Pilot Symbol Assisted Weighted Data Fusion Scheme for Uplink Base-Station Cooperation System

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Abstract

Base Station Cooperation (BSC) has been a promising technique for combating the Inter-Cell Interference (ICI) by exchanging information through a high-speed optical fiber back-haul to increase the diversity gain. In this paper, we propose a novel pilot symbol assisted data fusion scheme for distributed Uplink BSC (UBSC) based on Differential Evolution (DE) algorithm. Furthermore, the proposed scheme exploits the pre-defined pilot symbols as the sample of transmitted symbols to constitute a sub-optimal Weight Calculation (WC) model. To circumvent the non-linear programming problem of the proposed sub-optimal model, DE algorithm is employed for searching the proper fusion weights. Compared with the existing equal weights based soft combining scheme, the proposed scheme can adaptively adjust the fusion weights according to the accuracy of cooperative information, which remains the relatively low computational complexity and back-haul traffic. Performance analysis and simulation results show that, the proposed scheme can significantly improve the system performance with the pilot settings of the existing standards.

Keywords: Uplink base station cooperation, inter-cell interference, weighted data fusion, pilot symbols, differential evolution algorithms

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1. Introduction

As the ever increasing demands for high frequency efficiency, multi-cell communication systems have emerged by reusing frequency among different cells. However, Inter-Cell Interference (ICI) has become a dominant factor that restricts the improvement of system performance due to the frequency reuse [1][2][3]. ICI may cause significant detriment to the Quality of Service (QoS) of the mobile terminal especially for those located at the cell edge and the overall system capacity [4]. Base Station Cooperation (BSC) has arisen as a promising technique in combating ICI [3][5]. The basic idea of BSC is that the adjacent Base Stations (BSs) exchange their information through a high-speed optical fiber back-haul, then the cooperative information is exploited by a centralized or distributed Central Processing Units (CPUs) for joint optimization in order to increase the diversity gain.

In the uplink, the received signals at BS can be classified into three groups: local information, adjacent information and additive noise. The local information represents information transmitted by the Mobile Stations (MSs) served by the current BS (denoted as anchor BS), and the information transmitted by the MSs located in the adjacent cells is usually viewed as the inter-cell interference to the anchor BS. However, the anchor BS of the BSC system exploits the dormant information from interference induced by adjacent cells. Two intuitive signal processing methods are widely explored for combating inter-cell interference in Uplink Base Station Cooperation (UBSC) system. With distributed CPUs, the Interference Cancellation (IC) method cancels the adjacent interference by utilizing signals forwarded from adjacent BSs, which are the detected signals of MSs from adjacent cells [6][7][8]. This method is highly dependent on the channel estimation accuracy, which limits the promotion of the attainable performance. The other method is known as data fusion, which aims to enhance the reliability of local information from anchor BS's serving MSs [5][9]. Specifically, adjacent BSs recover information from their serving MSs and then transmit them to the anchor BS. The anchor BS combines cooperative information and fuses these data to enhance the reliability of desired MS's information.

Wu etc. adopted the Soft Combining (SC) approach and proposed a three-stage information exchange technique to perform UBSC in [5]. In this scheme, each BS performed local decoding and generated Log-Likelihood Ratios (LLRs) for all the information bits. The LLRs generated in different BSs were then forwarded to a centralized CPU and were combined for enhancing signal estimation. A Distributed Probabilistic Data Association and Soft Combining (DPDA-SC) UBSC scheme was developed [9] to combat ICI, where all BSs shared their recovered information with each other and exchanged the recovered information in the term of soft information, then the anchor BS combined the cooperative information as a distributed CPU. Benefited from the information sharing and data fusion, the SC scheme reduced ICI with a mediocre computational complexity. But equal fusing weights were assigned to the cooperative information from different BSs, which can not distinguish the reliability of the cooperative information. However, the channel links suffer different qualities due to their specific scattering environment. Hence, it is necessary to explore weighted data fusion algorithms, which can adaptively update the weights in accordance with channel link's qualities.

Against this background, a novel DE based pilot aided weighted data fusion is proposed for distributed UBSC system. Using the pilot information as reference, a sub-optimal weighted calculation model is proposed. However, the proposed model is an intractable non-linear programming problem, which is challenge to acquire a closed-form solution. We adopts Differential Evolution (DE) algorithm to approach sub-optimal fusing weights in this paper. Compared with the traditional soft combining scheme with equal weights, the proposed scheme can highlight the information undergone high-quality channel links and weaken the contribution of the information undergone poor-quality channel links. Specifically, the contributions in this work were:

- A sub-optimal Weight Calculation (WC) model for UBSC system is proposed. As the optimal WC model is difficult to solve, we employ the pilot information establishing a sub-optimal WC model, which reduces the computational complexity of the optimization for the fusing weights compared with the optimal WC model.
- A DE algorithm based data fusion scheme is proposed. Against the non-linear programming problem of the proposed sub-optimal WC model, the DE algorithm is used to optimize the sub-optimal objective function iteratively. Furthermore, we apply the convergence and computational complexity analysis of the proposed DE aided weighted data fusion scheme.

The rest of this paper is organized as follows. The UBSC system model is given in Section 2. A sub-optimal WC model for UBSC system and a DE based weighted data fusion scheme are proposed in Section 3, the convergence and computational complexity of the proposed scheme are also analysed in this section. Section 4 investigates the performance of the proposed scheme, and Section 5 gives the conclusions.

2. Weighted Data Fusion Model for Uplink Base-Station Cooperation System

A distributed base-station cooperation scheme for the scenario of three cells in term of hexangular cellular is illustrated in **Fig. 1.** Three adjacent cells surrounded by the thick solid line form a cooperative transmission area indicated by the shaded hexagon, where the three cooperative cells exchange their information through the optical fiber back-haul between BSs.

