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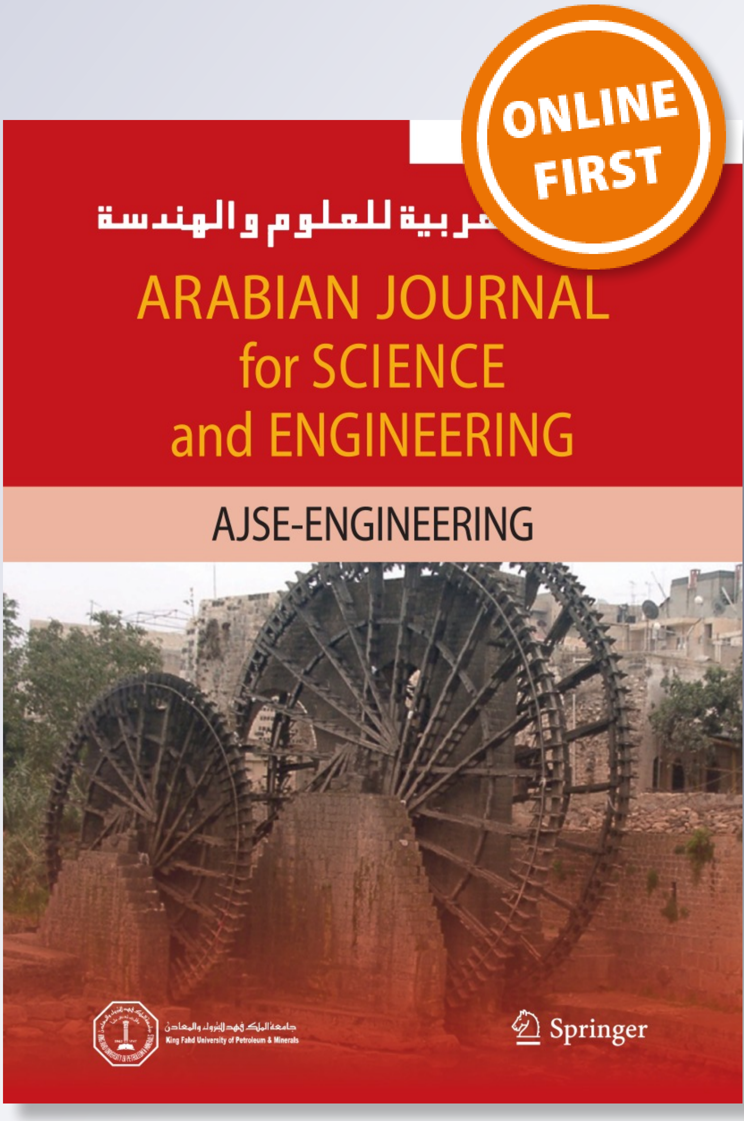

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RESEARCH ARTICLE - ELECTRICAL ENGINEERING

Multiuser Detection For DS-CDMA Systems Using Honeybees Mating Optimization Algorithm

N. Larbi · F. Debbat · A. Boudghene Stambouli

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Abstract The future wireless mobile communication systems will be required to support high-speed transmission rate and high quality of service. Direct sequence code division multiple access (DS-CDMA) is an important scheme for high-rate wireless communication. The capacity of DS-CDMA can be impaired by two problems; near-far effect and multiple-access interference (MAI). The use of conventional-matched filter detector for multiple users in DS-CDMA fails to combat any of these problems. The performance degradation caused by MAI can be overcome using multiuser detection (MUD). The use of maximum likelihood (ML) sequence estimation detector provides excellent results, but involves high computational complexity. In this paper, we propose a new meta-heuristic approach for MUD using honeybees mating optimization (HBMO) algorithm to detect the user bits based on the ML decision rule for DS-CDMA systems in additive white-Gaussian noise and flat Rayleigh fading channels. In order to improve the solutions generated by the HBMO, a second meta-heuristic method simulated annealing is used. By computer simulations, the bit error rate performance and the complexity curves show that the proposed HBMO-SA MUD is capable of outperforming the other conventional detectors and genetic algorithm detector.

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Keywords DS-CDMA · MUD · Honeybees mating optimization (HBMO) · Simulated annealing (SA)

الخلاصـة

إن أنظمة الاتصالات اللاسلكية المتنقلة المستقبلية مطالبة بإرسال المعلومات بسرعة عالية مع جودة خدمة ممتازة. وتعتبر تقنية النفاذ المتعدد بتقسيم الشفرة إلى تتابعات مباشرة (DS-CDMA) تقنية مهمة في أنظمة الاتصالات اللاسلكية الناقلة للمعلومات بسرعة عالية. وهناك مشكلتان يمكن أن تعيقا قدرة DS-CDMA، وتأثير البعد-القرب والتداخل متعدد الوصول (MAI). وفشل استخدام الكاشف المرشح التلاؤمي التقليدي في DS-CDMA لمعالجة أي من هذه المشاكل. ولكن يمكن التغلب على تدهور الأداء الناتج عن التداخلات (MAI) باستخدام الكاشف متعدد المستخدمين. ((MUDإنّ استعمال الكاشف الذي يعتمد على الحد الأقصى للتشابه (ML) يعطي نتائج ممتازة ولكن بتعقيد حسابي عالي. ونقترح في هذه الدراسة طريقة ما فوق إرشادية جديدة (ميتاهيورستيك) للكاشفات متعددة المستخدمين لنظام DS-CDMA في قناة ضوضاء غوسية بيضاء مضافة (AWGN) وقناة خفوت رايلي (Rayleigh fading channels). وتعتمد هذه المقاربة على خوارزمية تكاثر نحل العسل (HBMO) مهجنة مع طريقة ما فوق إرشادية أخرى هي طريقة تمثيل الانصهار (SA) وهذا من أجل الحصول على امتيازية الحلول. وأظهرت منحنيات المحاكاة الحاسوبية لخطأ البيتات والتعقيد الوقتي في الأداء بأنّ الطريقة المقترحة قدمت أحسن النتائج مقارنة بغيرها من طرق الكشف الكلاسيكية ومقاربة الخوارزميات الجينية.

1 Introduction

Direct sequence code division multiple-access (DS-CDMA) system is the most popular multiple-access technology for wireless communication. In DS-CDMA, near-far effect and multiple-access interference (MAI) are regarded as the main source limiting the system capacity [1]. The use of conventional-matched filter (MF) detector for multiple users

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in DS-CDMA fails to combat any of these problems. The performance degradation caused by MAI can be overcome using multiuser detection (MUD), where information about the other users is used in detection. The theory of multiuser detection technique has been developed during the 90s, but the interest on the domain increased with the development of modern mobile communications systems. The domain is still under research, since it has not been found yet an optimal solution that maximizes the performances, minimizes the cost and takes into account the channel impairments and system imperfections.

