Genetic Algorithm Assisted Multiuser Detection in Asynchronous CDMA Communications

K. Yen, L. Hanzo

Dept. of Electronics and Computer Science, University of Southampton, SO17 1BJ, UK.
Tel: +44-1703-593 125, Fax: +44-1703-594 508
Email:lh@ecs.soton.ac.uk http://www-mobile.ecs.soton.ac.uk

Abstract— **The up-link transmissions of mobile stations are typically uncoordinated, which lead to asynchronous DS-CDMA systems. Provided that the propagation delay differences of users are less than one symbol duration, every bit of each user is interfered by two consecutive bits of every other user supported by the system which are overlapping with the bit of interest. This is only true, however, with the proviso of an identical channel bit rate for all the users. Hence the multiuser detector (MUD) must have knowledge of these two overlapping bits, in order to efficiently detect the desired bit (DB). Suboptimal MUDs have been proposed based on a truncated observation window, in which the overlapping 'edge' bits are tentatively estimated by some other means. Using a similar approach, a MUD is developed in this contribution which invokes genetic algorithms (GAs), in order to estimate the DBs within the truncated observation window as well as to simultaneously improve the edge bits' error probability (EBEP). Computer simulations showed that by using GAs for improving the reliability of the edge bits, our proposed MUD can achieve a near-optimum DBEP performance, while imposing a lower complexity compared to that of the optimum MUD.**

I. Introduction

In an asynchronous DS-CDMA system, every bit of each user is interfered by two bits of every other user in the system which are overlapping with the bit of interest, assuming an identical channel bit rate for all the users. Hence the multiuser detector (MUD) must have knowledge of these two overlapping bits, in order to efficiently detect the desired bit (DB). Conventional MUDs, such as the decorrelator [2], operate on the entire length M of the users' bit sequence. This results in a long detection delay as well as in a significant receiver complexity, when M is high. In order to reduce the detection delay and the receiver complexity in asynchronous DS-CDMA systems, several MUDs [3–5] have been proposed based on truncating the detection observation window [3–5], such that only a portion of the bit sequence length M is considered at any one time. The bits that coincide with the window's edge, referred to as the *edge bits* in this contribution, are then tentatively estimated by other means. It was demonstrated in [3–5] that a low edge bit error probability is essential, in order to attain a high overall bit error rate (BER) performance.

A GA-based MUD was first proposed by Juntti *et al.* [8], where the analysis was based on a synchronous CDMA system communicating over an AWGN channel. It was found that good initial guesses of the possible solutions are needed for the GA, in order to obtain a high performance. However, by incorporating an element of local search prior to invoking the GA, Yen *et al.* [9] showed that the performance of the GA-based MUD approaches the single-user performance bound at a significantly lower computational complexity, than that of the optimum MUD [1]. Instead of providing good initial guesses for the GA, the proposal by Ergün *et al.* [10] used a multi-stage MUD as part of the GA-aided detection procedure, in order to improve the convergence rate of the GA. The performance of a GA-based MUD employed in an asynchronous CDMA system in conjunction with a modified Viterbi algorithm was studied by Wang *et al.* [11]. It was shown that the GA-based MUD achieves almost the same performance as that of the MMSE MUD at a lower computational complexity.

In this contribution we proposed a GA-based MUD for an asynchronous DS-CDMA system transmitting over L-path Rayleigh fading channels using the truncation window approach. Here we assumed that the observed window is truncated such that it encompasses at most one complete symbol interval of all users in any detection window. Hence if the DBs are constituted by the ith bit of all users, then the edge bits will be the $(i-1)$th bits and the $(i+1)$th bits of all interfering users, referred to in this contribution as the start edge bits (SEBs) and the end edge bits (EEBs), respectively. The SEBs have been detected in the previous observed window and hence are known to the receiver. GAs are then developed, in order to detect the ith DBs, as well as to estimate the EEBs. In contrast to the previously proposed techniques [4, 5], the EEB and the DBs in our proposed technique are estimated simultaneously using the same process. This results in minimal detection delay and no additional hardware is required to predict the EEB. Our simulation results showed that upon using GAs to improve the accuracy of the edge bits, our proposed MUD can achieve a near-optimum DB error probability (DBEP) performance, while imposing a lower complexity as compared to that of the optimum MUD [1].