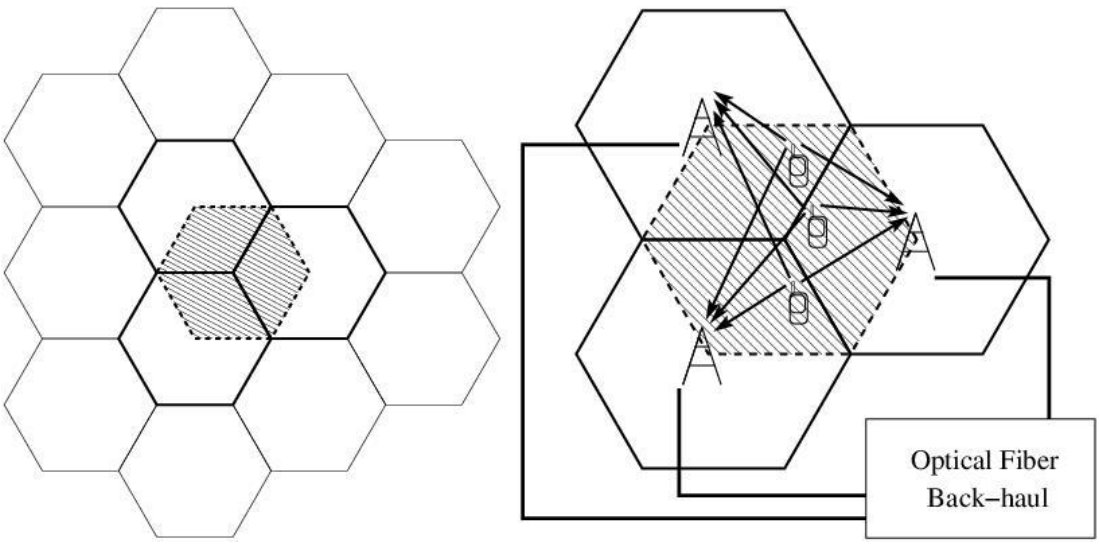

Fig. 1. Three-cell base-station cooperation model in a hexangular cellular system

Assume an uplink cooperation area of N_r BSs, where each BS is equipped with K_r receive antennas supporting N_t single antenna co-channel MSs located in these cooperation cells. Here we refer the n_r-th BS as the anchor BS. The received signal in the frequency domain $\mathbf{Y}_{n_r}^{k_r}$ at the k_r-th antenna of the n_r-th BS can be expressed as:

$$\mathbf{Y}_{n_r}^{k_r} = \sum_{n_t=1}^{N_t} \mathrm{diag}(\mathbf{X}_{n_t})\mathbf{H}_{n_t,n_r}^{k_r} + \mathbf{W}_{n_r}^{k_r}, \tag{1}$$

$$= \sum_{i\in A_{n_r}} \mathrm{diag}(\mathbf{X}_i)\mathbf{H}_{i,n_r}^{k_r} + \sum_{j\in B_{n_r}} \mathrm{diag}(\mathbf{X}_j)\mathbf{H}_{j,n_r}^{k_r} + \mathbf{W}_{n_r}^{k_r}, \tag{2}$$

where $\mathbf{X}_{n_t} \in \mathbf{C}^{N_c\times 1}$ denotes the transmitted signal by the n_t-th MS in the frequency domain[1], $\mathrm{diag}(\cdot)$ represents the diagonal operation, and N_c is the number of sub-carriers. $\mathbf{H}_{n_t,n_r}^{k_r} \in \mathbf{C}^{N_c\times 1}$ denotes the frequency domain channel transfer function(FD-CHTF) of the link between the n_t-th MS and the k_r-th antenna of the n_r-th BS, and $\mathbf{W}_{n_r}^{k_r} \in \mathbf{C}^{N_c\times 1}$ represents the Additive White Gaussian Noise (AWGN) with zero mean and co-variance σ_W^2. The N_t indexes of the co-channel MSs can be decomposed into two sub-sets according to whether the n_t-th MS belongs to the anchor BS(the n_r-th BS). The indices of the MS belong to the n_r-th BS cell are classified into the sub-set A_{n_r}, which contains $C_{A,n_r} = 1$ index. By contrast, the rest are classified into the sub-set B_{n_r}, which contains $C_{B,n_r} = N_t - 1$ indices. The first term $\sum_{i\in A_{n_r}} \mathrm{diag}(\mathbf{X}_i)\mathbf{H}_{i,n_r}^{k_r}$ in (2) represents the received signals at the k_r-th receive antenna of the n_r-th BS, which are the signals sent by the MS belonging to the n_r-th BS itself. The second term $\sum_{j\in B_{n_r}} \mathrm{diag}(\mathbf{X}_j)\mathbf{H}_{j,n_r}^{k_r}$ represents the received signals sent by the MSs belonging to other cooperating BSs, which is denoted as $\mathbf{Y}_{B,n_r}^{k_r}$.

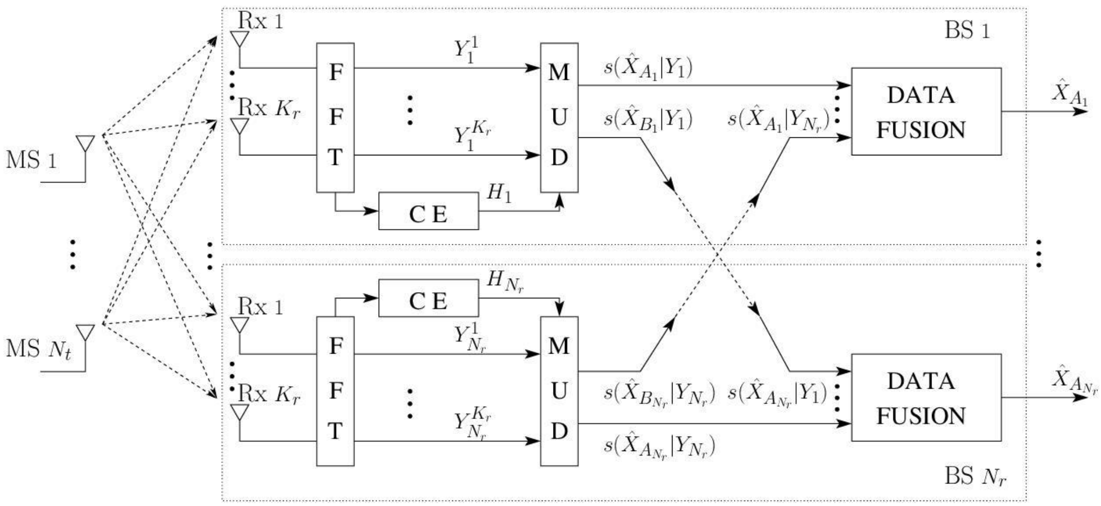

Fig. 2. Receiver model of the data fusion based UBSC system

[1] For simplicity, we do not introduce modulation operations, $\mathbf{X}_{n_t}$ refers to $1/0$ bits vector here. But without loss of generality, the proposed model is also feasible with modulations.

