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Optimization of Dynamic Allocation of Transmitter Power in a DS-CDMA Cellular System Using Genetic Algorithms*

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SUMMARY In this paper, we propose an approach to solve the power control issue in a DS-CDMA cellular system using genetic algorithms (GAs). The transmitter power control developed in this paper has been proven to be efficient to control co-channel interference, to increase bandwidth utilization and to balance the comprehensive services that are sharing among all the mobiles with attaining a common signal-to-interference ratio(SIR). Most of the previous studies have assumed that the transmitter power level is controlled in a constant domain under the assumption of uniform distribution of users in the coverage area or in a continuous domain. In this paper, the optimal centralized power control (CPC) vector is characterized and its optimal solution for CPC is presented using GAs in a large-scale DS-CDMA cellular system under the realistic context that means random allocation of active users in the entire coverage area. Emphasis is put on the balance of services and convergence rate by using GAs.

key words: *digital cellular system (DS-CDMA), genetic algorithms (GAs), power control strategy, dynamic power allocation, balance of services*

1. Introduction

Recently, direct sequence spread code division multiple access (DS-CDMA) becomes a leading multiple access technology for cellular wireless systems, in which there have been significant works. In the literature, there have been researches on power control algorithms [1]–[3], channel allocation strategy [4], [5], expert systems [6], safe and distributed rate admission [7] in DS-CDMA cellular systems and so forth. Efficient channel reuse is of critical importance in the design of the cellular wireless system of higher capacity. Co-channel interference caused by the frequency reuse in each cell with DS-CDMA is the single most restraining factor on the system capacity. Transmitter power control schemes have been proposed to control this interference for a given channel, in particular for DS-CDMA cellular systems [8], [9]. The main idea is to adjust the transmitter power in each link in such a way that the interference in other receivers is minimized. Maintaining sufficient transmission quality in the actual links is an important and obvious constraint.

Transmitter power control is an effective way to increase the system capacity and transmission quality in cellular wireless systems. Transmitted power is regulated to provide each user an acceptable connection while limiting the interference seen by other users. Significant works are on power control strategy, such as Refs. [1], [2] and [3] which have focused on centralized power control(CPC) and distributed power control strategy (DPC). Reference [1] investigated just a simplified case because of difficulties in computation and search for an optimal solution. References [2] and [3] have focused on maximizing the minimum SIR using a complicated method to obtain a local optimum in the solution space using DPC for simplicity.

In this paper, we first propose an approach to solve the power control issue in a DS-CDMA cellular system using genetic algorithms (GAs) to obtain a global optimal solution. As is well known, GAs are powerful and broadly applicable stochastic search and optimization techniques based on the principles in the evolution theory [10]–[12]. For the power control issue, most of the previous studies [4]–[6] have assumed that the transmitter power level is controlled in a constant domain under the assumption of uniform distribution of users in the coverage area or in a continuous domain. In this paper, the optimal centralized power control (CPC) scheme which helps in the design of distributed power control schemes that are easy to implement is characterized and its optimal solution for CPC is presented using GAs in a typical case [1] and a large-scale DS-CDMA cellular systems under the realistic context that means random allocation of the active users in the entire coverage area. Furthermore, Emphasis is put on the balance of services and the convergence rate by using GAs.

This paper is organized as follows. In Sect. 2, fundamentals of GAs, CPC issue and how to use GAs to solve the CPC issue in a DS-CDMA cellular system

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are presented. Section 3 describes the important genetic operators such as crossover, mutation and selection used in our investigation. Section 4 describes the two situations in the DS-CDMA cellular system and gives simulation results and discussions. Finally, conclusions are given in Sect. 5.

2. Genetic Algorithms and the CPC Problem

2.1 GAs

There are currently three main avenues of this research: *Genetic Algorithms* (GAs), *Evolutionary Programming* (EPs) and *Evolution Strategies* (ESs). The usual form of genetic algorithms was described by Goldberg. A genetic algorithm is one of the stochastic search techniques based on the mechanism of natural selection and natural genetics, which differs from conventional search techniques. It starts with an initial set of random solutions termed as population. Each individual in the population is called a chromosome composed of many genes, and represents a possible solution to the problem at hand. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated by exchanging related genes using some measures of fitness. To create the next generation, new chromosomes called offsprings, are generated by either merging two chromosomes at a current generation using a crossover operator or modifying a chromosome using a mutation operator. A new generation is formed by selection according to the fitness values, and at the same time some of the parents and offsprings are rejected so as to keep the population size to be constant. Chromosomes of higher fitness have higher probabilities of being selected. After many generations, the algorithm converges to the best chromosomes, which hopefully represents the optimal or sub-optimal solution to the problem. Let $\mathbf{P(t)}$ and $\mathbf{C(t)}$ be parents and offsprings in current generation t; the general structure of genetic algorithms is shown in the following procedure as in [13]

Procedure: A Genetic Algorithm
begin
 $\mathbf{t} \leftarrow 0$;
initialize $\mathbf{P(t)}$;
evaluate $\mathbf{P(t)}$;
  while (not termination condition) **do**;
  recombine $\mathbf{P(t)}$ to yield $\mathbf{C(t)}$;
  evaluate $\mathbf{C(t)}$;
  select $\mathbf{P(t+1)}$ from $\mathbf{P(t)}$ and $\mathbf{C(t)}$;
  $\mathbf{t \leftarrow t+1}$;
  end
end

There are two types of operations in GAs
· Genetic Operation: crossover and mutation
· Evolution Operation: selection

Crossover is the main operator. It operates on two chromosomes at a time and generates offsprings by combining both chromosomes or genes' features. So the crossover rate is defined as the ratio of the number of offsprings produced in each generation to the population size. This ratio controls the expected number of chromosomes to experience the crossover operation. A higher crossover rate allows deeper exploration of the solution space and reduces the chances of settling in a false optimum.