The remainder of this paper is organised as follows. Section II describes our asynchronous CDMA system communicating over multipath Rayleigh fading channels. The log-likelihood function (LLF) required for the optimisation process is also developed. Section III describes the GAs used to implement our proposed MUD. Our simulation results are presented in Section IV, while Section V concludes the paper.

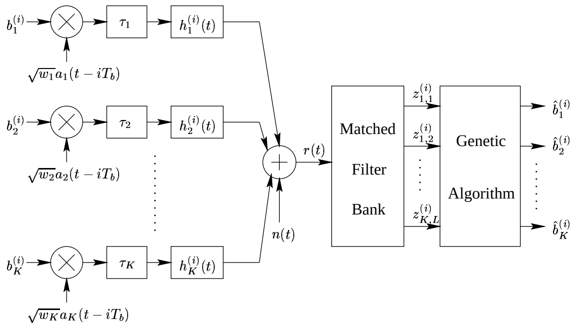

Fig. 1. System model for asynchronous GA-assisted multiuser DS-CDMA.

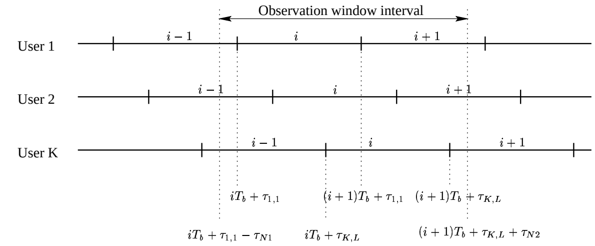

Fig. 2. Received sequences model of an asynchronous DS-CDMA system.

II. System Description

Our system model is illustrated in Fig. 1. The signal of each of the K users is assumed to be propagating over L independent slowly Rayleigh fading paths to the base station's receiver. The baseband received signal at the base station can be written as :

$$r(t) = \sum_{m=0}^{M-1} \boldsymbol{a}^T(t - mT_b)\boldsymbol{w}\boldsymbol{c}^{(m)}\boldsymbol{b}^{(m)} + n(t), \qquad (1)$$

where M is the number of transmitted data symbols in a frame, $\boldsymbol{w} = \text{diag}\left[\sqrt{w_1}\boldsymbol{I}, \sqrt{w_2}\boldsymbol{I}, \ldots, \sqrt{w_K}\boldsymbol{I}\right]$ is a diagonal matrix containing the power of the users and $\boldsymbol{I}$ is an $L \times L$ identity matrix, $\boldsymbol{c}^{(m)} = \text{diag}\left[c_{1,1}^{(m)}, \ldots, c_{1,L}^{(m)}, \ldots, c_{K,L}^{(m)}\right]$ is the diagonal complex channel gain matrix, $\boldsymbol{b}^{(m)} = \left[\boldsymbol{b}_1^{(m)}, \boldsymbol{b}_2^{(m)}, \ldots, \boldsymbol{b}_K^{(m)}\right]^T$ is the data vector and $\boldsymbol{b}_k^{(m)}$ is the kth $1 \times L$ user bit vector, while $\boldsymbol{a}(t) = [a_1(t-\tau_{1,1}), \ldots, a_K(t - \tau_{K,L})]^T$ is the users' signature sequence vector. For simplicity and without loss of generality, we assumed an ordering of the random delays $\tau_{k,l}$, such that $0 = \tau_{1,1} < \ldots < \tau_{1,L} < \tau_{2,1} < \ldots < \tau_{K,L} < T_b$. The channel noise $n(t)$ is modelled by a zero mean, complex white Gaussian process with a double-sided power spectral density of $N_0/2$. We can define the $KL \times KL$ cross-correlation matrix $\boldsymbol{R}(m)$ of the signature sequences, such that the (p,q)th element is given by :

$$\rho_{p,q}(m) = \int_{-\infty}^{+\infty} a_{k_p}(t - \tau_{k_p,l_p})a_{k_q}(t + mT_b - \tau_{k_q,l_q})dt, \qquad (2)$$