In the data fusion based distributed UBSC system, $\mathbf{Y}_{B,n_r}^{k_r}$ is treated as exploitable cooperating signals instead of interference, as illustrated in **Fig. 2.** After the signal processing of channel estimation and Multi-User Detection (MUD), the anchor BS may recover the initial estimate $s\left(\hat{X}_{n_t}(n_c)\middle|\mathbf{Y}_{n_r}\right)$ concerning the n_c-th transmitted bit $X_{n_t}(n_c)$, which may be an elementary recovered bit information and/or the Log-Likelihood Ratio (LLR)[2] of the bit,

$$s\left(\hat{X}_{n_t}(n_c)\middle|\mathbf{Y}_{n_r}\right)=\begin{cases}\hat{X}_{n_t,n_r}(n_c), & \text{hard}\\ \mathrm{LLR}\left(\hat{X}_{n_t}(n_c)\middle|\mathbf{Y}_{n_r}\right), & \text{soft}\end{cases} \tag{3}$$

where

$$\mathrm{LLR}\left(\hat{X}_{n_t}(n_c)\middle|\mathbf{Y}_{n_r}\right)=\ln\frac{\Pr\left[\mathbf{Y}_{n_r},X_{n_t}(n_c)=1\right]}{\Pr\left[\mathbf{Y}_{n_r},X_{n_t}(n_c)=0\right]}, \tag{4}$$

where $\Pr[\mathbf{Y}_{n_r},X_{n_t}(n_c)=u]$ is the joint probability of the initial transmitted bit $X_{n_t}(n_c)=u$, $u=0,1$ and $\mathbf{Y}_{n_r}$.

The recovered information $s\left(\hat{\mathbf{X}}\middle|\mathbf{Y}_{n_r}\right)$ are further classified into $s\left(\hat{\mathbf{X}}_{A_{n_r}}\middle|\mathbf{Y}_{n_r}\right)$ and $s\left(\hat{\mathbf{X}}_{B_{n_r}}\middle|\mathbf{Y}_{n_r}\right)$, which is a subset that consists of $s\left(\hat{\mathbf{X}}_{A_1}\middle|\mathbf{Y}_{n_r}\right),\cdots,s\left(\hat{\mathbf{X}}_{A_{n_r-1}}\middle|\mathbf{Y}_{n_r}\right),s\left(\hat{\mathbf{X}}_{A_{n_r+1}}\middle|\mathbf{Y}_{n_r}\right),\cdots,s\left(\hat{\mathbf{X}}_{A_{N_r}}\middle|\mathbf{Y}_{n_r}\right)$. The n_r-th BS keeps its desired signal $s\left(\hat{\mathbf{X}}_{A_{n_r}}\middle|\mathbf{Y}_{n_r}\right)$ for data fusion and sends $s\left(\hat{\mathbf{X}}_{B_{n_r}}\middle|\mathbf{Y}_{n_r}\right)$ to their own anchor BSs for their cooperatively processing. The n_r-th BS gathers $s\left(\hat{\mathbf{X}}_{A_{n_r}}\middle|\mathbf{Y}_1\right),\cdots,s\left(\hat{\mathbf{X}}_{A_{n_r}}\middle|\mathbf{Y}_{n_r-1}\right),s\left(\hat{\mathbf{X}}_{A_{n_r}}\middle|\mathbf{Y}_{n_r+1}\right),\cdots,s\left(\hat{\mathbf{X}}_{A_{n_r}}\middle|\mathbf{Y}_{N_r}\right)$ from cooperative BSs by exchanging information with each other, and then fuses the collected cooperative information with $s\left(\hat{\mathbf{X}}_{A_{n_r}}\middle|\mathbf{Y}_{n_r}\right)$ in the data fusion processor.

With the assumption of $n_t\in A_{n_r}$, the fusion result concerning X_{n_t} in the anchor BS can be written as:

$$s\left(\hat{\mathbf{X}}_{n_t}\middle|\mathbf{Y}_{coop}\right)=\omega_{n_t,n_r}s\left(\hat{\mathbf{X}}_{n_t}\middle|\mathbf{Y}_{n_r}\right)+\sum_{n'=1,n'\neq n_r}^{N_r}\omega_{n_t,n'}s\left(\hat{\mathbf{X}}_{n_t}\middle|\mathbf{Y}_{n'}\right), \tag{5}$$

where $\mathbf{Y}_{coop}$ represents the assembled result consists of the received signal Y_{n_r} of the anchor BS and the received signal $\mathbf{Y}_{n'}, n'\neq n_r$ from the cooperative BSs, ω_{n_t,n_r} denotes the fusing weight of the fused information $s(\hat{\mathbf{X}}_{n_t}\mid\mathbf{Y}_{n_r})$. By mapping the initial $1/0$ bit into the $1/-1$, a generalized decision model for (5) can be formulated as:

[2] The LLR information is an elementary estimated soft information generated from limited receiving signals, so further multi-BS cooperation is needed even the LLR information used here.

$$\hat{X}_{n_t,\mathrm{coop}}(n_c)=\begin{cases}1, & \text{if } s\left(\hat{X}_{n_t}(n_c)\middle|\mathbf{Y}_{\mathrm{coop}}\right)>0\\ 0, & \text{if } s\left(\hat{X}_{n_t}(n_c)\middle|\mathbf{Y}_{\mathrm{coop}}\right)\le 0\end{cases}. \tag{6}$$

Compared to the traditional distributed UBSC schemes, the weighted based data fusion scheme could achieve the same performance without imposing additional information exchange, except that the information was exchanged using the backhaul. The proposed scheme of the model of soft cooperative information retains the same information exchange with the soft combining scheme. While the proposed scheme of the model of hard cooperative information remains the same level of information exchanging with the interference cancellation scheme.

3. Differential Evolution Algorithm Based Weighted Data Fusion Scheme

3.1 Optimization Criterion of Weights Calculating

Without loss of generality, we use the elementary recovered bit information as the fused information, i.e. $s(\hat{\mathbf{X}}_{n_t}\mid\mathbf{Y}_{n_r})=\hat{\mathbf{X}}_{n_t,n_r}$. The final object of weighted data fusion is to lead $\hat{\mathbf{X}}_{n_t,\mathrm{coop}}$ to approach to the initial transmitted signal $\mathbf{X}_{n_t}$, which means that the optimal objective function of WC can be written as:

$$J_{\mathrm{opt}}\left(\boldsymbol{\omega}_{n_t}\right)=\left\|\hat{\mathbf{X}}_{n_t,\mathrm{coop}}-\mathbf{X}_{n_t}\right\|^2, \tag{7}$$

where $\boldsymbol{\omega}_{n_t}=[\omega_{n_t,1},\cdots,\omega_{n_t,n_r},\cdots,\omega_{n_t,N_r}]$ represents the weight vector. In fact, we don't know the actual information of $\mathbf{X}_{n_t}$, and it is a challenge to acquire the optimal solution of (7).