A maximum likelihood (ML) multiuser receiver was first proposed by [2]; however, the complexity of this optimal multiuser detector increases exponentially with the number of users, which makes it difficult to implement in practical system. As consequently, a variety of suboptimum alternatives detectors have been proposed [3–5].

Recently, the meta-heuristic methods have emerged as an efficient optimization tool in various engineering problems [6–9]. In DS-CDMA MUD, several research studies have been made in order to determine less complex receiver algorithms. The global optimization techniques like Genetic Algorithms (GA) [10–14], micro-genetic algorithms (μ-GA) [15], Evolutionary Programming (EP) [16,17], Tabu Search (TS) [18] and Particle Swarm Optimization (PSO) [19] have been applied for optimal detection in DS-CDMA systems.

In this article, a new multiuser detection scheme is proposed, which uses honeybee mating optimization (HBMO) meta-heuristic algorithm to detect the user bits based on the ML decision rule for DS-CDMA systems. The HBMO algorithm is a typical swarm-based approach to optimization, in which the search algorithm is inspired by the process of mating in real honeybees. The behavior of honeybees is the interaction of their genetic potentiality, ecological and physiological environments, and the social conditions of the colony, as well as various prior and ongoing interactions between these three parameters [20]. A honeybee colony consists of the queen(s), drones, worker(s), and broods. The HBMO algorithm mimics the natural mating behavior of the queen bee when she leaves the hive to mate with drones in the air. Each time a mating takes place, the genetic pool is enhanced to by adding sperm to the spermatheca. Abbass [21] developed an optimization algorithm based on honeybee marriage process. Unlike the other heuristic techniques, the HBMO algorithm has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. HBMO have been employed for solving many complex optimization problems in numerous fields. It has been used in water resources optimization [20]. It has been proposed to tune optimal gains of a proportional integral derivative controller for load frequency control design in an interconnected power system [22] and on state estimation of power distribution system including distributed generators [23]. Also, it has been applied to extract the linear monthly operation rules of reservoirs for both irrigation and hydropower purposes [24], and it has been used to solving examination timetabling problems [25].

In this article, the proposed approach was hybrid with the simulated annealing (SA) as workers in order to achieve a better intensification of research in the areas of solution generated after the HBMO mating flight phase. This avoids local minima and rapidly approaching to the best solution. The efficiency optimization of SA has been shown in various research areas [26–30]. The SA is a technique based on successive update steps where the update step length is proportional to an arbitrarily set parameter, which can play the role of a temperature. Then, in analogy with the annealing of metals, the temperature is made high in the early stages of the process for faster minimization or learning and then is reduced for greater stability.

The article is organized as follows: the problem formulation is provided in Sect. 2. In Sect. 3, we describe the HBMO-based multiuser detection. In Sect. 4, simulations and results are given. Finally, conclusions are drawn in Sect. 5.

2 Problem Formulation

Consider a DS-CDMA system shared by K synchronous users simultaneously as illustrated in Fig. 1. The model presented here is the discrete-time model. We consider a binary phase-shift-keying (BPSK) transmission through two different types of channels: the first one is an additive white-Gaussian noise (AWGN) channel, and the second one is flat Rayleigh fading channel.

2.1 AWGN channel

The k^{th} user is assigned a signature sequence $\mathbf{c}_k(n)$, and the received amplitude of the k^{th} user is A_k. The combined received signal from the channel is given by the sum:

$$\mathbf{y}(n) = \sum_{k=1}^{K} A_k \mathbf{b}_k \mathbf{c}_k(n) + \sigma \aleph(n) \tag{1}$$

where,

- $\mathbf{b}_k \in \{+1, -1\}$ is the input bit-vector corresponding to the k^{th} user.
- A_k is the received amplitude of the k^{th}user.
- $\aleph(n)$ is White-Gaussian Noise sequence.
- σ is the standard deviation of the noise present in the channel.

The normalized cross-correlations of the signature waveforms are defined as:

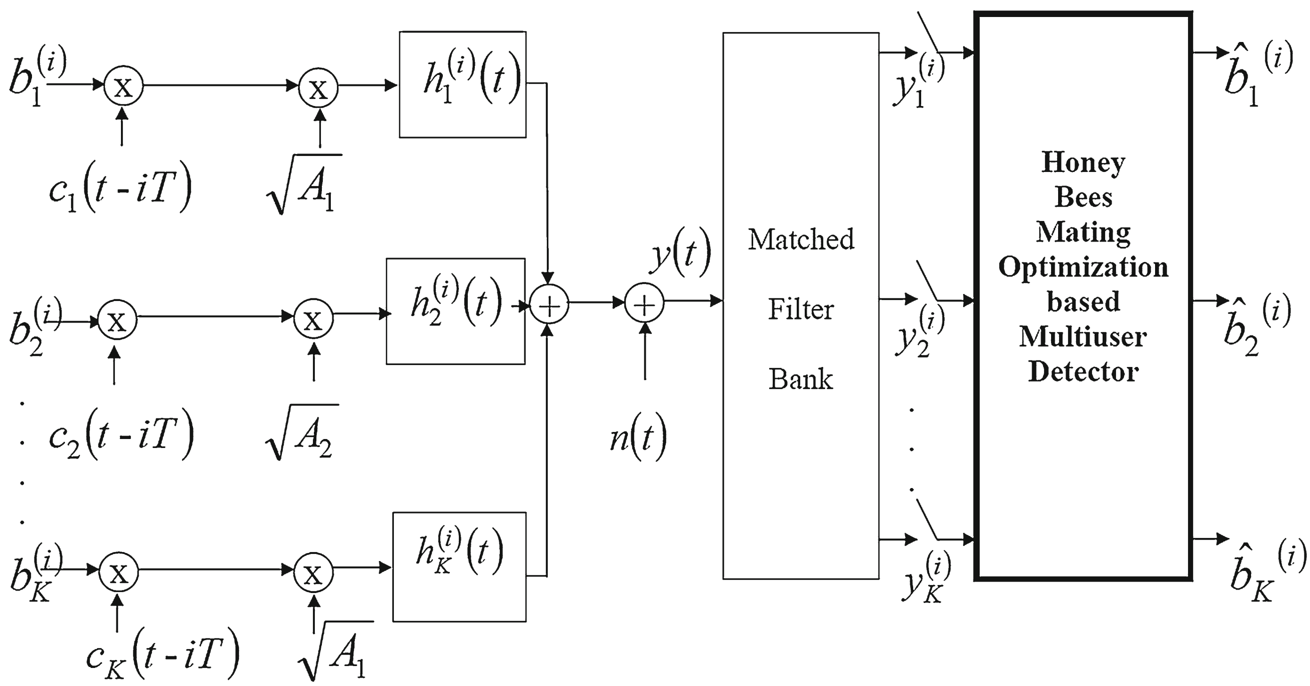


Fig. 1 HBMO-based multiuser detector

$$\rho_{ij} = \langle c_i, c_j \rangle = \sum_{l=1}^{N} c_i(l) c_j(l) \tag{2}$$

where, N is the length of the signature sequence.

