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ACO-Based Multi-User Detection in Cooperative CDMA Networks

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Abstract– **In this paper, the cooperative diversity is investigated in the uplink of a Code Division Multiple Access (CDMA) network in which users cooperate by relaying each other's messages toward the Base Station (BS). It is assumed that the spreading waveforms are not orthogonal and hence, Multiple Access Interference (MAI) exists at the relay nodes as well as the BS. MAI degrades the signal quality at both relays and BS and decreases the cooperative diversity gain. To alleviate this problem, an Ant Colony Optimization (ACO) based Multi-User Detector (MUD) has been proposed to efficiently combine the received signals from the direct and relay paths and sub-optimally extract transmitted bits at the BS. The computational complexity of proposed algorithm is significantly lower than that of the Maximum Likelihood (ML) detector. More explicitly, for a cooperative network supporting 15 users, the computational complexity of the proposed ACO algorithm is a factor of 103 lower than that of the optimum Bayesian detector. Simulation results show that the performance of the proposed ACO-based detector can closely approach the maximum diversity in terms of BER and efficiently cancel the MAI at the BS.**

Keywords– **Cooperative diversity, DS-CDMA systems, multiuser detection, ant colony optimization.**

1 Introduction

Recently, cooperative communication has been proposed as a new technique to combat wireless channel's impairments, especially multipath fading [1, 2]. Using this technique, single antenna terminals, acting in a multiuser environment, exploit the broadcast nature of the wireless channel to share the existing physical resources, e.g. antennas, to form a virtual transmit and/or receive antenna array [3–5]. Since each message may be transmitted through independent different relay paths, spatial diversity gain can be achieved without requiring multiple antennas at each communication terminal.

Many cooperation strategies have been proposed in the literature such as Decode-and-Forward (DAF), Amplify-and-Forward (AAF) and coded cooperation [3–9]. In the first case, each relay decodes its source's messages and then re-transmits them toward the BS. In addition to cooperation strategies, the choice of partner allocation strategy is one of the important issues determining the performance of cooperative networks [4, 10].

CDMA is a common multiple access technique used in cooperative networks [1, 2, 6–9]. However, when the spreading waveforms adopted in CDMA networks are not orthogonal, the MAI will be produced at the relays as well as the BS, causing cooperative diversity gain to degrade. Therefore, the MUD techniques must be employed to mitigate the MAI effect [3, 6–9, 11, 12]. In the literature, several MUD techniques have been proposed to eliminate the MAI effect in CDMA networks [10–13]. Among them, the ML detector optimally minimizes the error probability at the receiver side [11]. Recently, a simple evolutionary search method, ACO, has been modified to be utilized as an efficient low complexity MUD technique [14, 15].

Some recent articles have addressed the MUD issue in CDMA based cooperative networks. In [3, 7], MMSE MUD technique has been modified to be used in cooperative networks. It was shown that utilizing the MMSE detector at both relay terminals and the BS enhances the total network performance and hence, the maximum cooperation diversity can be achieved. Moreover, in [3], a Relay-Assisted Decorrelating MUD (RAD-MUD) is proposed to separate interfering signals at the destination with the help of precoding techniques at the relays in conjugation with pre-whitening at the destination. Also, the ML detector formulation for a CDMA based cooperative DAF scenario has been derived in [13]. However, the computational complexity of the proposed ML detector grows exponentially as the number of users in the network increases.

In this paper, a general cooperation scenario consisting of independent direct and relay paths in a CDMA based DAF scheme has been considered. An ACO-based MUD technique has been proposed to efficiently combine the received signals from the direct and relay paths and sub-optimally extract transmitted bits at the BS. The proposed algorithm significantly reduces the computational complexity of the ML detector while the BER performance does not degrade considerably. Simulation results show that the proposed ACO-based

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detector efficiently decreases the MAI effect at the BS and hence nearly approaches the second order diversity bound for the cooperation scenario.

The rest of this paper is organized as follows. In Section 2, the system model and cooperative protocol are introduced. In Section 3, the formulation for maximum likelihood multiuser detection is presented. Also, in this section, the simplified ML detector is demonstrated. In Section 4, the proposed ACO-based MUD is introduced. The simulation results are presented in Section 5, and finally, the conclusion is given in Section 6.

2 System Model

A synchronous cooperative DS-CDMA network has been considered with K users employing non-orthogonal spreading codes with length N. The user nodes of the network are indicated with the indices $k = 1, 2, \ldots, K$ and the BS is represented with the index $k = K+1$. Also, it is assumed that each node is able to simultaneously receive and transmit, and perfect echo cancellation is performed at the relay nodes [7]. Moreover, every user as well as the BS are equipped with a single antenna.