In typical physical resource blocks, some resource blocks are assigned to pre-defined pilot information to aid channel estimation or some other processing at the receivers [10]. Hence, the WC processing at the anchor BS with the proposed pilot-aided distributed UBSC system can be described as:

$$\left[\omega_{n_t,1},\cdots,\omega_{n_t,n_r},\cdots,\omega_{n_t,N_r}\right]=\mathsf{F}_{\mathrm{WC}}\left(\mathbf{X}_{n_t}^p,\mathbf{Y}_{n_r},\hat{\mathbf{H}}_{n_r},\left[\hat{\mathbf{X}}_{n_t,1},\cdots,\hat{\mathbf{X}}_{n_t,n_r},\cdots,\hat{\mathbf{X}}_{n_t,N_r}\right]\right), \tag{8}$$

where $\mathsf{F}_{\mathrm{WC}}(\cdot)$ represents a WC sub-processor within the data fusion processor. $\mathbf{X}_{n_t}^p$ represents the n_t -th MS's pre-defined pilot information.

In (7), the receiver doesn't know the actual $\mathbf{X}_{n_t}$. However, the receiver has the information of the pre-defined pilot $\mathbf{X}_{n_t}^p$, which may be viewed as the sample of $\mathbf{X}_{n_t}$. Thus, the optimal objective function (7) can be rewritten as an sub-optimal version, which is a Minimum Mean Square Error (MMSE) problem,

$$J_{\mathrm{sub-opt}}\left(\boldsymbol{\omega}_{n_t}\right)=\left\|\hat{\mathbf{X}}_{n_t,\mathrm{coop}}^p-\mathbf{X}_{n_t}^p\right\|^2, \tag{9}$$

where $\hat{\mathbf{X}}_{n_t,\mathrm{coop}}^p$ represents the fused information at pilot positions. Similarly, a sub-optimal objective function can be written for soft fused information (LLR) as:

$$J_{\mathrm{sub-opt}}\left(\boldsymbol{\omega}_{n_t}\right)=\left\|\mathrm{LLR}\left(\hat{\mathbf{X}}_{n_t}^p\middle|\mathbf{Y}_{\mathrm{coop}}\right)-\mathrm{LLR}\left(\mathbf{X}_{n_t}^p\middle|\mathbf{Y}_{n_r}\right)\right\|^2, \tag{10}$$

where $\mathrm{LLR}(\hat{\mathbf{X}}_{n_t}^{p} \mid \mathbf{Y}_{\mathrm{coop}})$ represents the LLR information at pilot positions after data fusion process, $\mathrm{LLR}(\mathbf{X}_{n_t}^{p} \mid \mathbf{Y}_{n_r})$ represents the LLR information at pilot positions with initial pilots. An approximate technique in [11][12] can be employed for generating the LLR information.

The sub-optimal objective function (9) depends on the pre-defined pilot. Assuming the pilot ratio of initial transmitted symbols is p_p with $0 < p_p < 1$. Apparently, if $p_p \to 1$, all transmitted symbols will be used as pilot symbols, then we have:

$$\lim_{p_p \to 1} \mathbf{X}_{n_t}^{p} = \mathbf{X}_{n_t}. \tag{11}$$

Furthermore, (11) means that the sub-optimal objective function (9) can converge to the optimal objective function (7) with $p_p \to 1$, which can be formulated as:

$$\lim_{p_p \to 1} \left\| \hat{\mathbf{X}}_{n_t,\mathrm{coop}}^{p} - \mathbf{X}_{n_t}^{p} \right\|^2 = \left\| \hat{\mathbf{X}}_{n_t,\mathrm{coop}} - \mathbf{X}_{n_t} \right\|^2. \tag{12}$$

It can be easily seen that (9) and/or (10) is a multi-dimensional global optimization problem with non-linear objective function, it is a challenge to obtain a closed-form solution. In this paper, we propose a DE algorithm based weighted data fusion scheme, which employs DE algorithm to iteratively search the solution space with regard to the Cost Function (CF) of (9) and/or (10).

3.2 Differential Evolution Algorithm based Weights Optimization

As a relatively new member in the family of Evolutionary Algorithms (EAs), the DE [13] algorithm constitutes a random guided population-based optimizer, which employs difference vectors to explore the objective function landscape. Compared to most other EAs, DE holds easier operation steps and lower space complexity while exhibits remarkable performance on a wide variety of problems including the multi-dimensional global optimization [14]. Hence, it is suitable to circumvent the optimization problem in Equation (9).

Fig. 3 shows a flow chart of DE, which mainly includes the initialization, mutation, crossover, selection, adaptation steps to constitute an iterative progression. Specifically, the algorithmic steps in DE are formulated in more details as follows:

1) Initialization.

Generate the population of P_s real-valued weight vectors, where the p_s-th vector of the population in the first generation of $g = 1$ can be expressed as:

$$\boldsymbol{\omega}_{1,p_s} = \left\lfloor \tilde{\omega}_{1,p_s,1}, \tilde{\omega}_{1,p_s,2}, \cdots, \tilde{\omega}_{1,p_s,N_\omega} \right\rfloor \tag{13}$$

where N_ω represents the number of weights, which equals to N_t here. Evaluate the CF value $J(\boldsymbol{\omega}_{1,p_s})$ of each vector $\boldsymbol{\omega}_{1,p_s}$ using Equation (9), then sort the CF value according to the descending order.

2) Mutation.