Mutation is a background operator that produces spontaneous random changes in various chromosomes or genes. The mutation rate is defined as the percentage of the total number of genes in the population. the mutation rate controls the rate at which new genes are introduced into the population for trial.

2.2 The CPC Problem

As shown in Figs. 1 and 2, we assume N users and M base stations. All users use the common radio channel in a DS-CDMA cellular system. Let p_i denote the

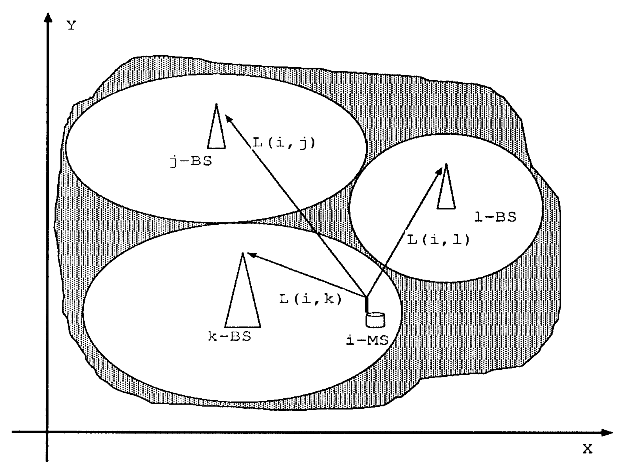

Fig. 1 A typical case [1] of wireless cellular geometry.

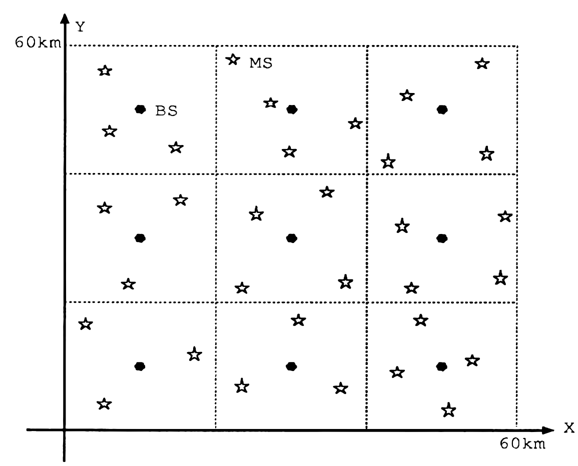

Fig. 2 A large-scale DS-CDMA cellular system.

transmitter power of user i so that $\mathbf{P}=[p_1, p_2, ...p_N]$ denotes the transmitter power vector of the DS-CDMA cellular system. The corresponding received signal power of user i at base station k is $p_i L(i,k)$ where $L(i,k)$ denotes the gain for user i to base station k. The interference seen by user i at base station k is $\sum_{j=1,j\neq i}^{N} p_j L(j,k)$. It is assumed that the system is interference-limited and therefore noise can be ignored. A mobile user i uses the closest base station k. All gains, $L(j,k)$ are of positive values. The signal to interference ratio (SIR) of mobile user i at its base station k is then written by

$$SIR_i = \frac{p_i L(i,k)}{\alpha \sum_{j=1,j\neq i}^{N} p_j L(j,k)} = \frac{p_i}{\alpha \sum_{j=1,j\neq i}^{N} p_j G_{j,k}} \quad \text{for} \quad 1 \leq i \leq N \qquad (1)$$

where

$$G_{j,k} = \begin{cases} \dfrac{L(j,k)}{L(i,k)} & \text{for} \quad j \neq i \\ 0 & \text{for} \quad j = i \end{cases} \qquad (2)$$

and, α is defined as the voice activity factor [4], [14] when the voice activity detection is adopted. A typical value of α is 0.375 [14]. When the voice activity detection is not used, $\alpha = 1$.

In order to achieve the balance of services, the optimization problem of the same SIR for all users in the system is expressed as [5], [6]

$$SIR_{opt}^{-} = \min_{1\leq i\leq N} SIR_i$$
$$SIR_{opt}^{+} = \max_{1\leq i\leq N} SIR_i \qquad (3)$$

where SIR_{opt}^{-} and SIR_{opt}^{+} are the minimum value of SIR_i and the maximum value of $SIR_i, i = 1...N$, respectively.

Due to the theorems and lemmas of R. Vijayan and J. Zender [1], let us define G as an $N \times N$ matrix that has $G_{j,k}$ as its elements. The matrix G has a few important properties that are described as follows.