Let $d_{k,q}$ denote the distance between the k^{th} and q^{th} users. In addition, corresponding fading coefficient $h_{k,q}$ can be expressed as a circularly symmetric complex Gaussian random variable whose variance is $1/(d_{k,q})^a$, where a denotes the path loss exponent [7]. Also, it is assumed that the channel has slow fading characteristics and does not vary during $2L$ successive symbol intervals. Furthermore, it is assumed that the channel has reciprocal property (i.e. $h_{k,q} = h_{q,k}$). In addition, it should be pointed out that $h_{k,k} = 0$.

Here, the case of DAF cooperation strategy is considered where each user can be assisted by a relay node which relays its signal toward the BS. Let $F = \{1, 2, \ldots, K\}$ be the set of present terminals in the network. It is assumed that for each user index $k \in F$ a partner, named $f(k) \in F$, exists that provides the secondary data link toward the destination. Here, bidirectional cooperation is assumed where the partners have to relay each other's data. If a user is not able to use the advantages of cooperation, without any loss of generality, it can be considered that $f(k) = k$. In addition, in the network transmission scenario, each user transmits only one new symbol per a couple of symbol intervals and we suppose that cooperation occurs in two consequent intervals as explained bellow [7]:

- During odd symbol intervals, each user transmits its own information (utilizing its own spreading code), which is received by the BS as well as the partner.
- During even symbol intervals, each relaying node retransmits a processed version of the information received in the previous symbol interval using its own spreading code.

The normalized transmitted symbol sequence of users is shown by $\{b_k(i), i = 1, 2, \ldots, L\}$, $k \in F$. Hence, the discrete time signal representation received at p^{th} terminal, $p = 1, 2, \ldots, K+1$ during the odd symbol interval and at the BS during the even ones respectively are given by [7] for $i = 1, 2, \ldots, L$:

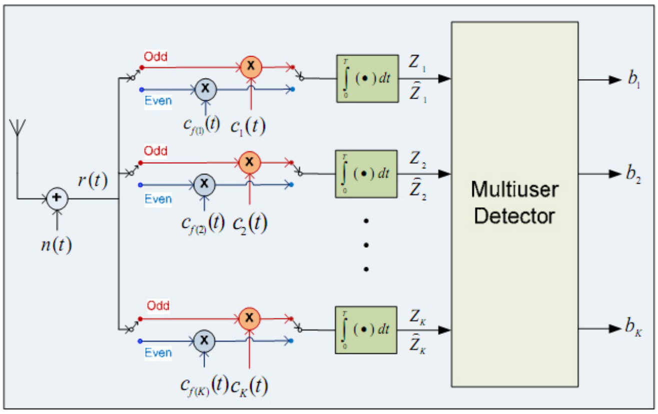

Figure 1. Receiver structure at the BS.

$$r_p(2i-1) = \sum_{k=1, k\neq p}^{K} \nu_{k,p} b_k(i) + n_p(2i-1), \tag{1}$$

$$r_{K+1}(2i) = \sum_{k=1}^{K} \nu_{f(k),K+1} \tilde{b}_k(i) + n_{K+1}(2i), \tag{2}$$

where $\nu_{k,p} = \sqrt{\xi_k} h_{k,p} c_k$ is the filtered signature of the k^{th} user received at p^{th} terminal, ξ_k denotes the k^{th} user's symbol energy, c_k is the N-dimensional normalized signature vector, $\tilde{b}(i)$ represents the hard decision estimate of $b_k(i)$ (for non-cooperating users, it can be written as $\tilde{b}(i)$=$b_k(i)$). Also, $n_{K+1}(2i)$ and $n_p(2i-1)$ are N-dimensional circularly symmetric white Gaussian noise vectors received at the BS and at p^{th} terminal, respectively [7]. Hereafter, an uncoded BPSK signaling with unit amplitude will be considered, i.e., $b_k(i) \in \{\pm 1\}$.

As mentioned before, in DAF strategy each user totally decodes and relays its partner's symbols that are received during odd intervals. Let $f(q) \in F$ denote the node of interest, then, the corresponding Matched Filter (MF) receiver to estimate the $b_q(i)$ is given by $m_{q,f(q)} = v_{q,f(q)}$. If the output of the receiver's MF is expressed by $Z \equiv m^H_{q,f(q)} r_{f(q)}$, then $\tilde{b}_q(i)$ can be obtained by

$$\tilde{b}_q(i) = \text{sgn}[\Re\{Z\}], \; i = 1, \ldots, L. \tag{3}$$

3 Maximum Likelihood Multiuser Detection in Cooperative DAF Networks

Continuous time representation of the transmitted signal by k^{th} user in one symbol duration can be expressed by $s_k(t) = \sqrt{\xi_k} b_k c_k(t)$ [14], where $c_k(t)$ is the continuous time signature waveform of k^{th} user with the correlation matrix as follows

$$\mathbf{R} = [\rho_{i,j}], \qquad \rho_{i,j} = \int_0^{T_b} c_i(t) c_j(t) dt \tag{4}$$