where $k_p = \lceil \frac{p}{L} \rceil$, $k_q = \lceil \frac{q}{L} \rceil$, $l_p = p - \lfloor \frac{p-1}{L} \rfloor \cdot L$ and $l_q = q - \lfloor \frac{q-1}{L} \rfloor \cdot L$. At the front end of the receiver illustrated in Fig. 1, the output $\boldsymbol{z}^{(i)}$ of the matched filter bank at the ith symbol interval can be written as :

$$\begin{aligned} \boldsymbol{z}^{(i)} &= \left[z_{1,1}^{(i)}, \ldots, z_{1,L}^{(i)}, \ldots, z_{K,L}^{(i)}\right]^T \\ &= \boldsymbol{R}(1)\boldsymbol{w}\boldsymbol{c}^{(i-1)}\boldsymbol{b}^{(i-1)} + \boldsymbol{R}(0)\boldsymbol{w}\boldsymbol{c}^{(i)}\boldsymbol{b}^{(i)} \\ &\quad + \boldsymbol{R}^T(1)\boldsymbol{w}\boldsymbol{c}^{(i+1)}\boldsymbol{b}^{(i+1)} + \boldsymbol{n}^{(i)}. \qquad (3) \end{aligned}$$

From Eq. 3, we can see that any joint decision made concerning the ith bits of the K users has to take into account the decisions related to either the $(i-1)$th bit or the $(i+1)$th bit of each user, as shown in Fig. 2. Let us now introduce :

$$\boldsymbol{R}'(0) = \begin{bmatrix} \rho'_{1,1} & \cdots & \rho'_{1,L} & \cdots & \rho'_{1,KL} \\ \rho'_{2,1} & \cdots & \rho'_{2,L} & \cdots & \rho'_{2,KL} \\ \vdots & \vdots & & \vdots & \\ \rho'_{KL,1} & \cdots & \rho'_{KL,L} & \cdots & \rho'_{KL,KL} \end{bmatrix}$$
$$\boldsymbol{R}''(0) = \begin{bmatrix} \rho''_{1,1} & \cdots & \rho''_{1,L} & \cdots & \rho''_{1,KL} \\ \rho''_{2,1} & \cdots & \rho''_{2,L} & \cdots & \rho''_{2,KL} \\ \vdots & \vdots & & \vdots & \\ \rho''_{KL,1} & \cdots & \rho''_{KL,L} & \cdots & \rho''_{KL,KL} \end{bmatrix}, (4)$$

where the (p,q)th element is given by :

$$\rho'_{p,q} = \int_{\tau_{1,1}+T_b-\tau_{N1}}^{\tau_{k_p,l_p}+T_b} a_{k_p}(t - \tau_{k_p,l_p})a_{k_q}(t - \tau_{k_q,l_q})dt$$
$$\rho''_{p,q} = \int_{\tau_{k_p,l_p}+T_b}^{\tau_{K,L}+T_b+\tau_{N2}} a_{k_p}(t - \tau_{k_p,l_p})a_{k_q}(t - \tau_{k_q,l_q})dt.$$

The truncated observation window duration is governed by τ_{N1} and τ_{N2}, where $0 \leq \tau_{N1}, \tau_{N2} < \tau_{1,1} - \tau_{K,L} + T_b$, as illustrated by Fig. 2. The SEBs $\boldsymbol{b}^{(i-1)}$ can be derived from the previous detection process and hence are known to the receiver. In this case, only the DBs $\boldsymbol{b}^{(i)}$ and the EEBs $\boldsymbol{b}^{(i+1)}$ are unknown to the receiver.

Based on the observation vector $\boldsymbol{z}^{(i)}$ given in Eq. 3, it can be shown that the LLF required for detecting the ith bit of all K users within the truncated observation window can be written as :

$$\Omega(\boldsymbol{b}^{(i)}, \boldsymbol{b}^{(i+1)}) = 2\Re\left\{\boldsymbol{B}^T\boldsymbol{C}\boldsymbol{W}\boldsymbol{Z}\right\} - \boldsymbol{B}^T\boldsymbol{C}\boldsymbol{W}\boldsymbol{R}\boldsymbol{W}\boldsymbol{C}^*\boldsymbol{B}, \qquad (5)$$