A. G is an irreducible nonnegative matrix
B. There exists a unique SIR^* given by

$$SIR^* = \max_{\mathbf{P}\in\Re} SIR_{opt}^{-} = \min_{\mathbf{P}\in\Re} SIR_{opt}^{+} \qquad (4)$$

where the feasible set $\Re$ is given by

$$\Re = \{\mathbf{P} : 0 \leq p_i \leq p_{max}, \quad i = 1, 2, ...N\}$$

So we have the same SIR^* that is achievable by all users. In a large-scale DS-CDMA cellular system and when random allocation of users takes place in its coverage area, it is not easy to find the optimized solution. In this work, we adopt a GA to search a unique optimized solution as fast as possible.

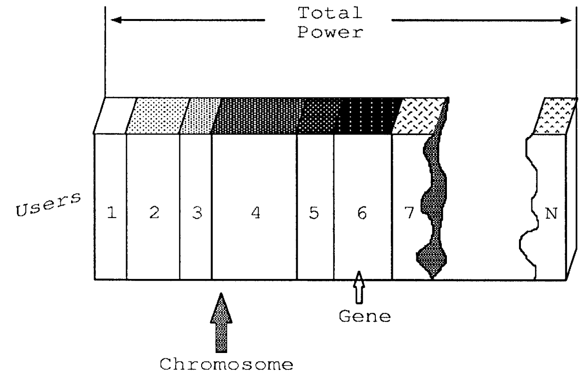

Fig. 3 Power allocation issue in a DS-CDMA cellular system.

In order to solve the power control by GAs, we must define the relationship between the power allocated to the users and the terms of GAs. As shown in Fig. 3, the total power used here consists of a string structure that is called a chromosome in GAs, of which total length is the sum of the total power required by all users in total in the system. The total power is divided into N parts allocated to the N users. In order to use a GA to solve the power allocation, each part is referred to as a gene. By definitions, the crossover and mutation between N parts will be processed on the related genes. The components of the algorithm are examined in the following subsections.

3. Performance Evaluation

3.1 Selection of N in the Simulation Environment

Several approaches to estimate the DS-CDMA cellular system capacity have been developed. One of the most insightful capacity analysis is that developed by Gilhousen et al. [14]. We employ this approach as a reference for the selection of N throughout this investigation.

The accepted propagation model in the cellular environment is path loss attenuation, that is the product of the fourth power of the distance and a log-normal random variable of which standard deviation is 8 dB. The authors in [14] assume a uniform density of users per cell, the perfect power control and a normalized hexagonal cell radius. They found the mean and variance for the total interference to signal ratio to be

$$E\left(\frac{I}{S}\right) \leq 0.247 N_c, \qquad Var\left(\frac{I}{S}\right) \leq 0.078 N_c \qquad (5)$$

where N_c is the number of users per cell. Finally, the authors in [14] find the outage probability for the required performance $P_{out} = P_r(BER \leq 10^{-3})$. The system capacity reaches over $N_c \geq 30$ users per cell when $P_{out} = 0.01$ under IS-95 protocols [4]. Therefore the total number of users in the system, N is the product of N_c and the number of base stations.

3.2 Objective Function

The objective function will essentially determine the survival of each chromosome by providing a measure of its relative fitness. The primary goal of an approach to solve the power control problem is to decrease the multi-user interference, to balance the services and to achieve the optimized power allocation, while satisfying the required quality of signal transmission. By assigning the power to each user in order to satisfy the same SIR for all users, a comprehensive objective function that involves all of the considerations is described as

$$\eta(t) = |SIR^{+}_{opt}(t) - SIR^{-}_{opt}(t)| \tag{6}$$

In order to retain the balance of services among all users, we must minimize $\eta(t)$ as small as possible.

3.3 Crossover

After reproduction, crossover proceeds with a probability, p_c. This operator takes two randomly chosen parent individuals as input and combines them to generate two offsprings. This combination is achieved by choosing two crossing points in the strings of the parents and then exchanging the allelic values between these two points as shown in Fig. 4 if we use the binary encoding. If we use the decimal encoding method(the real number), the exchanged amount by crossover must be determined by some kinds of decreasing functions. According to the fundamentals of CPC, preliminary simulation results show that with the simple crossover operator, a significant number of configurations will be generated. In order to greatly speed up the convergence rate and computation, evolution is then proceeded via the partially matched crossover (PMX) [10] operator. At the same time, we introduce a discarding strategy of the invalid parents in the process of PMX crossover. Furthermore, our solution representation allows us to further reduce the search space. It is very much suitable for investigating the practical large-scale CDMA cellular system and the optimal solution can be searched as soon as possible. Our crossover operator will be referred to as adaptive partially matched crossover, abbreviated to APMX.

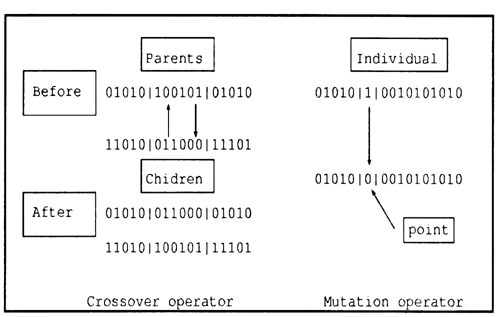

Fig. 4 Operators of genetic algorithms, such as crossover and mutation.