Randomly generate the scaling factor λ_{p_s} according to a Cauchy distribution $\lambda_{p_s} = \mathrm{randc}_{p_s}(\mu_\lambda, 0.1)$ [11], which controls the rate at which the population evolves. Select the $(100 pP_s)\%$ best vector that has the lowest CF value to generate the "best archive", which includes the vectors owning more meritorious characteristics, and will be further exploited to generate new vectors. Here p represents a greedy factor, which determines the greediness of

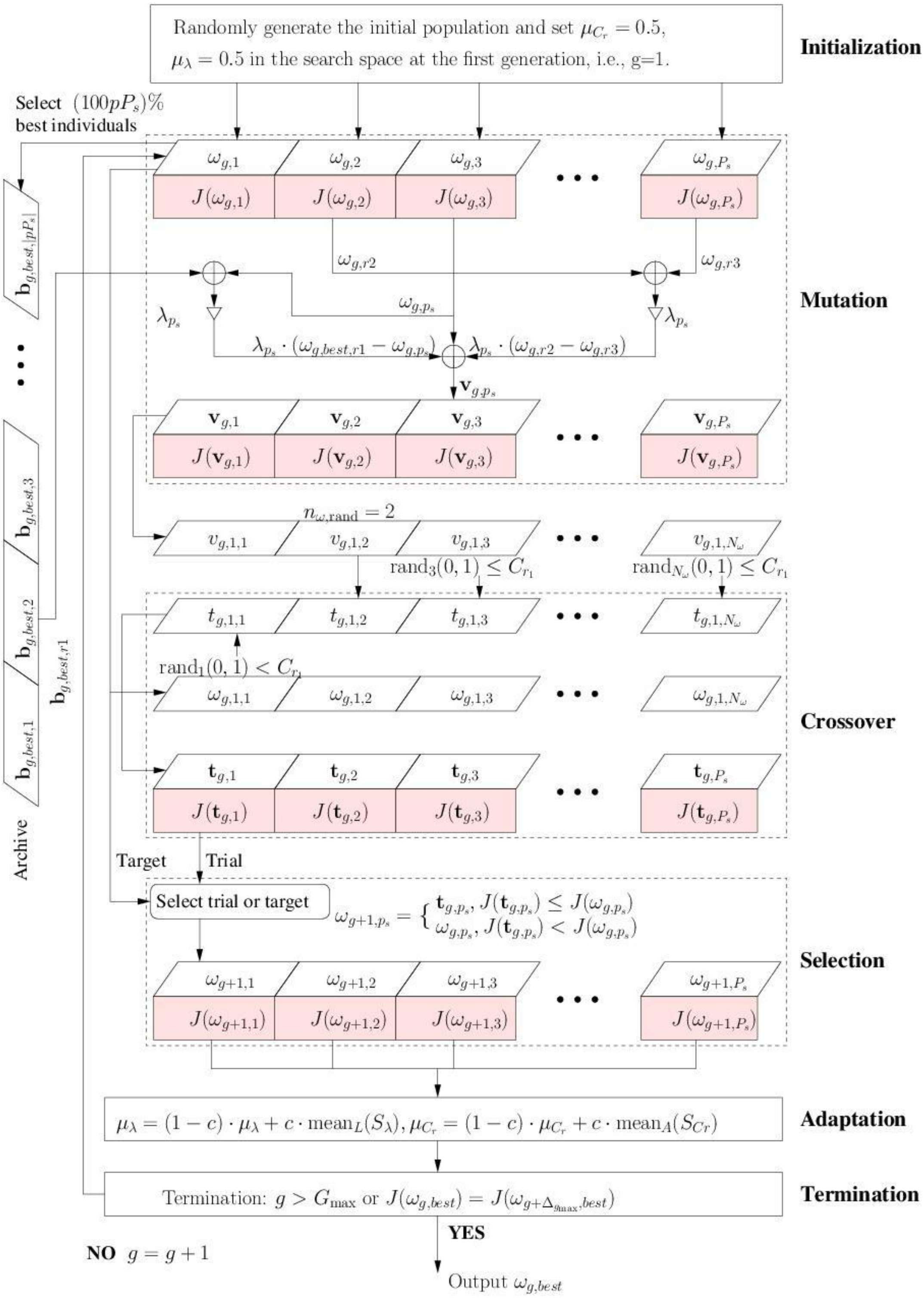

Fig. 3. Flowchart of DE based weight calculation scheme

the mutation strategy. For each p_s, $p_s = 1, \cdots, P_s$, randomly choose a vector index $r1$ from the "best archive" indexes, and select two vector indexes $r2$ and $r3$ from the current population indexes to further generate the difference vector, while $p_s \neq r1 \neq r2 \neq r3$. Create a mutant vector $\mathbf{v}_{g,p_s}$ for the target vector $\boldsymbol{\omega}_{g,p_s}$ by combining it with the "best" vector $\boldsymbol{\omega}_{g,\text{best},r1}$, the difference vector $\boldsymbol{\omega}_{g,r2}$ and $\boldsymbol{\omega}_{g,r3}$, which can be written as:

$$\mathbf{v}_{g,p_s} = \boldsymbol{\omega}_{g,p_s} + \lambda_{p_s} \cdot \left(\boldsymbol{\omega}_{g,\text{best},r1} - \boldsymbol{\omega}_{g,p_s}\right) + \lambda_{p_s} \cdot \left(\boldsymbol{\omega}_{g,r2} - \boldsymbol{\omega}_{g,r3}\right) \tag{14}$$

3) Crossover.

Randomly generate the crossover probability $C_r \in [0,1]$ using a uniform random number generator $C_{r_{p_s}} = \text{randn}_{p_s}(\mu_{C_r}, 0.1)$, which is a problem-specific value that controls the fraction of parameter values that copied from the mutant vectors. For each n_ω, $n_\omega = 1,\cdots,N_\omega$, build trial vectors out of parameter values that have been copied from the base vectors or the mutant vectors. Specifically, the n_ω-th parameter value of the p_s-th vector in the population at the g-th generation is given by:

$$t_{g,p_s,n_\omega} = \begin{cases} v_{g,p_s,n_\omega}, & \text{rand}_{n_\omega}(0,1) \le C_{r_{p_s}} \text{ or } n_\omega = n_{\omega,\text{rand}} \\ \omega_{g,p_s,n_\omega}, & \text{else} \end{cases} \tag{15}$$

where $n_{\omega,\text{rand}}$ is a randomly chosen index from $n_\omega = 1,\cdots,N_\omega$, aiming at ensuring the trial parameter with index $n_{\omega,\text{rand}}$ does not duplicate $\boldsymbol{\omega}_{g,p_s}$, which means that at least one element of $\mathbf{t}_{g,p_s}$ is inherited of $\mathbf{v}_{g,p_s}$.

4) Selection.