where $\boldsymbol{B} = \left[\boldsymbol{b}^{(i-1)^T}, \boldsymbol{b}^{(i)^T}, \boldsymbol{b}^{(i+1)^T}\right]^T$, $\boldsymbol{W} = \text{diag}[\boldsymbol{w}, \boldsymbol{w}, \boldsymbol{w}]$, $\boldsymbol{Z} = \left[\boldsymbol{z}^{(i-1)'}, \boldsymbol{z}^{(i)}, \boldsymbol{z}^{(i+1)''}\right]^T$, $\boldsymbol{C} = \text{diag}\left[\boldsymbol{c}^{(i-1)}, \boldsymbol{c}^{(i)}, \boldsymbol{c}^{(i+1)}\right]$ and :

$$\boldsymbol{R} = \begin{bmatrix} \boldsymbol{R}'(0) & \boldsymbol{R}^T(1) & \boldsymbol{0} \\ \boldsymbol{R}(1) & \boldsymbol{R}(0) & \boldsymbol{R}^T(1) \\ \boldsymbol{0} & \boldsymbol{R}(1) & \boldsymbol{R}''(0) \end{bmatrix}.$$

The vectors $\boldsymbol{z}^{(i-1)'}$ and $\boldsymbol{z}^{(i+1)''}$ represent the partial matched filter correlations between $[iT_b + \tau_{1,1} - \tau_{N1}, iT_b + \tau_{k,l}]$ and $[(i+1)T_b + \tau_{k,l}, (i+1)T_b + \tau_{K,L} + \tau_{N2}]$, respectively, for $k = 1, 2, \ldots, K$ and they are given as :

$$\boldsymbol{z}^{(i-1)'} = \boldsymbol{R}'(0)\boldsymbol{w}\boldsymbol{c}^{(i-1)}\boldsymbol{b}^{(i-1)} + \boldsymbol{R}^T(1)\boldsymbol{w}\boldsymbol{c}^{(i)}\boldsymbol{b}^{(i)} + \boldsymbol{n}^{(i-1)'} \qquad (6)$$

$$z^{(i+1)''} = R(1)wc^{(i)}b^{(i)} + R''(0)wc^{(i+1)}b^{(i+1)} + n^{(i+1)''}. \quad (7)$$

The optimum decision concerning $\boldsymbol{b}^{(i)}$ is formulated as $\hat{\boldsymbol{b}}^{(i)} = \left[\hat{\boldsymbol{b}}_1^{(i)}, \hat{\boldsymbol{b}}_2^{(i)}, \ldots, \hat{\boldsymbol{b}}_K^{(i)}\right]^T$, which maximises the LLF given in Eq. 5. Hence, it is imperative that the EEBs $\boldsymbol{b}^{(i+1)}$ are estimated as reliably as possible. One way of estimating the EEBs is by taking a hard decision based on their maximum ratio combined correlator outputs [3]. However, due to the presence of MAI, as shown in Eq. 7, the EBEP is high, especially in a worst-case single-path scenario, where no diversity gain is achieved. This high EBEP will limit the overall performance of the MUD, as we shall see in Section IV. In order to lower the EBEP, we invoke the proposed GA to improve the tentative decision accuracy of the EEBs $\boldsymbol{b}^{(i+1)}$, and at the same time we optimise the LLF in order to detect $\boldsymbol{b}^{(i)}$. Hence, the estimated transmitted bit vector $\hat{\boldsymbol{b}}^{(i)}$ of the K users can be found by optimising Eq. 5 with respect to the DBs $\boldsymbol{b}^{(i)}$ and the EEBs $\boldsymbol{b}^{(i+1)}$, yielding :

$$\hat{\boldsymbol{b}}^{(i)}, \tilde{\boldsymbol{b}}^{(i+1)} = \arg\left\{ \max_{\boldsymbol{b}^{(i)}, \boldsymbol{b}^{(i+1)}} \left[\Omega\left(\boldsymbol{b}^{(i)}, \boldsymbol{b}^{(i+1)}\right)\right]\right\}, \quad (8)$$

where $\tilde{\boldsymbol{b}}_{GA}^{(i+1)}$ denotes the tentative decisons concerning the EEBs based on the proposed GA-assisted optimisation. In the next section we will highlight the philosophy of our GA-assisted MUD, in order to simultaneously estimate the users' DBs and the EEBs.