In order to achieve APMX easily, each individual is represented by a real number vector, that means the decimal encode. We also created two First-In First-Out (FIFO) stacks two stacks with stack depth, N, to store the genes. All the genes are popped into the first stack with the sequence from the gene with the maximum of SIR to the gene with minimum SIR. The second stack is used to store all genes with the sequence from the gene with minimum SIR to the gene with maximum SIR in the purpose of easy crossover and speed up in the convergence rate. When we select the parents, based on FIFO principle, select parents from those two stacks. In this case, pop up two parents A and B from those two stacks step by step; that means A is the gene with the maximum of SIR, and B is the gene with the minimum of SIR. The crossover is performed on two parents A and B after determining the exchanged amount during the entire crossover procedure by N times. At the end of each generation, we will rank the individuals by using FIFO stacks again and at the same time, discard the worse individuals with the very significant changes between $SIR^{+}_{opt} - SIR^{-}_{opt}$.

For a unique solution to our problem [1] and to speed up the convergence rate, we design the APMX algorithm in which nonlinear decreasing functions for determining the amount of exchanged power are used in the crossover operation. The crossover is performed by the combination of two parents, $p_i(t)$ in t-th generation with SIR^{+}_{opt} and $p_j(t)$ in t-th generation with SIR^{-}_{opt}. It is expressed as follows.

$$\begin{aligned} p_i(t+1) &= p_i(t) - \lambda p_j(t) \\ p_j(t+1) &= p_j(t) + \lambda p_i(t) \end{aligned} \tag{7}$$

where the three types of nonlinear decreasing functions for the crossover factor, λ are introduced in the crossover operation.

$$\text{Case 1: } \lambda = \frac{1}{\beta + \mu t} \tag{8}$$

$$\text{Case 2: } \lambda = e^{-\xi t} \tag{9}$$

$$\text{Case 3: } \lambda = \tau^{-\gamma t} \tag{10}$$

where β, μ, ξ, τ, and γ are control parameters in three functions. They will determine the convergence rate of the GA.

In Eq. (8), β and μ are control parameters used to determine the amount of exchanged power between the two parents in t-th generation. If β and μ are large enough, the amount of exchanged power will decrease rapidly. In order to flexibly control the decreasing rate of this function, two parameters are used. In Eq. (9), the exponential function with a single control parameter, ξ, is defined for the same purpose. If ξ is large, the amount of exchanged power will decrease rapidly. Equation (9) can be generalized into Eq. (10). This two-parameters function offers rich flexibility in getting a better convergence rate.

3.4 Mutation

The mutation operator provides opportunities for long jumps from local minima. This is because the crossover operator might lead to falling into a local minimum of the fitness function, since the generated offsprings tend to be very similar to their parents. The mutation operates with a probability p_m and creates a new generation by modifying one or more of genes in an existing individual as shown in Fig. 4. A low level of mutation serves to prevent any one element in the chromosome from remaining fixed to a certain value in the entire population. On the other hand, a high level of mutation will essentially result in a random search. To maintain a balance between such extremes, an appropriate value for p_m has been suggested to be 0.01 [10]. During the mutation, as the crossover operator, the discarding strategy of the invalid individuals is adopted.

3.5 Selection

The selection operator produces individuals with higher potential to be optimal solutions. The selection operator is very important as it must usually accomplish a trade-off between two opposite and undesirable tendencies. Thus, individuals with higher fitness have more chances to reproduce by themselves. On the other hand, if only the most fitting individuals are selected for generating a new generation, it may result in a quick convergence rate to local optimal solutions. Therefore we adopted those two stacks. The same parents, A and B will be selected twice for reproducing new offsprings. It is more advantageous to select a more fitting individuals and at the same time, to discard worse individuals. Using this procedure, qualified individuals have higher probabilities of being chosen. According to the simple selection procedure based on a roulette wheel [13], the probability of any individual to be selected from the population can be defined as

$$\psi(t) = 1 - \frac{|SIR^{+}_{opt}(t) - SIR^{-}_{opt}(t)|}{\sum_{j=1}^{N} SIR_j(t)} \tag{11}$$

3.6 Termination Criteria

In this paper, to achieve the balance of services at the receivers and speed up the convergence rate by using GAs, to individuals in the current population are processed by the genetic operators described in the above subsections to form a new generation. When the best candidate in a certain generation does not violate any of constraints in the problem, the search will be terminated. In each iteration step, the search can also be terminated, when there are no significant changes in the difference between $SIR^{+}_{opt}(t)$ and $SIR^{-}_{opt}(t)$. The genetic algorithm will be implemented under the following stopping conditions.

$$|\eta(t)| \le \delta \tag{12}$$

where, δ is the termination constant.

4. Simulation Results

Needless to mention, the performance of the GAs in solving CPC problem has to be investigated. In addition, this investigation can be expected to offer more useful knowledge for designing the algorithms to DPC [2]. This is important for the system operators and system designers. In this work, two types of DS-CDMA cellular systems have been examined, which may be divided into a typical example obtained in Ref. [1] and a large-scale DS-CDMA cellular system.