Normalize the trial vector $\mathbf{t}_{g,p_s}$ and valuate the CF value $J(\mathbf{t}_{g,p_s})$ of each $\mathbf{t}_{g,p_s}$ according to Equation (9). If the trial vector $\mathbf{t}_{g,p_s}$ has an equal or lower CF value than that of the target vector $\boldsymbol{\omega}_{g,p_s}$, it replaces the target vector in the next generation; otherwise, the target retains its place in the population for at least one more generation. Specifically, the selection procedure can be described as

$$\boldsymbol{\omega}_{g+1,p_s} = \begin{cases} \mathbf{t}_{g,p_s}, & J\left(\mathbf{t}_{g,p_s}\right) \le J\left(\boldsymbol{\omega}_{g,p_s}\right) \\ \boldsymbol{\omega}_{g,p_s}, & J\left(\mathbf{t}_{g,p_s}\right) > J\left(\boldsymbol{\omega}_{g,p_s}\right) \end{cases} \tag{16}$$

5) Adaptation.

The update of μ_λ and μ_{C_r} is according to:

$$\mu_\lambda = (1-c)\cdot \mu_\lambda + c \cdot \text{mean}_L\left(S_\lambda\right), \tag{17}$$

$$\mu_{C_r} = (1-c)\cdot \mu_{C_r} + c \cdot \text{mean}_A\left(S_{C_r}\right), \tag{18}$$

where $c \in (0,1]$ is the adaptive update factor, which controls the rate of the parameter adaptation. S_λ and S_{C_r} corresponds to the set of successful scaling factors λ_{p_s} and crossover probabilities $C_{r_{p_s}}$ in the current generation, respectively. The adaptation of μ_{C_r} uses the usual arithmetic mean mean_A, while the Lehmer mean [11][15] is adopted to augment the weight of larger successful mutation factors, i.e. $\text{mean}_L(S_\lambda) = \sum_{\lambda_{p_s} \in S_\lambda} \lambda_{p_s}^2 / \sum_{\lambda_{p_s} \in S_\lambda} \lambda_{p_s}$.

6) Termination.

When any of the following stopping criteria are met, the optimization procedure should be halted:

a. The pre-defined maximum affordable number of generations $G_{\max}$ has been exhausted.

b. $\Delta g_{\max}$ generations have passed without a trial vector being accepted.

Obviously, the set of $G_{\max}$ and $\Delta g_{\max}$ is essential. A large enough $G_{\max}$ gives an optimizer enough time to find the optimum, while the $\Delta g_{\max}$ also should not be set too low.

The DE optimization algorithm used in the proposed scheme is capable of converging to the optimal solution, which can be proved in a probability viewpoint. Due to the non-continuous of (9), there may exists more than one optimal solution for the sub-optimal objective function. With a certain accuracy of potential solutions, assume the optimal solutions set as $\mathbf{\Omega}_{\text{opt}}$, which contains R optimal solutions $\boldsymbol{\omega}_1, \boldsymbol{\omega}_2, \cdots, \boldsymbol{\omega}_R$. For the g-th generation, assume the newly generated individual vector $\boldsymbol{\omega}_{g,p_s}$ stands out the ε-neighborhood of its nearest ω_r, $r = 1,2,\cdots,R$ with a probability of p_g. As the DE algorithm always choose the best individual vectors to survive into the next generation, as the generation evolving, i.e., the number of generations g increases, p_g decreases monotonically. Thus, when g approaches to infinity,

$$\lim_{g\to\infty} \Pr\left(\min_r \left\|\boldsymbol{\omega}_g - \boldsymbol{\omega}_r\right\|^2 > \varepsilon\right) = 0, \tag{19}$$

where ε is an arbitrary positive but small value, and $\Pr(\cdot)$ represents the probability that the given event happens. (19) can be further written as:

$$\lim_{g\to\infty} \Pr\left(\min_r \left\|\boldsymbol{\omega}_g - \boldsymbol{\omega}_r\right\|^2 < \varepsilon\right) = 1, \tag{20}$$

Equation (20) shows that, as the number of generations g increasing to infinity, the DE optimization algorithm can converge to one of the optimal solution's ε-neighborhoods. Considering both (12) and (20), it is obvious that the proposed scheme has the ability to converge to the optimal fusing weights.

3.3 Computational Complexity

Generally, the computational complexity of population-based stochastic search techniques like DE usually depends on the stopping criterion [16]. Neglecting the very simple operations like copy/assignment, etc., we only consider the multiplication and addition operations in our analysis. Observing the algorithmic steps, we can see that the computational complexity is introduced by the initialization, mutation, selection and adaption operations.

Assume an N_r BSs uplink cooperation, where the block-fading channel is time-invariant over N_s consecutive OFDM symbols. Assume K sub-carriers are used and an M-QAM modulation is employed. For a given population size P_s terminated after G generations, the proposed DE based weighted data fusion scheme needs $(G+1)N_p(N_r\sqrt{M} - \sqrt{M} + 2)P_s + 5GN_rP_s + 2N_rP_s + GP_s - 2P_s - 2G + 2$ times additions and $(G+1)N_p(N_r\sqrt{M} + 1) + 3GN_rP_s + 2N_rP_s + GP_s + 6G$ times multiplications.

Due to the additional procedure, the computational complexity of the proposed DE based weighted data fusion scheme was analyzed and compared with other receiving procedures in non-cooperative systems. Compared with the DE algorithm based Multi-User Detection (DE-MUD) technique [11], using the default parameters in **Table 1**, the proposed DE based weighted data fusion scheme needs 0.0059% times additions and 0.0119% times multiplications of DE-MUD technique, respectively. Thus, the proposed DE based weighted data fusion scheme holds an affordable computational complexity.

Table 1. Default parameters settings in DE algorithm

Initialization of the population	Randomly generated
Population size P_s	15
Maximum number of generations G	20
$\Delta g_{\max}$	10
Greedy factor p	0.1
Adaptive update factor c	0.9

4. Simulation Results and Discussions

In this section, Monte Carlo simulations have been carried out in order to investigate the attainable performance of the proposed DE assisted weighted data fusion scheme in UBSC systems. Assuming that two MSs equipped with single transmit antenna located in two adjacent cells and they cause ICI to each other. Each BS has eight receive antennas, and three adjacent BSs (including the anchor BSs and two interfering MSs) constitute a cooperating area. A (2,1,3) convolution code and 16-QAM is employed. The number of sub-carriers in one OFDM symbol is 64, and each frame includes 50 OFDM symbols. A 5-paths Rayleigh fading channel is considered for each channel link. Unless specified, the first two OFDM symbols of each block are used as pilots, i.e., the default pilot ratio is set as 0.04% [17][18]. At the receiver, the cooperative information defaults to using the LLR information, and an approximate technique in [11][12] is adopted to generate the cooperative soft LLR information. Unless otherwise specified, the default parameter values in DE algorithm are listed in **Table 1**.