Thus, the transmitted signal of all users can be written as

$$s(t) = \sum_{k=1}^{K} s_k(t) = \sum_{k=1}^{K} \sqrt{\xi_k} b_k c_k(t) = \mathbf{CEb}, \quad (5)$$

where

$$\mathbf{C} = [c_1(t), \ldots, c_k(t)],$$
$$\mathbf{E} = \mathrm{diag}[\sqrt{\xi_1}, \ldots, \sqrt{\xi_K}],$$
$$\mathbf{b} = [b_1, \ldots, b_k]^T.$$

Vector $\mathbf{b}$ consists of all users' transmitted bits. There are 2^K states for this vector corresponding to 2^K different combinations of user's transmitted bits. Let denote the j^{th} combination of $\mathbf{b}$ as $\mathbf{b}^j$. Hence, the combined transmit signal of all users is given by $s^j(t) = \mathbf{CEb}^j$. Therefore, the received signal at the BS can be expressed as

$$r(t) = \sum_{k=1}^{K} s_k(t) h_{k,K+1} + n(t) = \mathbf{CHEb} + n(t), \quad (6)$$

where $\mathbf{H} = \mathrm{diag}[h_{k,K+1}, \ldots, h_{K,K+1}]$. Define $\|r(t)\|^2 = \int_0^{T_b} |r(t)|^2 dt$.

As it is shown in Figure 1, the output of BS's MF bank can be expressed as

$$\mathbf{Z} = [Z_1, Z_2, \ldots, Z_K]^T = \mathbf{RHEb} + \mathbf{n},$$

where $\mathbf{R}$ is calculated by (4) and $\mathbf{n} = [n_1, n_2, \ldots, n_K]^T$ is a zero mean Gaussian noise with a covariance matrix of $\mathbf{R}_n = 0.5 N_0 \mathbf{R}$. As it was mentioned in section 2, in the current cooperation scenario, the single bit transmission completes in two consecutive symbol intervals. Thus, for the sake of simplicity, the signals belonging to even intervals are shown with a bar as $\bar{\bullet}$. Therefore, the following equations can be written for the received signal in even intervals

$$\bar{r}(t) = \sum_{k=1}^{K} s_{f(k)}(t) h_{f(k),K+1} + \bar{n}(t) = \bar{\mathbf{C}}\bar{\mathbf{H}}\bar{\mathbf{E}}\bar{\mathbf{b}} + \bar{n}(t), \quad (7)$$

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$$\bar{\mathbf{C}} = [c_{f(1)}(t), \ldots, c_{f(K)}(t)],$$
$$\bar{\mathbf{E}} = \mathrm{diag}[\xi_{f(1)}, \ldots, \xi_{f(K)}],$$
$$\bar{\mathbf{H}} = \mathrm{diag}[h_{f(1),K+1}, \ldots, h_{f(K),K+1}],$$
$$\bar{\mathbf{b}} = [\widetilde{b_1}, \ldots, \widetilde{b_K}]^T.$$

Using the above expressed formulas, the ML criterion can be given by [13]

$$\widehat{\mathbf{b}} = \arg \max_{\mathbf{b}^j} [P(r(t)|s^j(t)) P(\bar{r}(t)|s^j(t))], \quad (8)$$

where $\hat{\mathbf{b}}$ is the optimal combination for detection of the network users' transmitted bits. Therefore, ML optimization criterion has two parts: the direct path $P(r(t)|s^j(t))$ and the relay path $P(\bar{r}(t)|s^j(t))$. Also, as $r(t)$ is a Gaussian distributed random variable, the former term has the probability distribution function [13] given by:

$$\begin{aligned} P(\mathbf{Z}|\mathbf{s}) &= \exp\Big\{-\frac{1}{2\sigma^2}\int_0^{T_b} |r(t) - s(t)|^2 dt\Big\} \\ &= \exp\Big\{-\frac{1}{2\sigma^2}\int_0^{T_b} \Big| r(t) - \sum_{k=1}^{K} \sqrt{\xi_k} c_k(t) b_k h_{k,K+1}(t)\Big|^2 dt\Big\} \\ &= \exp\Big\{-\frac{1}{2\sigma^2}\Big(\|r(t)\|^2 - 2\Re[\mathbf{b}^T \mathbf{E}\mathbf{H}^* \mathbf{Z}] - \mathbf{b}^T \mathbf{EHRH}^* \mathbf{Eb}\Big)\Big\}. \end{aligned} \quad (9)$$