4.1 Typical Example

In Ref. [1], an example was illustrated in a CPC scheme in a smaller scale of only three mobiles using the same channel. The link gains given by G matrix is as follows.

$$\begin{pmatrix} 1.0 \times 10^{-4} & 4.82253 \times 10^{-9} & 3.57346 \times 10^{-10} \\ 1.52416 \times 10^{-8} & 6.25 \times 10^{-6} & 3.50128 \times 10^{-9} \\ 7.67336 \times 10^{-10} & 2.44141 \times 10^{-8} & 1.23457 \times 10^{-6} \end{pmatrix}$$

Power control simulation has been done for the example to get the optimized solution. Figures 5 and 6 show the results of the situations with and without FIFO stacks when using Eq. (8) as the crossover function. The genetic algorithm with FIFO stacks is superior to that without FIFO stacks in 50 generations. As seen in Figs. 5 and 6, the FIFO stack-free algorithm converges to the level of $\delta = 0.01$ after 200 and more generations, while the FIFO stacks algorithm converges in the 160th generations. These results have been observed in use of Eq. (8). The parameters, $\beta = 1$ and $\mu = 1$, imply that the amount of exchanged power between two genes are large, and hence a better convergence rate has been obtained.

Figures 7 and 8 show the convergence rate of users' SIR to a target SIR with Eq. (9) solved by the genetic algorithm with and without FIFO stacks. Again, the APMX algorithm with FIFO stacks has shown a better performance. When $\xi = 0.01$, users' SIR reach the target SIR in near 270 generations. On the other hand, the target SIR has been satisfied at near 40th generation when $\xi = 0.1$, which wins a better convergence rate. As ξ increases, it takes a short processing delay time for a given convergence. Based on the simulation, we see that ξ should be controlled carefully in order to

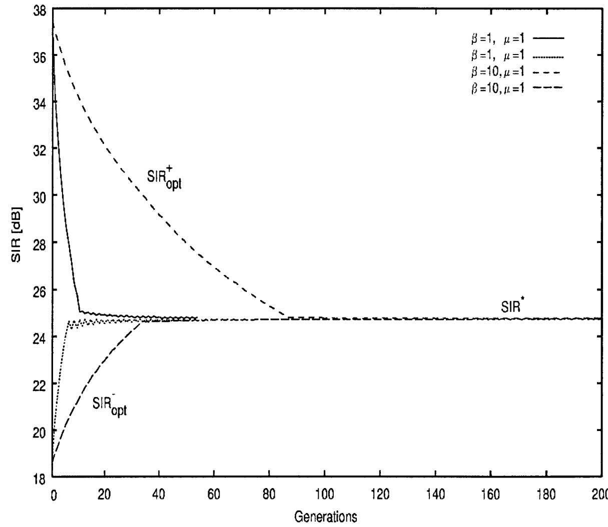

Fig. 5 SIR_{opt}^{+} and SIR_{opt}^{-} versus the generation using Eq. (8) without FIFO stacks ($\delta = 0.01$ dB, $\alpha = 1$, $p_c = 1$, $p_m = 0.01$, $N = 3$).

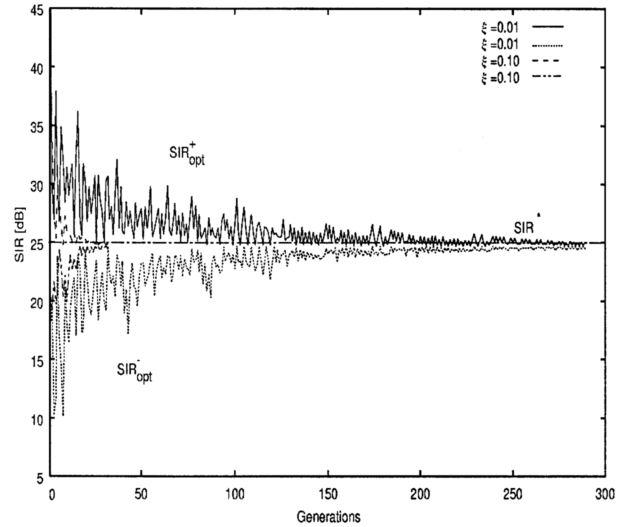

Fig. 7 SIR_{opt}^{+} and SIR_{opt}^{-} versus the generation using Eq. (9) without FIFO stacks ($\delta = 0.01$ dB, $\alpha = 1$, $p_c = 1$, $p_m = 0.01$, $N = 3$).

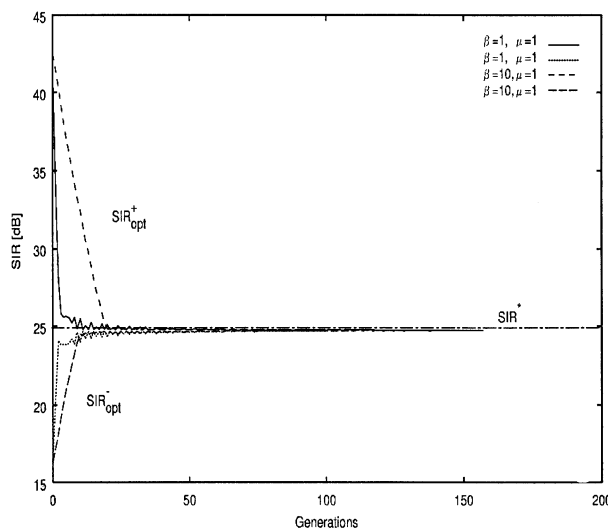

Fig. 6 SIR_{opt}^{+} and SIR_{opt}^{-} versus the generation using Eq. (8) with FIFO stacks ($\delta = 0.01$ dB, $\alpha = 1$, $p_c = 1$, $p_m = 0.01$, $N = 3$).