The Matched Filter in digital communication system is used to generate sufficient statics for signal detection. In the case of multiple-access system, the receiver consists of a bank of MF each matched to the corresponding users signature waveforms, as shown in Fig. 1. The out put of the j^{th} correlator is given by:

$$y_j = \sum_{n=1}^{N} y(n) c_j(n) \tag{3}$$

When expanded, the above equation becomes:

$$y_j = \sum_{k=1}^{K} A_k b_k \left(\sum_{n=1}^{N} c_k(n) c_j(n) \right) + \sigma \sum_{n=1}^{N} \aleph(n) c_j(n) \tag{4}$$

$$y_j = \sum_{k=1}^{K} A_k b_k \rho_{jk} + n_j \tag{5}$$

The above expression can be written in matrix notation form:

$$\mathbf{y}_j = \mathbf{r}_j \mathbf{A} \mathbf{b} + \mathbf{n}_j \tag{6}$$

where,

- $\mathbf{r}_j = \left[\rho_{j1}, \rho_{j2}, \ldots, \rho_{jK} \right]^T$, the cross-correlation vector of the j^{th} user with all other users,
- $\mathbf{A} = diag(A_1, \ldots, A_k)$, the matrix of received signal amplitudes,
- $\mathbf{b} = [b_1, \ldots, b_k]^T$, the vector of the received bits.

In matrix notation, the above equation can be represented as:

$$\mathbf{y} = \mathbf{RAb} + \mathbf{n} \tag{7}$$

It is well known that in the case of detecting signals corrupted by AWGN, the decoder that minimizes the probability of error is the ML decoder. The ML criterion is based on selecting the input bit that minimizes the Euclidean distance between the transmitted symbol (corresponding to the input bit) and the received symbol in the case of multiuser detection, the Euclidean distance between a transmitted symbol vector corresponding to the input bit-vector $\mathbf{b}$ and the received symbol vector is given by

$$d(b) = \sum_{n=1}^{N} \left[y(n) - \sum_{k=1}^{K} A_k b_k c_k(n) \right]^2 \tag{8}$$

Expanding the above expression, we get:

$$d(b) = \sum_{n=1}^{N} y(n)^2 - 2 \sum_{k=1}^{K} A_k b_k \sum_{n=1}^{N} y(n) c_k(n) + \sum_{n=1}^{N} \left(\sum_{k=1}^{K} A_k b_k c_k(n) \right)^2 \tag{9}$$

The first term in the expression is independent of $\mathbf{b}$ and so it can be removed from the minimization process (instead we define a likelihood function $\Omega(b)$ that differs from $d(\mathbf{b})$ by a constant). Using the definitions of y_j in Eq. (3) and using the definitions of $\mathbf{A}$ and $\mathbf{b}$, the above expression can be simplified as:

$$\Omega(b) = -2N\mathbf{b}^T\mathbf{Ay} + N\mathbf{b}^T\mathbf{ARAb} \tag{10}$$

Again, removing the common factor N and using the fact that maximizing the negative of a function is same as minimizing the function, the problem of optimal multiuser detection can be stated as:

$$\begin{aligned} &Minimize,\ \Omega(b) = \mathbf{b}^T\mathbf{ARAb} - 2\mathbf{b}^T\mathbf{Ay} \\ &\qquad\qquad \text{Subject to, } b \in \{+1, -1\}^K \end{aligned} \tag{11}$$

$$\hat{b} = \arg\left\{\min_{b\in\{+1,-1\}^K} \mathbf{b}^T\mathbf{ARAb} - 2\mathbf{b}^T\mathbf{Ay}\right\} \tag{12}$$

The minimization problem stated above is a combinatorial optimization problem, since the variables of the optimization problem are basically limited to a finite set. The straightforward method for solving such combinatorial optimization problem is an exhaustive search over all the possibilities. In the above case, since $b \in \{+1, -1\}^K$, there are 2^K possibilities. Thus, the search space increases in a geometric fashion with the number of users [2]. And it has been shown that traditional optimization algorithms are inefficient for its solution. In this paper, the HBMO is applied to solve the optimal multiuser detection problem using the log-likelihood function and (13) is used as basic fitness function for the heuristic algorithm.

$$F(b) = \mathbf{b}^T\mathbf{ARAb} - 2\mathbf{b}^T\mathbf{Ay} \tag{13}$$

2.2 Flat Rayleigh Fading Channel

Each user's signal is assumed to propagate over a flat Rayleigh fading channel, and the fading envelope of each path is statistically independent for all users. The complex low-pass channel impulse response for the link between the kth user's transmitter and receiver can be written as:

$$h_k(t) = \alpha_k(t)e^{j\varphi_k(t)}\delta(t), \quad \forall k = 1, \ldots, K \tag{14}$$

where the amplitude$\alpha_k(t)$ is a Rayleigh distributed random variable and the phase$\varphi_k(t)$ is uniformly distributed between$[0, 2\pi]$.