For the latter term, the following consideration should be taken into account. In even symbol intervals, there are 2^K possible combinations of $\bar{\mathbf{b}}$ due to the possible reception error in any of the data bits of $\bar{\mathbf{b}}$. Let show these combinations by $\bar{\mathbf{b}}^m$. It is assumed that $\mathbf{b}^j$ and $\bar{\mathbf{b}}^m$ are related to each other by a diagonal transition matrix $\Psi^{m,j}$ which is defined as $\bar{\mathbf{b}}^m = \Psi^{m,j}\mathbf{b}^j$, where $\Psi^{m,j} = \mathrm{diag}(\bar{\mathbf{b}}^m) / \mathrm{diag}(\mathbf{b}^j)$ is a $K \times K$ diagonal matrix of which the k^{th} diagonal element is given by

$$\Psi^{m,j}(k,k) = \begin{cases} +1, & \text{if } \mathbf{b}^j(k) = \bar{\mathbf{b}}^m(k), \\ -1, & \text{if } \mathbf{b}^j(k) \neq \bar{\mathbf{b}}^m(k). \end{cases} \quad (10)$$

It should be noted that for a given $\mathbf{b}^j$, there would be 2^K different $\Psi^{m,j}$ for $m \in \{1, 2, \ldots, 2^K\}$. In the rest of this paper, the j superscript is dropped in $\Psi^{m,j}$ for simplicity.

Consider that subset $\mathbf{A}$ of $\mathbf{F}$ consists of all relays which receive their partner's transmitted symbol correctly at a given bit interval, that is,

$$\forall f(k) \in \mathbf{F} \xrightarrow{\text{iff } \Psi^m(f(k),f(k))=+1} f(k) \in \mathbf{A}.$$

Also, subset $\mathbf{B}$ of $\mathbf{F}$ is made up of all relays that receive their partner's symbol incorrectly in that given transmission interval, that is,

$$\forall f(k') \in \mathbf{F} \xrightarrow{\text{iff } \Psi^m(f(k'),f(k'))=+1} f(k') \in \mathbf{B}.$$

It is obvious that users who do not always cooperate will be located in subset $\mathbf{A}$. Actually, it can be inferred that $\mathbf{A}$ and $\mathbf{B}$ are a partition of $\mathbf{F}$. Thus, there are 2^K different states for $\mathbf{A}$ and $\mathbf{B}$ over $\mathbf{F}$.

According to (10), probability that Ψ^m occurs is equal to

$$P(\Psi^m) = \prod_{\substack{f(k)=1 \\ f(k)\in\mathbf{A}}}^{f(K)} \Big(1 - P_{f(k)}\Big) \prod_{\substack{f(k')=1 \\ f(k')\in\mathbf{B}}}^{f(K)} P_{f(k')} \quad (11)$$

Consequently, for calculation of the second term of (8), there are 2^K terms corresponding to all possible combinations of bit decoding for K relays. Also, the weight of each combination equals to its corresponding transition matrix probability. Hence, probability of $\bar{s}(t) = \bar{s}^m(t) = \bar{\mathbf{C}}\bar{\mathbf{E}}\Psi^m\mathbf{b}^j$ is given by Equation (12). Thus, from [13], the second term in (8) can be expressed as in Equation (13). Then, the maximum likelihood criterion for optimal multiuser detection will be given by Equation (14).

The best solution in the sense of ML criterion for the cooperative DAF network is obtained through the following estimation $\widehat{\mathbf{b}} = \arg(\max_{\mathbf{b}}[\Omega(\mathbf{b})])$ employing (14). The ML formulation, expressed in (14), would be used as ACO-algorithms fitness function. However,

$$P(\bar{s}^m(t)|s^j(t)) = \prod_{\substack{f(k)=1 \\ f(k)\in\mathbf{A}}}^{f(K)} \left(1 - P_{f(k)}\right) \prod_{\substack{f(k')=1 \\ f(k')\in\mathbf{B}}}^{f(K)} P_{f(k')} = P(\Psi^m). \tag{12}$$

$$P[\bar{\mathbf{Z}}|\bar{\mathbf{s}}] = \exp\left\{-\frac{1}{2\sigma^2}\int_0^{T_b} |\bar{r}(t) - \bar{\mathbf{C}}\bar{\mathbf{E}}\Psi^m\mathbf{b}|^2 dt\right\} = \exp\left\{-\frac{1}{2\sigma^2}(\|\bar{\mathbf{r}}\|^2 - 2\Re[\mathbf{b}^T\Psi^m\bar{\mathbf{E}}\bar{\mathbf{H}}^*\bar{\mathbf{Z}}] - \mathbf{b}^T\Psi^m\bar{\mathbf{E}}\bar{\mathbf{H}}\bar{\mathbf{R}}\bar{\mathbf{H}}^*\bar{\mathbf{E}}\Psi^m\mathbf{b}).\right\} \tag{13}$$