III. Genetic Algorithm based Multiuser Detection

In this contribution we employed GAs [6, 7] in order to detect the transmitted users' bit vector $\boldsymbol{b}^{(i)}$, where the so-called objective function is defined by the LLF of Eq. 5. The structure of the proposed GA-based MUD can be best understood with the aid of the flowchart shown in Fig. 3.

Let us assume that the current bit of interest is the ith bit of all K users. GAs commence their search for the optimum solution at the so-called $y = 0$th *generation* with an initial population of so-called *individuals*, each consisting of $3 \times K$ antipodal bits. The number of $3K$-bit individuals in the population is given by the *population size* P. We shall express the pth individual here as $\tilde{\boldsymbol{b}}_p(y) = \left[\hat{\boldsymbol{b}}_{p,SEB}^{(i-1)}, \tilde{\boldsymbol{b}}_p^{(i)}(y), \tilde{\boldsymbol{b}}_{p,EEB}^{(i+1)}(y)\right]$, where $\hat{\boldsymbol{b}}_{p,SEB}^{(i-1)}$, $\tilde{\boldsymbol{b}}_p^{(i)}(y)$ and $\tilde{\boldsymbol{b}}_{p,EEB}^{(i+1)}(y)$ are K-bit strings denoting the SEBs, the DBs and the EEBs at the yth generation, respectively. At this point, the SEBs $\hat{\boldsymbol{b}}^{(i-1)}$ will have been detected in the previous observation window, when the $(i-1)$th bits were the DBs. Therefore, we can assign $\hat{\boldsymbol{b}}_{p,SEB}^{(i-1)} = \hat{\boldsymbol{b}}^{(i-1)}$ for $p = 1, \ldots, P$. Assuming that upon termination of the GA at the end of every observation window, the error probability of the EEBs will be sufficiently low, these bits can be considered as the tentative solutions for the GA during initialisation, when these EEBs become the DBs in the next observation window. Hence according to Eq. 8, $\tilde{\boldsymbol{b}}_p^{(i)}(0) = \tilde{\boldsymbol{b}}^{(i)}$ for $p = 1, \ldots, P$. The unknown EEB $\tilde{\boldsymbol{b}}_p^{(i+1)}(0)$

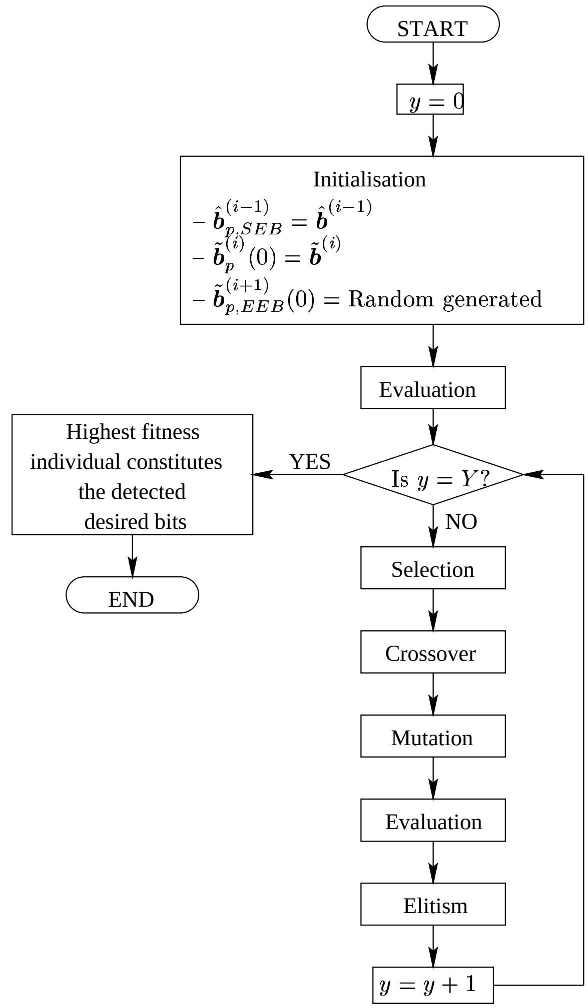

Fig. 3. A flowchart depicting the structure of the proposed genetic algorithm used to detect the transmitted users' bit $\boldsymbol{b}^{(i)}$ as well as providing the tentative solutions of $\boldsymbol{b}^{(i+1)}$ at the ith observation window.

for $p = 1, \ldots, P$ are randomly generated, in order to ensure a diversified search.