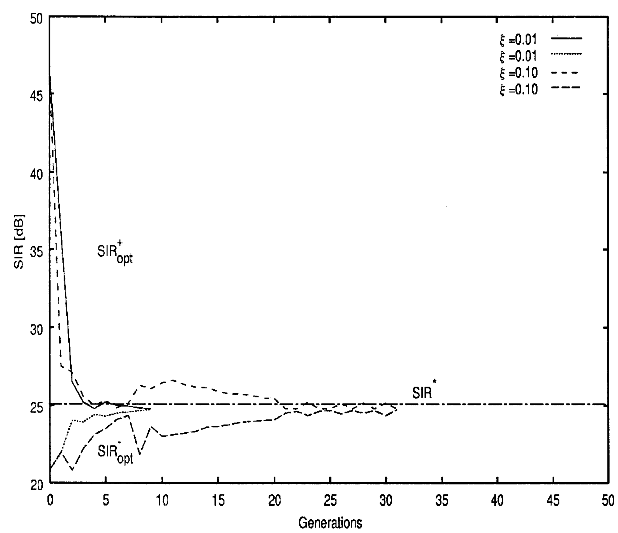

Fig. 8 SIR_{opt}^{+} and SIR_{opt}^{-} versus the generation using Eq. (9) with FIFO stacks ($\delta = 0.01$ dB, $\alpha = 1$, $p_c = 1$, $p_m = 0.01$, $N = 3$).

ensure the convergence to the optimum.

Figures 9 and 10 show the convergence rate of the users' SIR to a target SIR with Eq. (10). In this situation, the simulation results show that APMX algorithm with FIFO stacks slightly improves the convergence rate. That is, the users' SIR reaches the target SIR in the 18th generation without FIFO stacks and in the 14th generation with FIFO stacks when $\tau = 20$ and $\gamma = 0.1$.

For the above examples, if we use equal transmitter power, three different values in SIR in three mobiles are 42.85 dB, 25.23 dB and 16.90 dB, respectively. Throughout the simulations, we obtained three results of equal SIR as 24.74 dB, and this is the same to the result in Ref. [1]. We also found the unique solution of the power allocation problem, and the solution are 1.79×10^{-3}, 8.67×10^{-2} and 5.11×10^{-1}, respectively. In addition, one can see an improvement of 7.8 dB in minimum SIR by the CPC strategy.

4.2 Large-Scale DS-CDMA Cellular System

In our simulation environment, we consider the system as a general multi-cell DS-CDMA cellular system on a rectangular grid shown in Fig. 11. In this system, there are nine base stations with (x, y) coordinates as ($10000i$+10000, $10000j$+10000) for $0 \le i, 0 \le j$. The x and y coordinates of each user are independent uni-

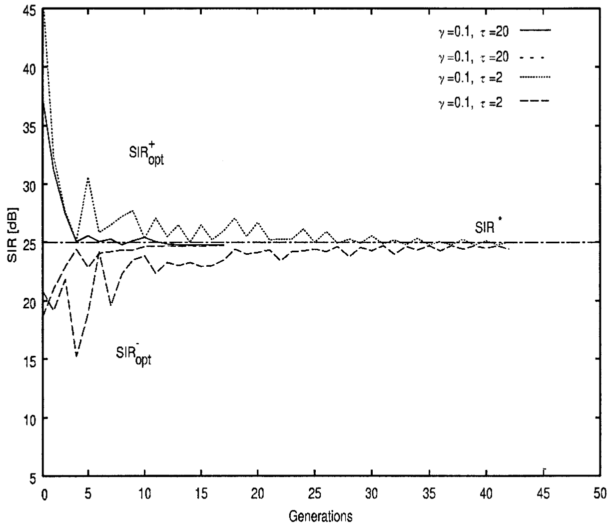

Fig. 9 SIR_{opt}^{+} and SIR_{opt}^{-} versus the generation using Eq. (10) without FIFO stacks ($\delta = 0.01$ dB, $\alpha = 1$, $p_c = 1$, $p_m = 0.01$, $N = 3$).