The joint optimum decision rule for the BPSK-modulated K-user CDMA system based on the synchronous system model can be derived from [2], which is expressed in vectorial notation as:

$$\Omega(b) = 2\Re\left[\mathbf{b}^H\mathbf{C}^*\mathbf{Z}\right] - \mathbf{b}^H\mathbf{C}^*\mathbf{RCb} \tag{15}$$

where

- $\mathbf{C} = diag\left[\alpha_1 e^{j\varphi_1}, \alpha_2 e^{j\varphi_2}, \ldots, \alpha_K e^{j\varphi_K}\right]$
- $\mathbf{b} = \left[b_1, b_2, \ldots, b_K\right]^T$
- $\mathbf{Z}$ =output vector of the matched filters

More specifically, $(.)^H$ is the complex conjugate transpose of the matrix (.), and $(.)^*$ is the complex conjugate of the matrix (.). For BPSK modulation, the term $\mathbf{b}^H$ in Eq. 15 is substituted by $\mathbf{b}^T$, which is the transpose of the matrix $\mathbf{b}$, since only the real component is considered in the context of BPSK modulation. The decision rule for the optimum CDMA multiuser detection scheme based on the maximum likelihood criterion is to choose the specific symbol combination $\mathbf{b}$, which maximizes the correlation metric of Eq. 15, yielding:

$$\hat{\mathbf{b}} = \arg\left\{\max_{\mathbf{b}}\left[\Omega(\mathbf{b})\right]\right\} \tag{16}$$

3 HBMO-based Multiuser Detection

3.1 HBMO Principles

In this article, the HBMO Algorithm is used for solving the optimal multiuser detection problem. The reasons for its choice are:

1. It is applied for the first time for the solution of this problem.
2. It has been proven to be efficient as an optimization tool in various domains [20–25] [31–36].
3. It has a strong ability to find the most optimistic results [22]
4. It promotes hybridization with other methods. Since the mating process promotes the introduction of genetic operators such as crossover and the improvement process (by workers) can utilize various heuristics and metaheuristics to local search [37–39].

The HBMO meta-heuristic belongs to the class of nature-inspired algorithms. The mating flight may be considered as a set of transitions in a state space (the environment), where the queen moves between the different states in some speed and mates with the drone encountered at each state probabilistically. At the start of the flight, the queen is initialized with some energy content and returns to her nest when the energy is within some threshold from zero or when her spermatheca is full. A drone mates with a queen probabilistically using an annealing function as [22]:

$$\Pr ob(Q, D) = e^{\frac{-\Delta(F)}{S(t)}} \tag{17}$$

where, Prob(Q,D) represents the probability of the drones successful mating; that is, the probability of adding the sperm of drone D to the spermatheca of queen Q. $\Delta(F)$ represents the absolute difference between the drone fitness which constitutes the trial solution and the queen's fitness or best known solution ($\Delta(F) = [F(Q) - F(D)]$). However, according to the annealing function, the queen's speed is high at the beginning of her flights; therefore, the probability of mating is high, as it is when the fitness of the drone is as good as the queen's. As the mating flight continues, the queen's speed and energy decays according to equations (18) and (19).

$$Speed(t+1) = \alpha \times Speed(t) \tag{18}$$

$$Energy(t+1) = Energy(t) - \gamma \tag{19}$$

Where α is speed reduction factor and γ is the amount of energy reduction after each transition ($\alpha, \gamma \in [0, 1]$). Therefore, a HBMO algorithm may be constructed with the following five main stages:

1. The algorithm starts with the mating flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones). A drone is then selected from the list at random for the creation of broods.
2. Creation of new broods (trial solutions) by crossoverring the drones' genotypes with the queens.
3. Use of workers (heuristics) to conduct local search on broods (trial solutions).
4. Adaptation of workers fitness based on the amount of improvement achieved on broods.
5. Replacement of weaker queens by fitter broods.

3.2 Proposed HBMO-SA Algorithm

The HBMO-SA algorithm is proposed and shown in Fig. 2.

3.3 Generation of the Population

The proposed HBMO-SA algorithm is detailed as follows:

1. The input data are defined, including HBMO parameters: population size p, broods populations size B, spermatheca size η, initial and final queen speed $Speed_{initial}$, $Speed_{final}$, initial and final queen energy $Energy_{initial}$, $Energy_{final}$, speed reduction factor α, energy reduction factor γ and HBMO-SA algorithm iteration numbers itr. Additionally the SA parameters: initial temperature $T_{initial}$, final temperature T_{final}, temperature reduction factor β, number of iterations at fixed temperature itr_1. As well as the DS-CDMA MUD parameters: the number of users K and the length of spreading sequence N.
2. The algorithms start by initializing the population. The output of the Matched Filter is included as the first initial trial vector of the generation of the population