$$\begin{aligned}\Omega(\mathbf{b}) = &\exp\left\{-\frac{1}{2\sigma^2}(\|r(t)\|^2 - 2\Re[\mathbf{b}^T\mathbf{E}\mathbf{H}^*\mathbf{Z}] - \mathbf{b}^T\mathbf{E}\mathbf{H}\mathbf{R}\mathbf{H}^*\mathbf{E}\mathbf{b})\right\} \\ &\times \sum_{\Psi^m}\left[\exp\left\{-\frac{1}{2\sigma^2}(\|\bar{\mathbf{r}}\|^2 - 2\Re[\mathbf{b}^T\Psi^m\bar{\mathbf{E}}\bar{\mathbf{H}}^*\bar{\mathbf{Z}}] - \mathbf{b}^T\Psi^m\bar{\mathbf{E}}\bar{\mathbf{H}}\bar{\mathbf{R}}\bar{\mathbf{H}}^*\bar{\mathbf{E}}\Psi^m\mathbf{b})\right\} P(\Psi^m)\right]\end{aligned} \tag{14}$$

as it can be seen, the number of additive terms (following $\sum$ sign) will increase exponentially when the number of cooperating users increases. In fact these terms will cause a considerable increase in the computational complexity of the fitness function. As it will be shown in the following subsection, there are only $K+1$ significant terms in this expression; therefore, the fitness function can be simplified remarkably.

3.1 Fitness function simplification

It is assumed that a proper partner selection algorithm has been employed and, as a result, the error probability of inter-user channels would be small enough. Hence, in (11) if there is more than one user in set $\mathbf{B}$, the following approximation can be used

$$\prod_{\substack{f(n)\in\mathbf{B} \\ if|\mathbf{B}|>1}} P_{f(n)} \approx 0.$$

Using this approximation, the number of summation terms in (14) decreases from 2^K to $K+1$ terms. Without loss of generality, it can be assumed that Ψ^l, where $l = 1, 2, \ldots, K+1$, is the state transition matrix corresponding to the remaining terms. The l^{th} member of this set $(l = 1, 2, \ldots, K)$ is proportional to error occurrence in the l^{th} bit of $\bar{\mathbf{b}}$; therefore, Ψ^l is a $K \times K$ diagonal matrix whose elements on the major axis are one except the l^{th} member. Also, the $(K+1)^{th}$ member of $\{\Psi\} = \{\Psi^l | l = 1, 2, \ldots, K+1\}$ corresponds to the error free reception of $\bar{\mathbf{b}}$ (i.e., $\Psi^{K+1} = \mathbf{I}_{K\times K}$). Consequently, the probability distribution of Ψ^l occurrence will be denoted as

$$P(\Psi^l) = \begin{cases} P_l \prod\limits_{\substack{f(q)=l \\ f(q)\neq l}}^{K} (1 - P_{f(q)}), & l = 1, 2, \ldots, K, \\ \prod\limits_{f(q)=l}^{K} (1 - P_{f(q)}), & l = K+1. \end{cases} \tag{15}$$

Ψ^m can be replaced by Ψ^l in (14) and, then, the Simplified Maximum Likelihood (S-ML) criterion can be obtained by maximizing expression (16).

As it can be seen, the number of additive terms is decreased from 2^K terms in (14) to $K+1$ terms in (16). Here, for simplicity, (16) is used as the fitness function of the ACO algorithm given in the following section.

4 ACO Algorithm

ACO is an efficient evolutionary search technique to solve optimization problems with discrete and finite search space. This algorithm is based on artificially simulating the foraging behavior of natural ant colonies, wherein every artificial ant leaves a pheromone vestige which helps the other ants to find the shortest route to the source of the food. The result behind this approach is that there is more pheromones density in shorter routs, which can lead to their higher selection probability. By invoking this property, ACO can be used in CDMA based networks as an efficient nonlinear MUD technique to sub-optimally estimate the maximal point of the likelihood function as expressed in (14). This is due to the simple structure of ACO search technique that the ACO-based MUD not only approaches near optimal ML performance, but also significantly reduces the computational complexity of search process [15].

Considering the application of ACO-based MUD in a BPSK modulated cooperative CDMA network supporting K users, a so called *route table* with $(2 \times K)$ elements can be defined as in Table I, where the first row $(\mathbf{b}_{MF})$ represents the hard decision output of the BS's MF, and the second row $(\mathbf{b}'_{MF})$ is the complement of $\mathbf{b}_{MF}$. Therefore, all possible combinations of transmitted vectors can be represented by means of this table. Then, the ACO based MUD sub-optimally finds the best answer among the 2^K possible data bit combinations using different selections of $\mathbf{b}_{MF}(j)$ and $\mathbf{b}'_{MF}(j)$ for $j = 1, 2, \ldots, K$.