A fitness value, denoted as $f\left[\tilde{\boldsymbol{b}}_p(y)\right]$ for $p = 1, \ldots, P$ is associated with each $3K$-bit individual, which is computed by substituting the corresponding elements $\hat{\boldsymbol{b}}_{p,SEB}^{(i-1)}$, $\tilde{\boldsymbol{b}}_p^{(i)}(y)$ and $\tilde{\boldsymbol{b}}_{p,EEB}^{(i+1)}(y)$ into the LLF of Eq. 5. Based on the evaluated fitness, a new population of P individuals is created for the $(y+1)$th generation through a series of processes to be defined below, which are referred to in GA parlance as *selection*, *crossover*, *mutation* and *elitism* [7]. At the Yth generation, the DBs $\tilde{\boldsymbol{b}}_p^{(i)}(Y)$ of the $3K$-bit individual corresponding to the highest fitness value in the population constitute the detected K users' ith bit associated with the observation window interval considered, i.e. with $\hat{\boldsymbol{b}}^{(i)} = \tilde{\boldsymbol{b}}_j^{(i)}(Y)$ of the jth $3K$-bit individual $\tilde{\boldsymbol{b}}_j(Y)$, where $\tilde{\boldsymbol{b}}_j(Y) = \max\left\{f\left[\tilde{\boldsymbol{b}}_1(Y)\right], \ldots, f\left[\tilde{\boldsymbol{b}}_P(Y)\right]\right\}$. Let us now highlight the processes that are involved in the GA [7].

Selection - As suggested by the terminology, the *selection* process [7] selects two so-called $3K$-bit *parent* vectors from a *mating pool* consisting of T $3K$-bit individuals – where $2 \leq T < P$ – in order to produce two so-called *offspring* for the next generation population of $3K$-bit individuals. Individuals having the T highest fitness values in the population of $3K$-bit vectors are placed in the mating pool. We shall denote the $3K$-bit individuals in the mating pool as $\check{\boldsymbol{b}}_q(y)$ for $q = 1, \ldots, T$. The $3K$-bit individuals in the mating pool are selected as $3K$-bit parent vectors according to a probabilistic function based on their corresponding fitness values $f\left[\check{\boldsymbol{b}}_q(y)\right]$. In this contribution, the so-called *sigma scaling* [7] is employed, where the selection probability $p\left(\check{\boldsymbol{b}}_q(y)\right)$ for a $3K$-bit individual to become a parent is a function of its own fitness as well as that of the mating pool's mean fitness $\bar{f}$ and its associated standard deviation σ_f, as formulated below [7] :

$$p\left(\check{\boldsymbol{b}}_q(y)\right) = \begin{cases} 1.0 + \frac{f\left[\check{\boldsymbol{b}}_q(y)\right] - \bar{f}}{2\sigma_f} & \text{if } \sigma_f \neq 0 \\ 1.0 & \text{if } \sigma_f = 0, \end{cases} \quad (9)$$

where

$$\bar{f} = \frac{1}{T}\sum_{q=1}^{T} f\left[\check{\boldsymbol{b}}_q(y)\right]; \; \sigma_f = \sqrt{\frac{\sum_{q=1}^{T}\left\{f\left[\check{\boldsymbol{b}}_q(y)\right] - \bar{f}\right\}^2}{T-1}}.$$

Crossover - The antipodal bits corresponding to the DBs and the EEBs of the $3K$-bit parent vectors are then exchanged using the so-called *uniform crossover* [7] process, in order to produce two $3K$-bit offspring vectors. The process of uniform crossover invokes a so-called *crossover mask*, which is a sequence consisting of $2\times K$ randomly generated 1s and 0s. The DBs and the EEBs are exchanged between the pair of $3K$-bit parent vectors at bit locations corresponding to a 1 in the crossover mask. The selection of $3K$-bit parents from the mating pool of $3K$-bit vectors is repeated, until a new population of P $3K$-bit offspring is produced, in order to perform the crossover process.