$$s_1 = \hat{b}_{MF} = sign(y) \tag{20}$$

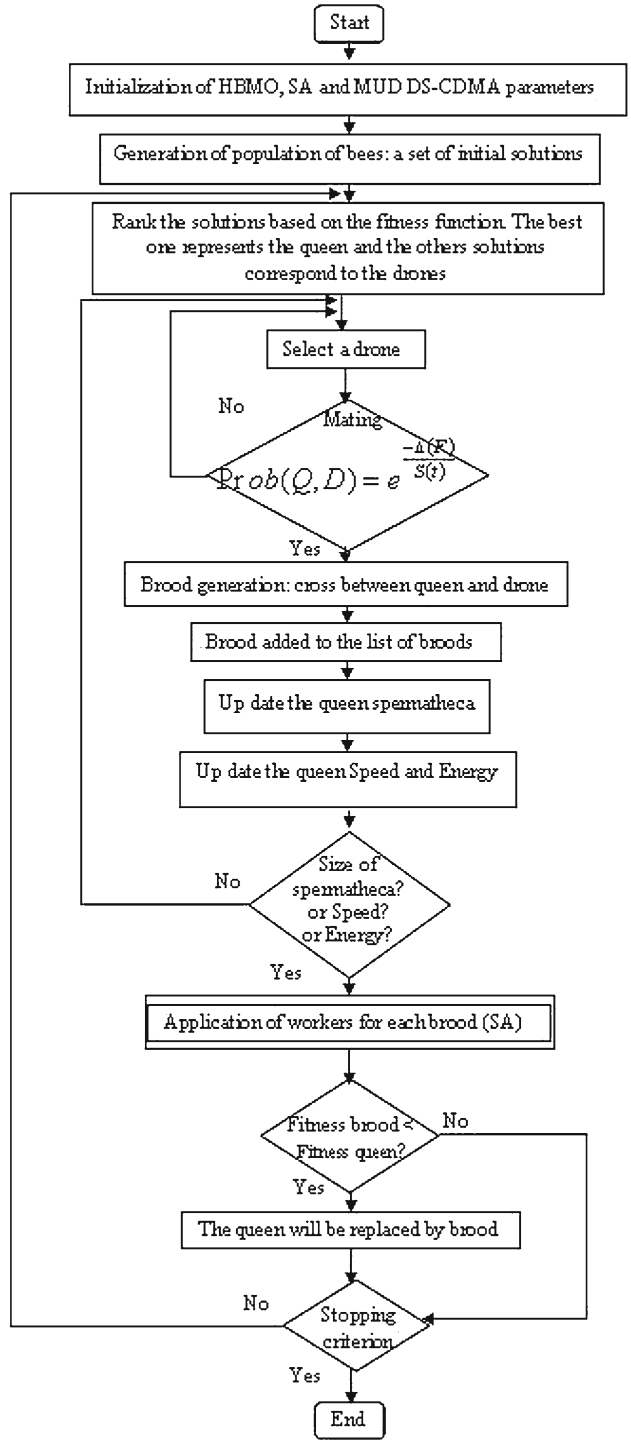


Fig. 2 HBMO-SA algorithm for MUD in DS-CDMA

The other initial vectors of the population are determined by setting

$$s_i = S_i \sim \mathrm{U}\{-1, +1\}^K, i = 2, \ldots, p \tag{21}$$

where S_i is a random vector and s_i is the outcome of the random vector,

$$s_i = \left[s_{i,1} \ \ldots \ s_{i,K} \right]^T \tag{22}$$

$U\{-1,+1\}^K$ denotes a K-dimensional uniformly distributed binary vector.

3. For each individual of the population $s_i, i = 1, \ldots, p$, the fitness value is calculated by:

$$F(s_i) = s_i^T ARAs_i - 2s_i^T Ay \tag{23}$$

4. Ordering each individual of the population according to the fitness value. The minimum value represents the best solution. The individual that has the minimum fitness value represents the best solution and should be selected as a queen. The rest of the solutions represent the drones.

3.4 The Mating Flight

At the start of a mating flight, the queen flies with her maximum speed. A drone is randomly selected from the population of drones. The mating probability is calculated based on the objective function values of the queen and the selected drones (Eq. 17). A number between 0 and 1 is randomly generated and compared with the calculated probability. If it is less than the calculated probability, the drone's sperm is sorted in the queen's spermatheca and the queen speed decreases. Otherwise, the queen speed decreases and another drone is selected from the population of drones until the speed of the queen reaches her minimum speed or the queen's spermatheca is full. By using the crossover of the drone and the queen's genotypes, a new brood (trial solution) is generated. The workers are then used to improve the brood.

3.5 Broods Improvement by Workers Using Simulated Annealing Algorithm

In this step, SA process is applied to each individual of brood population in order to improve them. This process is summarized as follow:

1. Initialization of the best solution of the SA algorithm by the selected brood.
2. Generation of a neighboring solution (new solution) from the current solution. The generation is performed by $F(x)$ which is a random transformation function of the solution x, in our case; it is based on a single mutation between elements selected randomly of the current solutions vector. If the fitness value of the new solution is less than the fitness value of the current solution, the current solution becomes the new solution. If not this current solution will become the new solution according to the Boltzmann probability $e^{\frac{-|\Delta Fitness|}{T}}$.
3. The fitness of this new solution is also compared with the fitness of the improved brood, if the fitness of this new solution is less than the fitness of the improved brood, improved brood will be the new solution.
4. This process is repeated for a number of iterations fixed in advance.
5. After the updated temperature, we test the algorithm stopping criterion $T < T_{final}$.

The description of this process is shown in Fig. 3.

We always keep the best solution found during the execution of the process, which will represent, at the end, the improved brood.

The fitness of the improved brood is in addition compared with the queen fitness; if the fitness of the improved brood is less than the queen fitness, the queen will be replaced by the improved brood. HBMO- SA process will be repeated until a stopping criterion initialized in initial parameters.

4 Simulations and Results

In this section, we present several simulations to evaluate the performance of multiuser detector based on the HBMO combined with simulated annealing (SA). The objective of these simulations is to investigate the bit error rate (BER) performance of the detector. The BER for each user is calculated by varying signal to noise ratio (SNR) per bit, namely Eb/No. Synchronous DS-CDMA systems over an AWGN and Rayleigh fading channels, respectively, with Gold spreading code $N = 31$ are used. All the users are transmitting with the same power. In HBMO algorithm, the number of queens is set equal to one, because in the real life only one queen will survive in a hive, and the number of broods is set equal to the number corresponding to the queen's spermatheca size.

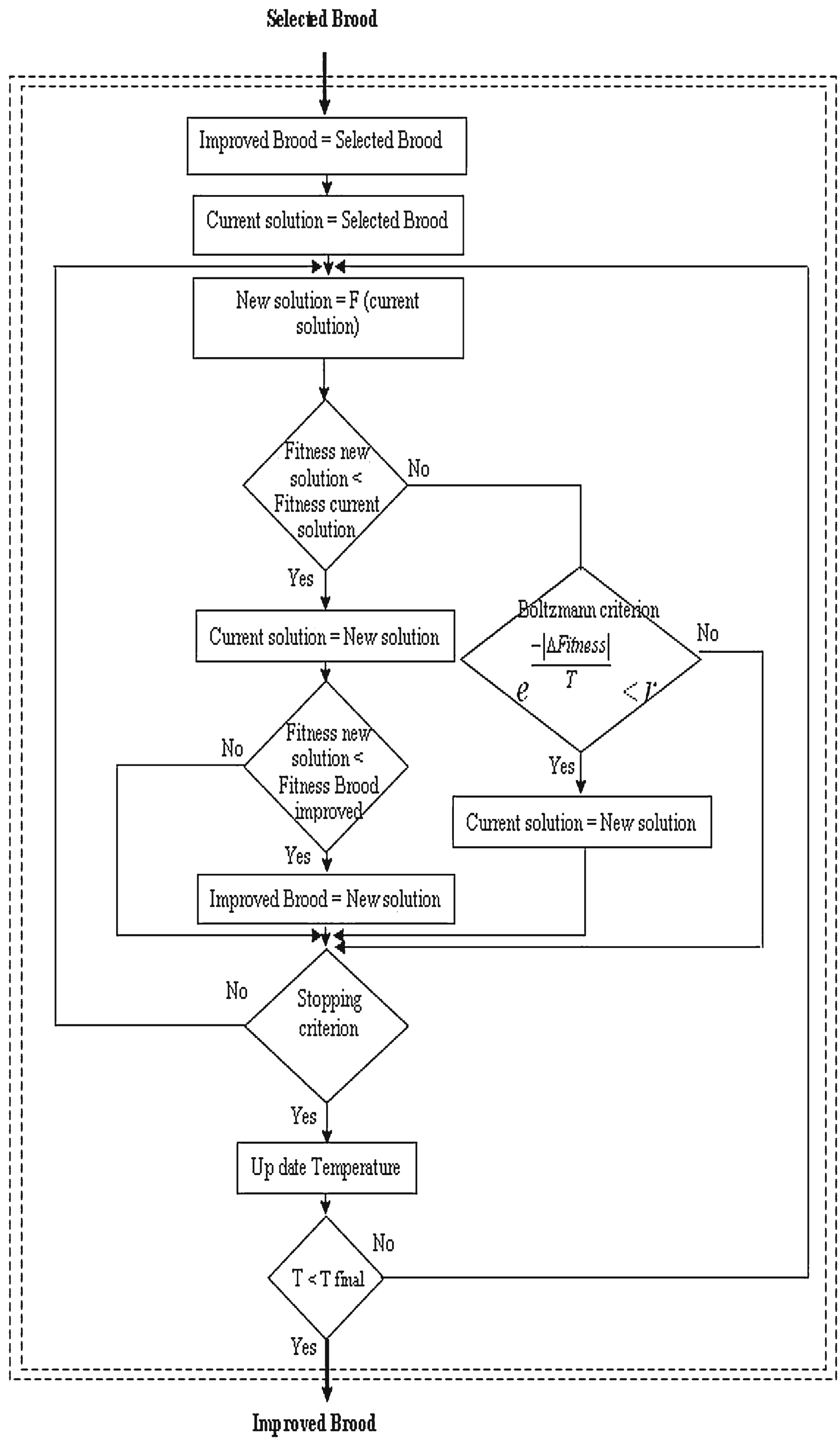
4.1 HBMO-SA Performances Evaluation Under AWGN Channel