The first experiment investigates the effect of settings about population size P_s and the terminating criterion $\Delta g_{\max}$. **Fig. 4** shows the average required number of CF-Evaluations (CF-Evals.) under different combination of $(P_s, \Delta g_{\max})$ when $E_b/N_0 = 6\text{dB}$ and $G_{\max} = 40$. Observed in **Fig. 4** that the average required number of CF-Evals. increases with the population size P_s increases. Actually, the number of CF-Evals. equals to $(G+1)P_s$, where G is the number of generations. But increasing the terminating criterion $\Delta g_{\max}$, the average required number of CF-Evals. shows an uneven increase. This can be explained by the relationship between G and $\Delta g_{\max}$. Apparently, $G \geq \Delta g_{\max}$ and is highly dependent on $\Delta g_{\max}$. The larger $\Delta g_{\max}$ is, the more difficulty it takes the iterations to be terminated, thus, the faster the average required number of CF-Evals. increases. The BER performance under different combination of $(P_s, \Delta g_{\max})$ is carried out in **Fig. 5**, where E_b / N_0 is also set as $6\,\text{dB}$. It can be seen that the increase of either P_s or $\Delta g_{\max}$ leads to the decrease of BER. This is because small settings of P_s and $\Delta g_{\max}$ can make the termination appear earlier than when the convergence is achieved. Especially for $P_s \le 5$ or $\Delta g_{\max} \le 4$, the BER performs very badly. **Fig. 5** shows a convergence of BER is achieved when $P_s \ge 12$ and $\Delta g_{\max} \ge 8$, which means the suitable $(P_s, \Delta g_{\max})$ should be set under these regions. Considering the computational complexity of CF-Evals. shown in **Fig. 4**, we set $P_s = 15$ and $\Delta g_{\max} = 10$ in this paper.

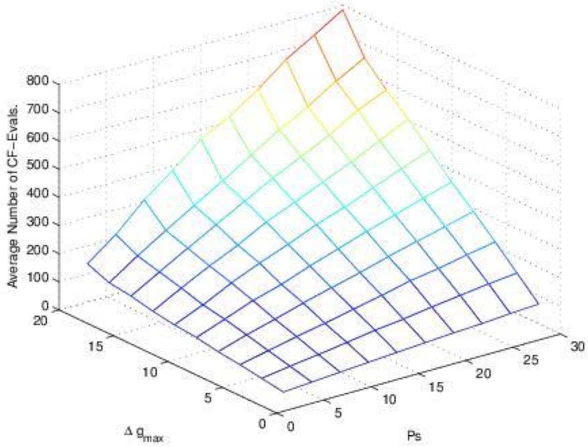

Fig. 4. Average required number of CF-Evals. under different combination of $(P_s, \Delta g_{\max})$

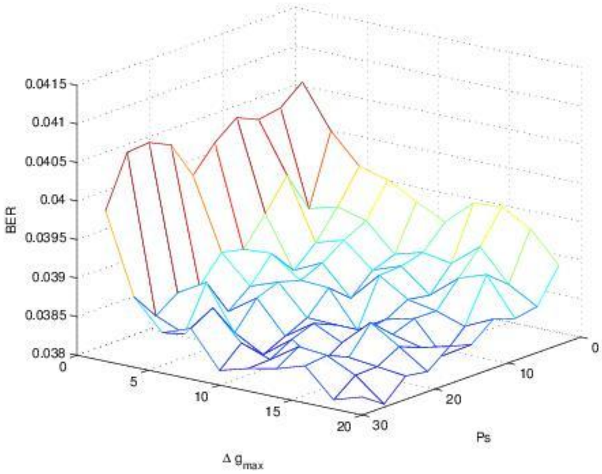

Fig. 5. BER performance under different combination of $(P_s, \Delta g_{\max})$

Fig. 6 illustrates the impact of pilot ratio p_p as the second experiment. As pilot ratio p_p increases, the BER performance shows a steady trend when E_b / N_0 equals $6\,\text{dB}$, $10\,\text{dB}$ and

$14\,\text{dB}$, respectively. When $p_p = 0.02\%$, the pre-defined pilot information is enough to generate accurate fusing weights. As the pilot ratio increases, more pilot information can be adopted, but little improvement can be performed. This means that even with a low p_p of 0.02%, the proposed pilot aided sub-optimal data fusion scheme performs well. However, in existing standards such as IEEE 802.11 a/p std. [17][18], $1-2$ OFDM symbols in each frame are usually set as pilots to aid channel estimation or other receiver processing, i.e., the pilot ratio is set as $0.02-0.04\%$. Therefore, the proposed scheme in this paper can effectively perform the WC based on the pilot settings according to the existing standards, without increasing extra pilot cost.