Mutation - The *mutation* process [7] refers to the alteration of the value of an antipodal bit corresponding to the DBs and to the EEBs in the $3K$-bit offspring vectors from 1 to -1 or vice versa, with a probability of p_m.

Elitism - Finally, upon invoking the process of elitism [7], we identify the lowest-merit $3K$-bit offspring in the population and replace it with the highest-merit $3K$-bit individual from the mating pool. This will ensure that the highest-merit $3K$-bit individual is propagated throughout the evolution process.

A. Complexity Issues

Since our proposed GA-based MUD optimises the LLF of Eq. 5, we will only consider its complexity in terms of the number of LLF computations required for the optimisation. The optimum MUD [1] using exhaustive search requires 2^K evaluations of the LLF. By contrast, our proposed GA-based MUD requires a maximum of $Y \times P$ LLF evaluations. In fact, the number of such LLF evaluations can be reduced by avoiding repeated evaluations of identical individuals, either within the same generation or across the entire iteration process, if the receiver has the necessary memory.

We should note here that the employment of our proposed GA-based MUD is not restricted to joint bit-by-bit detection. The truncated observation window can actually span over several users' bits. In such cases, the individuals of the GA must contain these bits. However, since there are more unknown bits to be detected, a higher P and perhaps more generations must be invoked.

IV. Simulation Results

In this section, our computer simulation results are presented, in order to characterise the DBEP performance of the GA-based MUD highlighted in the previous section. All the results in this section were based on evaluating the DBEP performance of a chip-asynchronous K-user CDMA system over single-path and two-path Rayleigh fading channels. For comparison, two sets of results will be presented, where the users' DBs will be detected by the GAs in both cases. However, according to our strategy S2, the EEBs are tentively estimated by the GAs, as suggested in our previous discussions. By contrast, in our conventional strategy S1, the EEBs are estimated based on previous hard decisions taken at the correlator outputs assuming the form of Eq. 3. Perfect power control, synchronisation and CIR estimation was assumed for all the simulations. We also assumed that the first bit $\boldsymbol{b}^0$ of all the users was known to the receiver.

Fig. 4 and Fig. 5 shows the DBEP performance and the EBEP performance, respectively, against w_k/N_0 for the GA-based $K = 10$-user MUD. As Fig. 4 shows, the DBEP of the GA-based MUD employing S1 was inferior to that of S2. The error floor observed for S1 in a single-path Rayleigh-fading scenario was caused by the high EBEP, as seen in Fig 5. The same outcome can be seen for a two-path Rayleigh-fading scenario, albeit only a small degradation was observed with respect to the single-user bound. On the other hand, we can see from Fig. 5 that the EBEP upon employing S2 is fairly low. As a result, the performance of the GA-based MUD utilising this strategy was not limited by the EEB errors and hence it was capable of achieving a near-optimum single-user-like DBEP performance. Furthermore, in comparison to the 'brute-force' optimum ML MUD requiring $2^{10} = 1024$ LLF evaluations, our proposed MUD is substantially less complex, requiring only a maximum of $10 \times 30 = 300$ LLF evaluations, yet performing close to the optimum performance of the ML MUD.

Fig. 6 shows the DBEP performance of our proposed MUD for $K = 15$ users. Because of the higher number of variables to be optimised, we increased the population size P to 40 and 50. We note from the figure that for $P = 40$, the GA employing strategy S1 now exhibits a more significant degradation in terms of its DBEP performance with respect to the single-user bound, than that employing strategy S2. This is due to the fact that as the number of users increases, the EBEP becomes higher. Increasing the population size to 50 does not show any significant improvement