Figure 4 illustrates a comparative BER performance of various detectors. In this simulation, the number of users is $K = 26$, the predefined number of iteration $itr = 100$, and the population size is $p = 100$. We observe that the proposed HBMO-SA algorithm outperforms the other detectors such as the matched filter, decorrelator and MMSE since it presents the least BER.

The performances of the proposed algorithm in this article depend on the choice of its parameter values. For this purpose, a series of test were carried out to find the optimal values in term of detection efficiency.

As observed in Fig. 5, for small population p less than 50, the HBMO-SA detector performance is degraded to

Fig. 3 The simulating annealing (SA) computational flowchart



$BER = 10^{-2}$; however, for populations of large size p more than 150, the detector presents the best performances with $BER = 10^{-5}$. Therefore, the population size plays an important role in the performance of this algorithm.

In the case of p less than 50, the detector performance for $K = 16$ are lower than for $K = 10$. This is similar in the case p more than 150 the detector performance for $K = 30$ is lower than for $K = 20$. Thus, for the same population

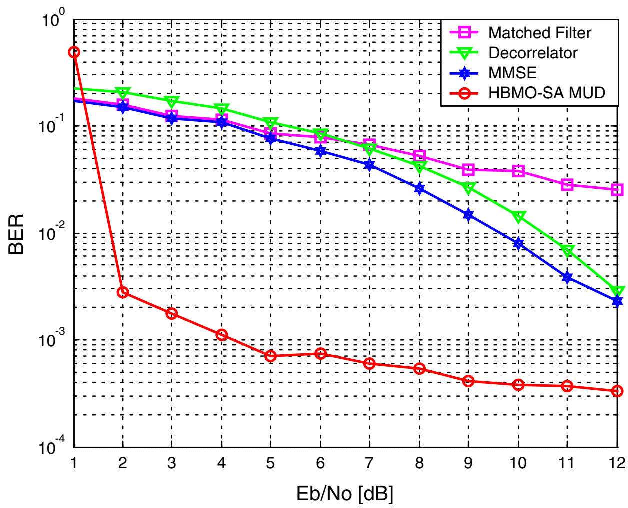


Fig. 4 The BER performance comparison of HBMO-SA with various detectors in AWGN channel ($N = 31$, $K = 26$, $p = 100$)

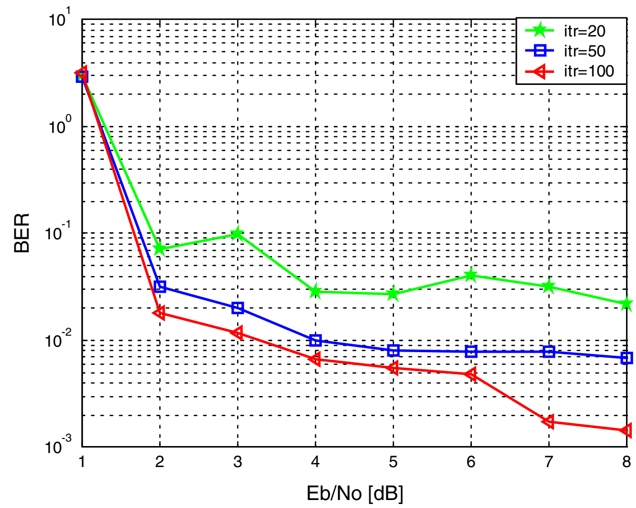


Fig. 6 The BER performance comparison of various iteration number ($N = 31$, $K = 26$, $p = 100$)

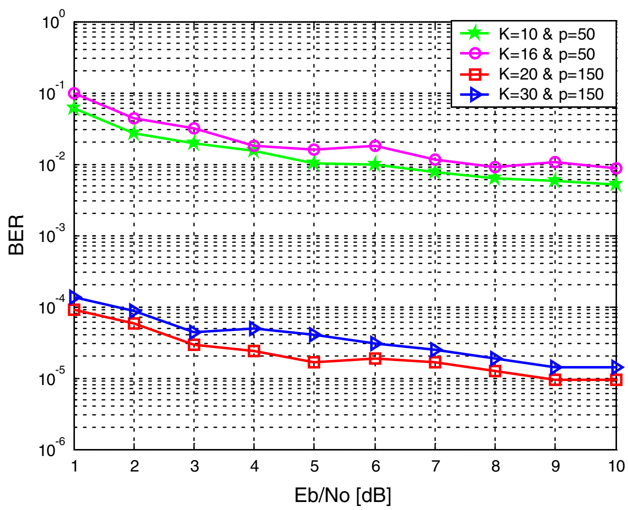


Fig. 5 The BER performance comparison of various user numbers (K) and population size (p)

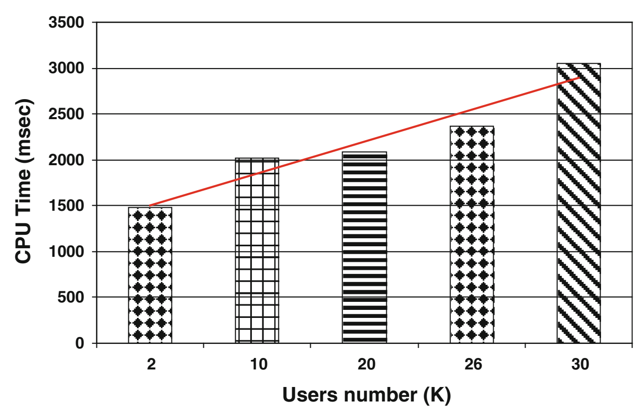


Fig. 7 The CPU Times comparison of various user numbers ($N = 31$, itr $= 100$, $p = 100$)

and with different users number, the detector performance is better if the number of users is smaller.