In ACO-based MUD, the search procedure starts from an initial stage corresponding to the hard decision output of the BS's MF $(\mathbf{b}_{MF})$. Afterward, at each iter-

Table I
Route Table

	1	2	…	K
1	$\mathbf{b}_{MF}(1)$	$\mathbf{b}_{MF}(2)$	…	$\mathbf{b}_{MF}(K)$
2	$\mathbf{b}'_{MF}(1)$	$\mathbf{b}'_{MF}(2)$	…	$\mathbf{b}'_{MF}(K)$

$$\Omega(\mathbf{b}) \approx \exp\left\{-\frac{1}{2\sigma^2}\left(\|r(t)\|^2 - 2\Re[\mathbf{b}^T\mathbf{E}\mathbf{H}^*\mathbf{Z}] - \mathbf{b}^T\mathbf{E}\mathbf{H}\mathbf{R}\mathbf{H}^*\mathbf{E}\mathbf{b}\right)\right\}$$
$$\times\left[\sum_{l=1}^{K+1}\exp\left\{-\frac{1}{2\sigma^2}(\|\bar{\mathbf{r}}\|^2 - 2\Re[\mathbf{b}^T\Psi^l\bar{\mathbf{E}}\bar{\mathbf{H}}^*\bar{\mathbf{Z}}] - \mathbf{b}^T\Psi^l\bar{\mathbf{E}}\bar{\mathbf{H}}\bar{\mathbf{R}}\bar{\mathbf{H}}^*\bar{\mathbf{E}}\Psi^l\mathbf{b})\right\}P(\Psi^l)\right] \tag{16}$$

ation, the pheromone concentration will be updated in order to find the optimum solution for likelihood function maximization problem. For simplicity, a *Pheromone Table* (PT) with $(2 \times K)$ elements can be defined which contains the pheromone density in each path in the *route table*. Here, a *desirability function* is introduced which can help the artificial ants whether to select $\mathbf{b}_{MF}$ or its complement $\mathbf{b}'_{MF}$. The value of this function is inversely proportional to the amplitude of MF's soft output as [14].

$$D_i(j) = \frac{1}{2 + |z^{(j)}| + \sum_{l \in \mathbf{C}_i} |z^{(l)}|} \qquad j = 1, \ldots, K, \tag{17}$$

where $D_i(j)$ is the desirability function at the j^{th} element in the $\mathbf{b}_{MF}$ vector for i^{th} ant, $|z^{(j)}|$ represents the absolute value of MF's soft output at the j^{th} element, and $\mathbf{C}_i$ is the set of bits where the i^{th} ant had previously deviated from the MF output $(\mathbf{b}_{MF})$ since the start of its movement (st_i). This equation prevents the ant's significant deviation from the initial solution introduced by $\mathbf{b}_{MF}$. Therefore, the selection probability, $p_i(j)$, of $\mathbf{b}'_{MF}(j)$ can be defined as

$$p_i(j) = \mathrm{PT}(2, j) \times D(j), \qquad \forall i = 1, 2, \ldots, P, \tag{18}$$

where N is the number of ants. To enhance the performance of the ACO-based MUD algorithm, the start point of each ant's movement (st_i) can be chosen randomly at each iteration. In addition, pheromone deposition and evaporation are done based on traversed paths (Tr) by the ants at each iteration. Tr_i has the same dimensions as the route table in which the other elements are 0. Selection of Deposition Rate (DR) and Evaporation Rate (ER) significantly affects the performance of the ACO-based MUD algorithm. Clearly at each iteration, the higher the pheromone value in PT results in the greater selection probability of corresponding path. In addition, elitism is employed to improve the performance of ACO-based MUD algorithm where only those ants with the highest value of likelihood function (the set $\boldsymbol{M}$) are permitted to deposit pheromone along their traversal path. Therefore, the pheromone deposition and evaporation procedure at each iteration is formulated as follows [14]:

$$\mathrm{PT} = (\mathrm{PT} + \mathrm{DR} \times \sum_{i \in \mathbf{M}} \mathrm{Tr}_i) \times (1 - \mathrm{ER}) \tag{19}$$

After a predetermined number of iterations (Y), the operation of ACO-MUD completes. Hence, the $\mathbf{b}_{\mathrm{elite}}$ in that iteration is the final estimate of user's transmitted data. In ACO based MUD, P ants perform ACO for Y iterations; therefore, the total number of likelihood function evaluations is $P \times Y$ while it is 2^K in the ML method. Therefore, the computation complexity