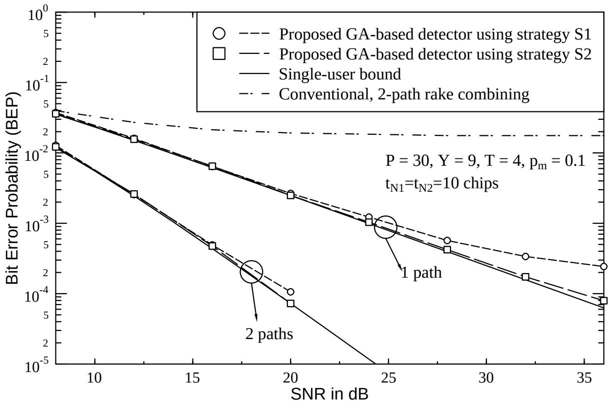

Fig. 4. The DBEP for the GA-based multiuser detector employing the EEB detection strategies S1 and S2 with a population size of $P = 30$ and supporting $K = 10$ users.

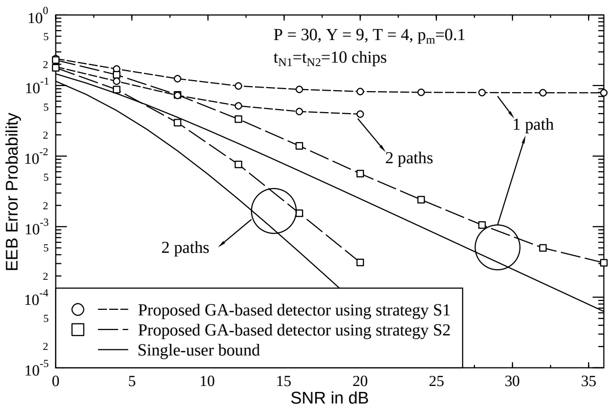

Fig. 5. The EBEP performance for the GA-based multiuser detector employing the EEB detection strategies S1 and S2 with a population size of $P = 30$ and supporting $K = 10$ users.

using the same strategy, since the performance is limited by the EEB interference. We also note that for $P = 40$ the DBEP performance of GAs employing strategy S2 did not match the single-user bound, even though it outperformed strategy S1. This was due to the limited population size, which was too small for optimising 2×15 variables. However, by increasing P to 50, the DBEP performance became near-optimum. Hence, while achieving a superior performance, the associated additional computational complexity has to be tolerated. An important observation is that when K is increased from 10 to 15 users, a near-optimum DBEP performance can be maintained by increasing the population size P from 30 to 50, while keeping $Y = 9$ by employing strategy S2. This constitutes a factor of 5/3 increase in the number of LLF computations. On the other hand, the computational complexity of the conventional optimum MUD using brute-force optimisation is increased by a factor of $2^5 = 32$.

V. Conclusions

In conclusion, we formulated the LLF of an asynchronous CDMA system in a multipath channel based on a truncated window size. GAs were invoked in order to improve

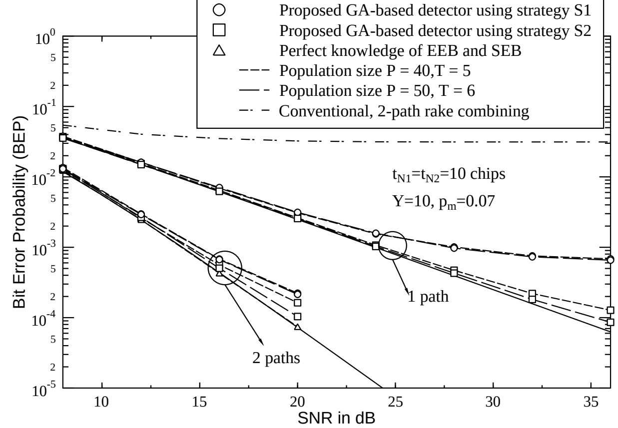

Fig. 6. The DBEP performance for the GA-based multiuser detector employing the EEB detection strategies S1 and S2 with population sizes of $P = 40$ and $P = 50$ and supporting $K = 15$ users.

the EBEP and at the same time to detect the DBs within the truncated observation window. By improving the reliability of the EEBs, simulation results showed that the GA-based MUD can achieve a near-optimal DBEP performance at the cost of a lower number of LLF evaluations compared to the optimum MUD using a brute-force approach. Furthermore, both the EEBs and the DBs are detected by the same GAs, resulting in potential complexity savings.

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