The main observation is that the HBMO-SA detector offers excellent performances if the initial population is increased even in the case of a high number of users (very small *BER* of about $10^{-4}$for a large number of users, more than 20 users). This is considered as a strong point for the proposed algorithm compared with other type of detectors.

Figure 6 shows the algorithm performance evolution according to the total iteration numbers (*itr*). The algorithm gives the best performances for a high iteration numbers.

A common form in order to compare algorithms complexity can be done through the: $\boldsymbol{O}$ notation which means the order of magnitude of the algorithm complexity, number of computed instructions or mean computational time required for a specific optimization [40]. In this work, the HBMO-SA algorithm complexity is presented by using mean computational time as illustrated in Fig. 7. The CPU time is obtained in the MATLAB environment on a 1.66 GHz; Pentium Intel(R) Core (TM)2 CPU T5500; personal computer with 1.00 Go of RAM.

The execution time is not significantly affected by increasing the number of users because it does not evolve exponentially.

4.2 HBMO-SA Performances Evaluation Under Flat Rayleigh Fading Channel

In the following, we consider the performance of the proposed algorithm under flat Rayleigh fading channel. We use one path fading channel and the path gain is Gaussian distributed with zero mean and equal variance.

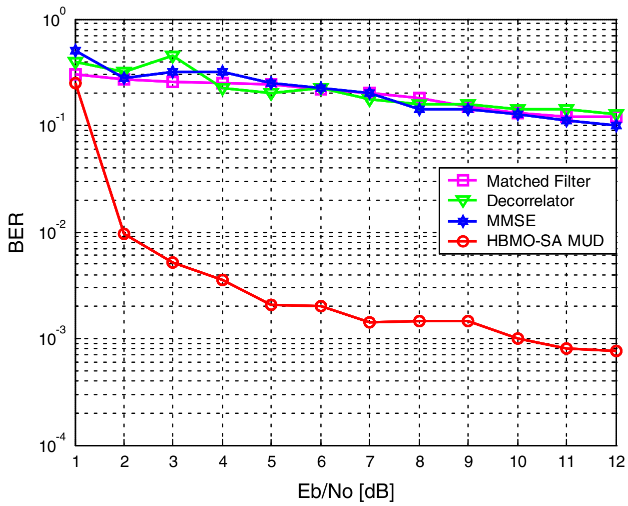


Fig. 8 The BER performance comparison of HBMO-SA with Matched Filter, Decorrelator, and MMSE detectors in flat Rayleigh fading channel ($N = 31$, $K = 26$)

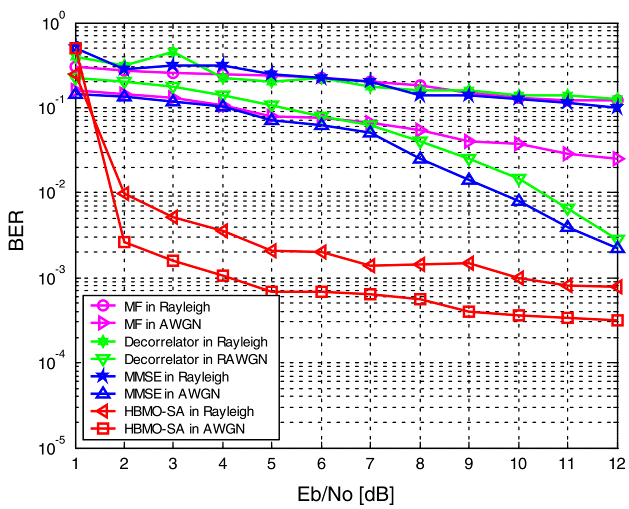


Fig. 9 The BER performance in AWGN and flat Rayleigh fading channels of all detectors ($N = 31$, $K = 26$, $p = 100$)

Figure 8 shows a comparison between the HBMO-SA and conventional detectors such as the Matched Filter, the MMSE and the Decorrelator in multi-user detection (MUD) context (N=31, K=26) in flat Rayleigh fading channel.

From Fig. 8, one can observe that the performance of the Matched Filter, the MMSE and the Decorrelator are very similar. However, it is observed that HBMO-SA is capable of achieving a better performance than the other detectors. By studying these results, we can assess, for Eb/No=12, the net BER amelioration in the adopted approach ($\sim 10^{-3}$) compared with the one obtained from classical detectors ($\sim 10^{-1}$).

Figure 9 illustrates BER performance comparison of the various detectors in both AWGN and flat Rayleigh fading

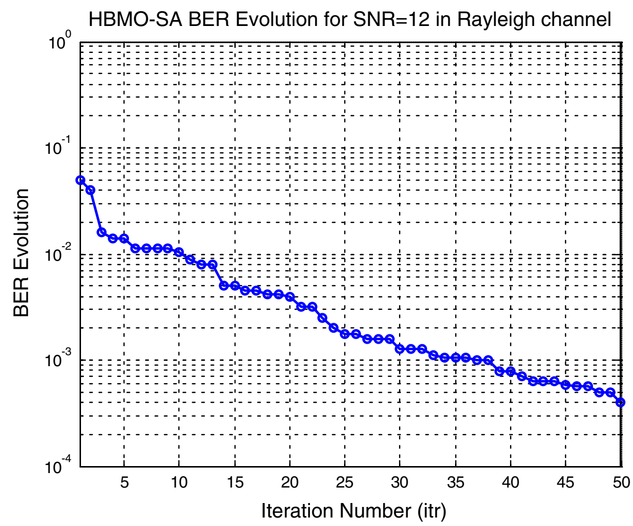


Fig. 10 The BER Evolution versus Iteration number performance of HBMO-SA MUD in flat Rayleigh fading channel ($N = 31$, $K = 30$, $p = 100$, Eb/No $= 12\,dB$)

channels. In this simulation, the same algorithm parameters ($N = 31$, $K = 26$, $p = 100$, $itr = 100$) are used.