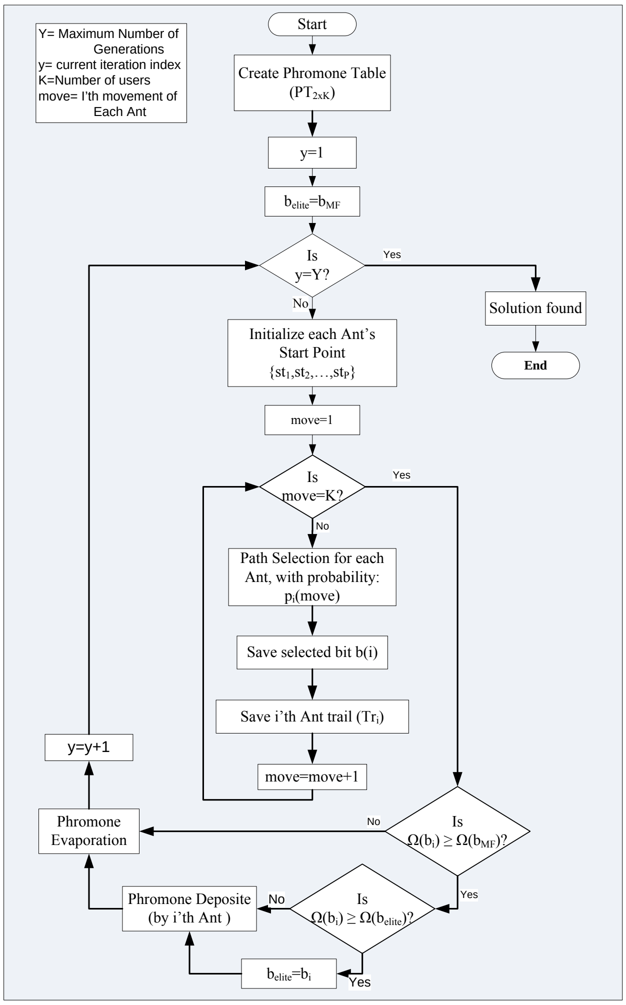

Figure 2. ACO algorithm's flowchart.

of ACO-based MUD is only a small fraction of ML method especially when K is high. Figure 2 shows the overall operational flowchart of the employed ACO-Based MUD algorithm.

5 Simulation Results

In this section, simulation results for performance evaluation of the proposed methods are presented. A DS/CDMA network has been considered which uses m-sequences spreading codes with length $N = 15$. The path loss exponent is considered to be $a = 3$. It is also assumed that the power density of noise is equal at all relay terminals as well as at the BS $(N_1 = N_2 = \cdots = N_{K+1})$. Therefore, the SNR in the network simulations is $\gamma \equiv \xi_K E[|h_{k,K+1}|^2]/N_{K+1}$. In Addition, all users are assumed to transmit equal

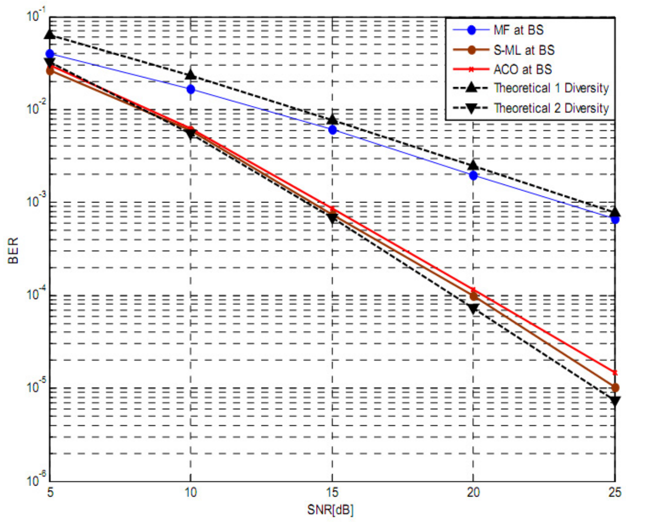

Figure 3. The comparison of the BER performance of different detectors at the Base Station of cooperative network.

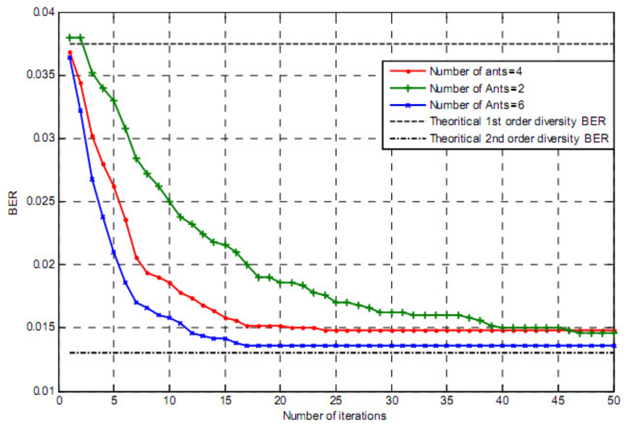

Figure 4. BER versus number of iterations in SNR=8dB.