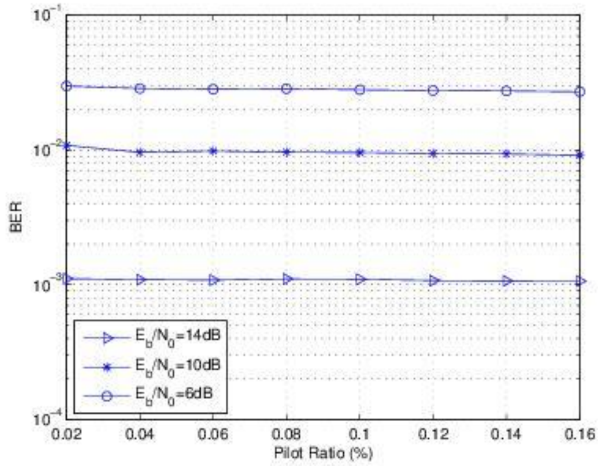

Fig. 6. BER performance with different pilot ratio p_p

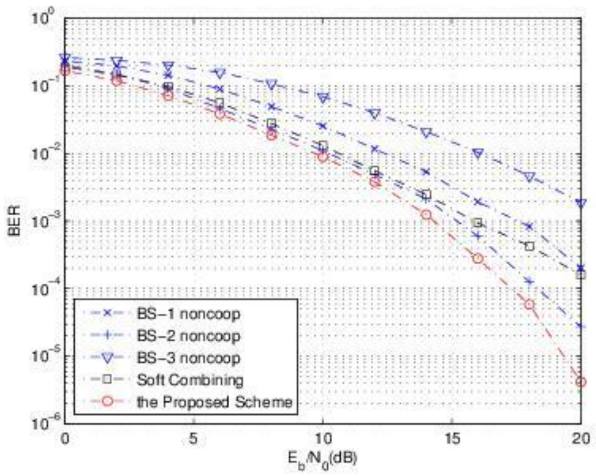

Fig. 7. BER performance of the proposed DE based weighted data fusion scheme

In **Fig. 7**, we investigate the performance of the proposed DE based weighted data fusion scheme in UBSC systems. The equal-weighted based soft combining scheme is included as a reference for comparison. Assume the 2-nd BS as the desired MS's serving BS, as the channel link qualities between the MS and three BSs are different, the accuracy of cooperative information from three BSs is different. The traditional soft combining scheme assigns equal weights to cooperative information from three BSs, which neglects the difference among cooperative information's accuracies, and can not extract useful information effectively. Observed in **Fig. 7** we can see the soft combining scheme even performs worse than the one of 2-nd BS without cooperation. However, the proposed DE based weighted data fusion scheme, which adopts pilot information as reference, designs fusing weights with consideration of different channel links' qualities to improve system performance. **Fig. 7** shows that, compared with soft combining scheme, the proposed DE based weighted data fusion scheme can achieve about $2\,\text{dB}$ improvement at the level of $\text{BER} = 10^{-3}$.

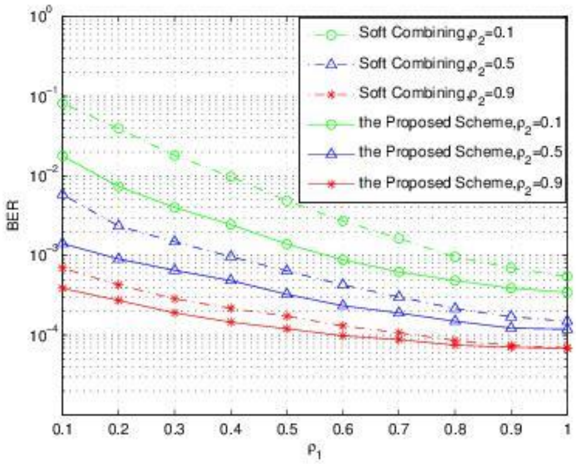

Fig. 8. BER performance under different channel qualities

Fig. 8 shows the BER plots of the proposed DE based weighted data fusion scheme and the soft combining scheme under different channel qualities. We use the channel gain ratio to represent the cooperative link's channel quality, which is specified as the ratio of cooperative link's channel gain over local link's channel gain. Assume the n_r -th BS as the anchor BS, the n' -th cooperative link's channel gain ratio can be written as $\rho_{n'} = \| H_{n',n_r} \|_F / \| H_{n_r,n_r} \|_F$, $n' = 1, \cdots, n_r - 1, n_r + 1, \cdots, N_r$, where $\| \cdot \|_F$ represents the Frobenius norm. Generally, we have that $0 \le \rho_{n'} \le 1$. It can be seen from **Fig. 8** that under higher ρ_1 and ρ_2 values, the system could achieve lower BER values both with the soft combining scheme or the proposed DE based weighted data fusion scheme. This is because the higher $\rho_{n'}$ ($n' = 1,2$) refers to the higher channel quality of the n' -th cooperative link, which means more accurate cooperative information can be applied to the data fusion process on the n' -th cooperative link. Further, as shown in **Fig. 8**, the proposed DE based weighted data fusion scheme always performs better than the soft combining scheme. Especially for the lower $\rho_{n'}$ case, the gain is higher. This is benefited from the fusion weights designing process in the proposed DE based weighted data fusion scheme, which fully considered the impact of different channel link's quality to design the fusion weights and thus improve the system performance. When $\rho_{n'}$ is lower, the channel links' qualities radically exhibit different. Then the fusion weights should be deliberately designed in order to fully achieve the cooperative gains.

The efficiency of the proposed scheme under imperfect channel estimation is investigated in **Fig. 9**, where the cooperative information is in term of hard information. The traditional

Maximum Ratio Combining (MRC) scheme and the Interference Cancellation (IC) scheme [6][7][8] are included as the benchmarks. The Least Square (LS) estimation is referred as the imperfect Channel State Information (CSI) in this experiment. Apparently, the proposed scheme outperforms both the MRC scheme and the IC scheme, and it shows stronger robustness to channel estimation errors. Due to the reuse of CSI in the cooperation procedure, the MRC and IC scheme suffers from the channel estimation errors again. Besides, the IC scheme cooperates with the BSs of the interfering MSs instead of all BSs in the cooperation area, which may further limit the achievable cooperative diversity. However, the proposed scheme exploits the pilot information as the reference for designing the fusing weights without CSI, which shuns from the propagation of channel estimation errors.

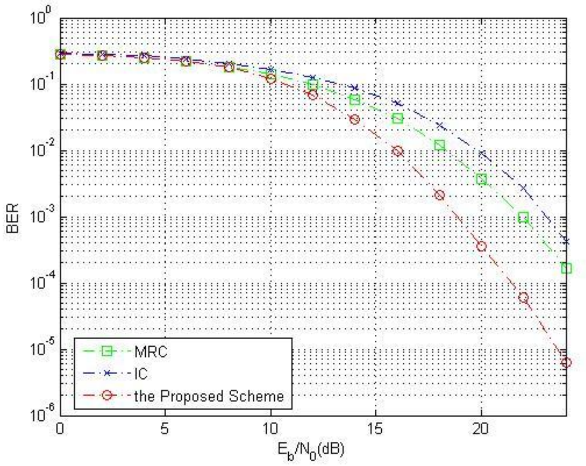

Fig. 9. BER performance using hard cooperative information under imperfect channel estimation

5. Conclusion

In this paper, a DE based pilot aided weighted data fusion scheme is proposed for UBSC system in order to combat ICI. A sub-optimal WC model is proposed for pilot aided data fusion in UBSC system, which employs pilot information as the sample of transmitted data. In order to solve the non-linear programming problem brought by sub-optimal model, the DE based weighted data fusion scheme is proposed by iteratively optimizing fusing weights. Convergence, computational complexity analysis and simulation results show that the proposed scheme can perform weights optimization effectively based on pilot settings in existing standards and remain back-haul traffic and a low computational complexity. Compared with the traditional equal-weighted soft combining scheme, the proposed scheme is capable of achieving about $2\,\text{dB}$ improvement at the level of $\text{BER} = 10^{-3}$.

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