We can see that the performance of the proposed algorithm HBMO-SA under flat Rayleigh fading channel are degraded in comparison with AWGN channel, but still perform better than the other detectors in both channels. The HBMO-SA algorithm has a good transmission quality even in flat Rayleigh fading channel.

In order to illustrate the improvement of the HBMO-SA solution quality in function of the search space exploration, the BER evolution in function of the algorithm iteration numbers for a fixed SNR value (Eb/No =12dB, *N=31, p=100, K=30*) is presented in flat Rayleigh fading channel.

Figure 10 shows the algorithm BER evolution according to the total iteration numbers (*itr*) for a fixed SNR value (*SNR=12dB)*. The algorithm gives the best performances for a high iteration numbers in Rayleigh channel.

In order to compare the performances of the HBMO-SA MUD with another heuristic algorithm, we have considered a Genetic Algorithm (GA). Since GA has been widely used in the MUD for CDMA system [11–13] [40,41], GA is a stochastic optimization algorithm, which adopts Darwin's theory of survival of the fittest. To apply GA, the following issues are taken into consideration: the methodology to produce the initial population, the fitness function, and the genetic operators such as crossover and mutation. The GA algorithm proposed in comparison with HBMO-SA in this study is composed of the following steps:

1. *Initial population generation*: For the MUD problem the estimates from the Matched Filter outputs is adopted as an initial individual of the population and the other members of the first population is randomly generated

(we used the same population generation process as employed in the HBMO-SA algorithm).

2. *Fitness value calculation*: It is necessary to find a value associated with each individual performance through the fitness value measured by Eq. (14) in DS-CDMA MUD context.
3. *Selection*: this operation is based on the Roulette-wheel rule [42].
4. *Crossover*: this operation combines parts from the two parents in order to produce offsprings that present genetic material from both parents. In this paper, a single-point crossover is adopted.
5. *Mutation*: this operation consists in a change in the individual's characteristics. These changes are necessary for introducing and maintaining genetic diversity. One manner to implement the mutation is generating a perturbation (noise), which will be added to each gene. In this work the Gaussian distribution is adopted.
6. *Replacement strategy*: this operation corresponds to the determination of the number of candidate vectors to be kept in the next generation. The elitism strategy forces the genetic algorithm to retain some number of the best individuals at each generation. In this work, only the best *pop* individuals from the joint population of parents and offsprings are maintained for the next generation.
7. *Termination Criteria*: In this work, the genetic optimization process will be stopped after a fixed number of generations (G).

In Fig. 11, we compare both HBMO-SA (p=100, itr=100) and GA MUD with the other classical detectors in terms of BER under flat Rayleigh fading channel. The GA algorithm parameters used in the following simulation are the population size *pop* is 100; the number of generation $G$is 50; the probability of crossover is 0.7; and the probability of mutation is 0.1.

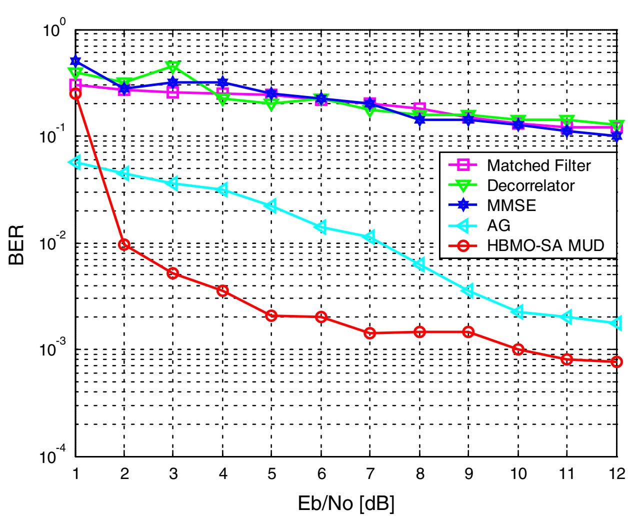


Fig. 11 The BER performance comparison of Matched Filter, Decorrelator, MMSE, AG and HBMO-SA MUD in flat Rayleigh fading channel ($N = 31$, $K = 25$)

As seen in Fig. 11, the HBMO-SA algorithm outperforms the GA algorithm which is considered one of the best algorithms used in DS-CDMA MUD in flat Rayleigh fading conditions.

5 Conclusions

DS-CDMA multiuser detection is one of the fastest growing areas in wireless communications. MUD problem in DS-CDMA system is a typical combinatorial optimization problem, i.e., it is an NP problem. The objective of this work is to investigate the performances of the new algorithm based on HBMO meta-heuristic approach combined with simulated annealing (SA) in order to improve the solutions generated by the HBMO-SA and compare the results with the existing detectors such as matched filter, decorrelator, MMSE and other meta-heuristic method. The performances in terms of BER are compared in both AWGN and flat Rayleigh fading channels for a synchronous DS-CDMA system using gold sequences. From the simulations analysis conducted in previous section, many fundamental results are highlighted. It was shown that the HBMO-SA MUD outperforms matched filter, decorrelator, MMSE and GA algorithm in terms of BER performance. It was also shown that the HBMO-SA BER performances are significantly affected by the number of users, the population size, iteration number and the channel model used (AWGN or flat Rayleigh fading). It offers excellent performances if the initial population is high even in the case of a high number of users. The algorithm mean computational time increases with the increase of the parameter values as well as the user number; however, it is not affected exponentially with regards to the user number due to its low structured complexity.

The proposed approach, HBMO-SA MUD for DS-CDMA systems, can be applied to real system such as IEEE 802.11b wireless local area network (WLAN) since the physical layer of this standard is based on direct sequence spread spectrum (DSSS) technology. The HBMO-SA algorithm can be implemented in VHDL for FPGA (Field-Programmable Gate Arrays). This detector (receiver) consists mainly of DBPSK demodulator, programmable chip sequence generator (Barker code generator), matched filters and HBMO-SA detector blocks. The most important goal of HBMO-SA algorithm is to reach high-quality detection in a multiuser environment. Wi-Fi is implemented in different environments such as home users, public and enterprise applications. Different types of terminals are already equipped with Wi-Fi such as laptops, cameras, automobiles and mobile phones. Some of our previous work was dedicated to Wi-Fi (IEEE 802.11b & a) simulations [43,44].

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