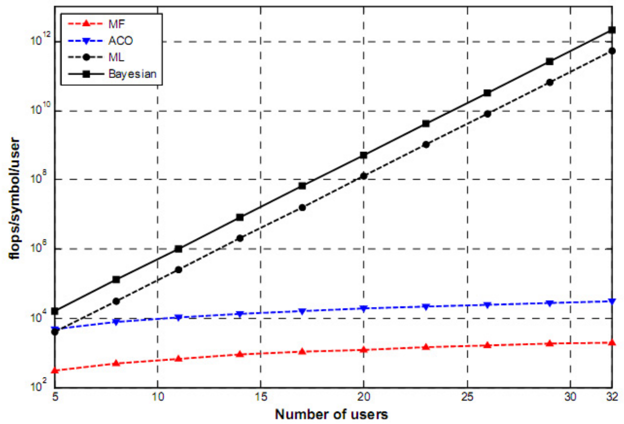

Figure 5. Complexity per transmitted signal per user versus the number of users of the DS-CDMA system employing N = 31 m-sequence codes.

powers, i.e. $\xi_1 = \xi_2 = \cdots = \xi_K$. The BER performance was obtained by averaging the simulation results over almost 100 000 channel realizations.

The partner selection strategy, used in this network, is based on the proposed strategy in [7]. In this strategy, each terminal monitors the average signal power received from other users and then, compiles and sorts a list of strong neighbors which can take the role of potential relays. Based on the received neighbor lists, BS starts with the user with the worst uplink channel state and tries to allocate a partner to each user.

The following parameter settings have been used for the ACO-based MUD: $P = 6$, $Y = 20$, $\text{DR} = 0.15$ and $\text{ER} = 0.05$. The simulation results for simplified optimum multiuser detection (S-ML) strategy will be evaluated for a network with $K = 10$ users. For comparison, theoretical bounds for diversity orders of one and two have been also presented as a benchmark [16].

The BER performance of the proposed ACO based MUD in cooperative CDMA network is presented in Figure 3. In this figure, the BER curve of S-ML algorithm is also depicted for the sake of comparison. It is assumed that the relay nodes are merely interested in their partner's transmitted bit and also they utilize MF detector because of their limited processing capability. As it is seen, when MF detector is employed at the BS besides the efficient partner selection, the network performance is better than the first order diversity, but it is quite far from the second order diversity performance. It is interesting that when the MUD techniques are employed at the BS, the BER performance of total network will approach the second order diversity results. As it can be seen in Figure 3, the ACO-based MUD performance nearly approaches the S-ML curve which is very close to the theoretical second order diversity bound while the complexity of the former is only a fraction of the latter case.

The performance of ACO-based MUD completely depends upon the choice of parameters. In Figure 4, the BER performance of the proposed ACO-based MUD algorithm is presented for SNR=8dB versus the number of iterations. As it seems, the BER curve can totally approach S-ML performance, if sufficient number of iterations have been passed. In addition, the more the number of artificial ants is, the faster and more accurate convergence of the ACO algorithm is achieved.

In Figure 5, the computational complexity of proposed ACO-based MUD algorithm for a two phase cooperative Network has been compared with some other prevalent techniques. It can be seen that in ML based algorithm similar to the Bayesian detector, the computational complexity exponentially increases as the number of users increases. On the contrary, while the ACO or MF based detectors are employed, the computational complexity increases linearly. To express more quantitatively, for the case where the number of users reaches 15, the computational complexity of the ACO algorithm is less than 0.1% of the optimum Bayesian detector.

6 Conclusion

The ACO-based MUD has been proposed for the uplink of a CDMA based cooperative DAF scenario. To reduce the computational complexity, the likelihood function has been simplified to be employed as the fitness function of the ACO algorithm which can be easily generalized to an arbitrary cooperation scenario by manipulating a few changes. Using the proposed detector, the BS will be able to sub-optimally extract transmitted bits using the signals received from both direct and relay paths. Simulation results show that the BER performance of the ACO-based MUD, in a cooperative scenario, closely approaches the performance bounds of the second order diversity at significantly lower computational complexity compared to the ML method. More explicitly, for a cooperative network supporting 15 users, the computational complexity of the proposed ACO algorithm is a factor of 10^3 lower than that of the optimum Bayesian detector.

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