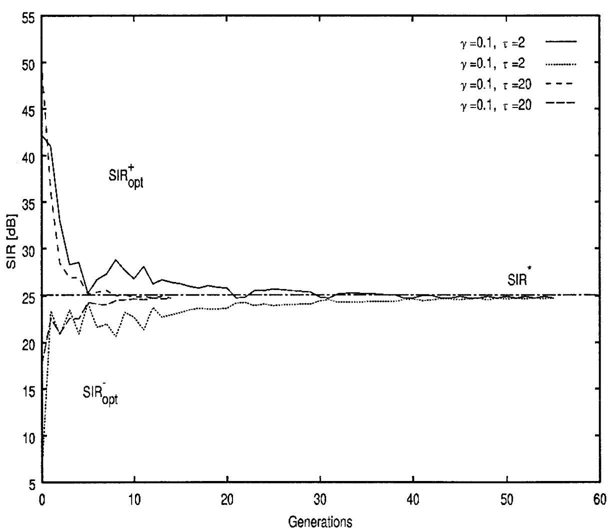

Fig. 10 SIR_{opt}^{+} and SIR_{opt}^{-} versus the generation using Eq. (10) with FIFO stacks ($\delta = 0.01$ dB, $\alpha = 1$, $p_c = 1$, $p_m = 0.01$, $N = 3$).

formly distributed random variables between 0–60 km. According to Sect. 3.1, experiments are conducted for the number of users, N as $9N_c$ and one hundred power vectors are considered in each generation for GAs. Figure 11 shows the positions of base stations and an example of randomly distributed users in the system when we set $N_c = 30$ users/cell. In this figure, there are high-density user distribution in some cells such as 1st, 5th and 9th cells and low-density areas in 3rd, 4th and 6th cells. During investigation, each user is assigned to its nearest base station. The path loss exponent used, while calculating the channel gains of the users, is taken to be four in our wireless environments. Based on our large-scale simulation system, at the beginning

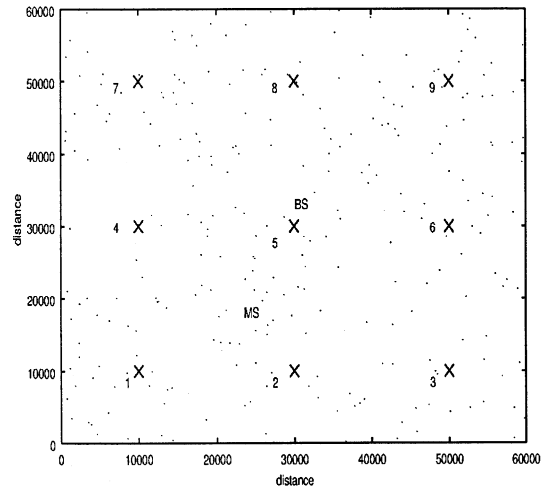

Fig. 11 Simulation environment for the number of active users, N_c and nine base stations ($N_c = 30$ users/cell).

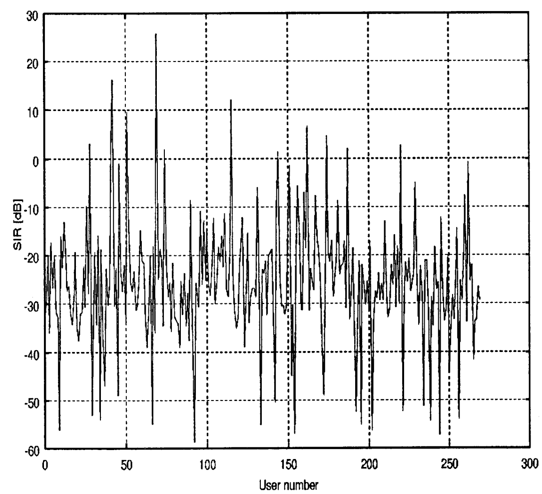

Fig. 12 SIR in dB versus the number of users without power allocation ($p_1 = p_2 = \ldots p_N = 1$, $\alpha = 0.375$, $N = 270$).

of iterations, power vectors are always initialized using a random approach to generate them.

Figure 12 shows the users' SIR versus the number of users when we set the equal power to each user. We see that the large variations in each user's SIR appear. This implies that some users have better transmitting quality, and some have worse quality, and it does not satisfy our purpose for balancing the services, especially in an integrated wireless cellular system.

In Sect. 4.1, we observed that GAs with FIFO stacks has a better convergence property to produce the unique optimal solution. In the investigation of a large-scale DS-CDMA cellular system, unless the FIFO stacks are adopted, it takes a very long processing delay time. For real-time applications, this strategy will be useless for solving the CPC problem in such a system. The FIFO stacks genetic algorithm can be a better and enough approach to realistic large-scale problems.

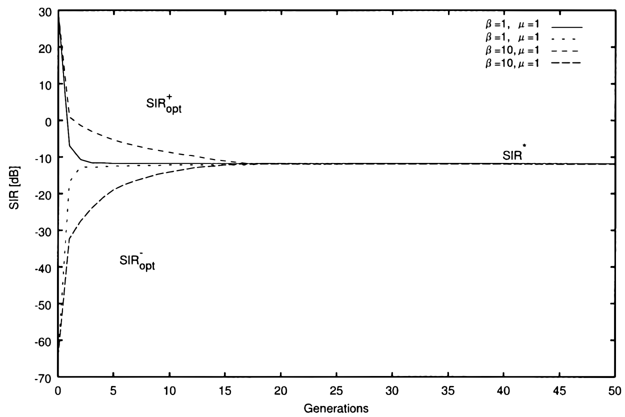

Fig. 13 SIR^+_{opt} and SIR^-_{opt} versus the generation using Eq. (8) with FIFO stacks for the large cellular system ($\delta = 0.1$ dB, $\alpha = 0.375$, $p_c = 1$, $p_m = 0.01$, $N = 270$).

