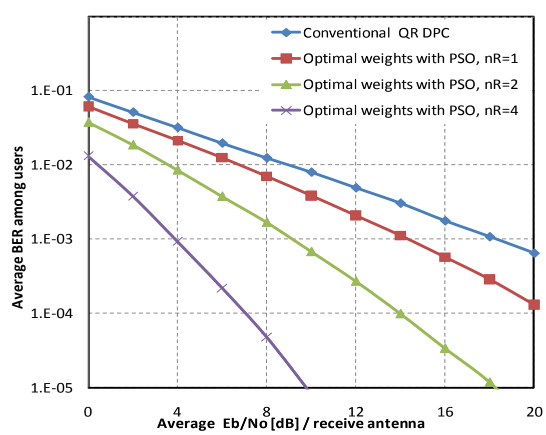

Fig. 4 Comparison of BER characteristics among the proposed PSO-DPC with optimal weights with multiple receives antennas and the conventional DPC

Fig. 5 shows the improvement of BER versus the iteration number. If the iteration number or swarm size is set too small, we cannot obtain the convergence values of transmit weight of users. Thus increasing the number of iteration is required to achieve the better performance, which cannot lead to large calculation if we control the swarm size to likely quantity. From Fig. 5 it is clearly visible that when the value of $I_{\max}^{k}$ is set greater than 20, the BER performance cannot be improved any more. So the selection of value of $I_{\max}^{k}$ also seems the key design element. The computational load has been discussed in Section IV, from which it is clear that the proposed scheme is feasible when the iteration number is set to $I_{\max}^{k} = 20$.

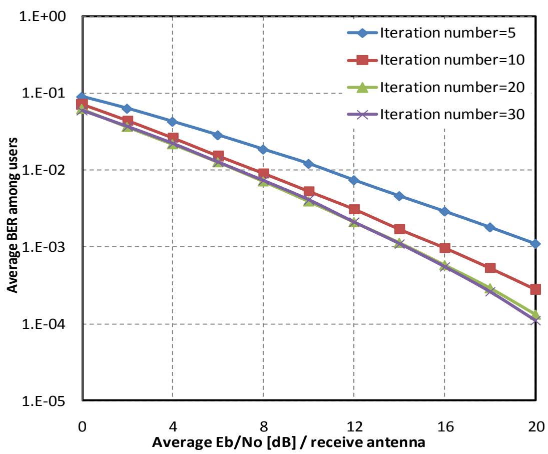

Fig. 5 BER improvement vs. iteration number

V. CONCLUSIONS

A novel scheme with optimal transmit weights for the downlinks of MU-MIMO has been proposed, in which we employed the PSO algorithm to search the optimal transmit weights and achieved the significantly better performance than the conventional DPC, BD and the channel inversion schemes. With the CSI known at both of BS and MS, BS determine the user order and corresponding transmit weights with as large transmit gain as possible to each user. DPC has been used not only to suppress the IUI, but also maintain the system capacity. In the case of single receive antenna, because of the optimal transmit weight design with the DPC principle and PSO, the proposed scheme approached more closely to the capacity of MU-MIMO than other conventional schemes. In addition, the proposed scheme can employ the multiple receive antennas, whereas the conventional DPC based on QR decomposition is equipped with only one receive antenna at the MS. Accordingly, multiple receive antennas enables the user to obtain better BER performance, especially for the users with weak receive SNR's. For the PSO algorithm, the swarm size and iteration number determine the search accuracy and required computation time, so we can make the optimal search for each user independently, according to the requirement of each user.

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