Figure 13 shows the convergence rate of users' SIR being maximum value of SIR and with minimum value of SIR by Eq. (8), respectively. We see that SIR^* reaches the target optimal value after about 50 generations as $\beta = 10$ and $\mu = 1$. When $\beta = 1$ and $\mu = 1$, it shows better results, because the SIR reaches the target optimal value after near 15 generations.

Figures 14 and 15 show the convergence rate of the users' SIR being maximum value of SIR and minimum value of SIR by Eqs. (9) and (10), respectively. The maximum SIR decreases and the minimum SIR increases rapidly toward the optimal value at the beginning of evolution and approaches slowly but steadily to the optimal value based on the required δ. For $\delta = 0.1$, SIR will reach the optimal solution in near 37th generation when $\xi = 0.1$ and in just the 7th generation when $\xi = 0.5$, as shown in Fig. 14. In Fig. 15, SIR hits the optimal solution in near 55th generation as $\gamma = 0.1$ and $\tau = 2$, and in just the 13th generation as $\gamma = 0.1$ and $\tau = 20$.

As a result, the final unique optimal solution, that is the best SIR^*, takes the value of -11.812542 dB whatever the nonlinear decreasing functions are used in GAs. In Ref. [14], Bit-Error-Rate is given as $BER \leq 10^{-3}$ to get better transmission quality. To achieve this, the bit-energy to noise density ratio, E_b/N_0 must be larger than 7 dB in the DS-CDMA system where $SIR = (E_b/N_0)/PG$, and processing gain, $PG = W_{ss}/R_b$. W_{ss} is the spreading bandwidth and R_b is the information bit rate. When IS-95 protocol ($W_{ss} = 1.25$ MHz, and $R_b = 9.6$ kbps) is used in the system, $SIR \geq -14$ dB. From the constraint relationship between SIR and BER, the converged SIR value can be used to check if the transmission quality satisfies the system transmission requirements or not. Based on the relationship among SIR, W_{ss} and R_b, the results are also useful to design the varying-processing gain DS-CDMA systems which have attracted much attention recently.

In order to achieve this purpose, the power allocation plot by CPC has been obtained as shown in Fig. 16 for the system structure of Fig. 11. One can see that a larger amount of power will be allocated to users located at the boundaries among the cells. The largest power demanded by users is located at the coordinates approximately (0, 40000) and the smallest power is located at approximate (10000, 30000) around the 4th BS. We also see that the power allocation graph of the users located in 3rd and 6th cells slowly varies and with a little amount power required because of lower density of users in this area shown in Fig. 11.

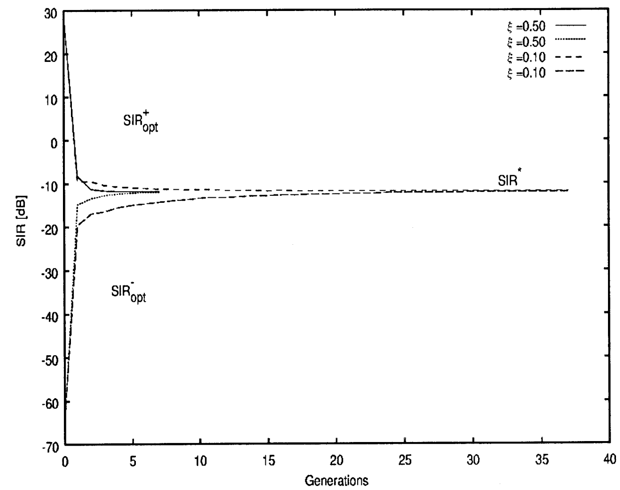

Fig. 14 SIR^+_{opt} and SIR^-_{opt} versus the generation using Eq. (9) with FIFO stacks for the large cellular system ($\delta = 0.1$ dB, $\alpha = 0.375$, $p_c = 1$, $p_m = 0.01$, $N = 270$).

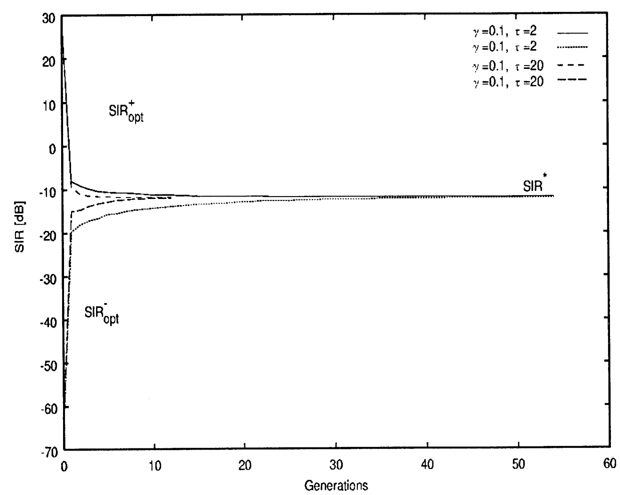

Fig. 15 SIR^+_{opt} and SIR^-_{opt} versus the generation using Eq. (10) with FIFO stacks for the large cellular system ($\delta = 0.1$ dB, $\alpha = 0.375$, $p_c = 1$, $p_m = 0.01$, $N = 270$).

4.3 Discussions

We have shown that GAs with FIFO stacks improve the search process for the optimal power allocation solution

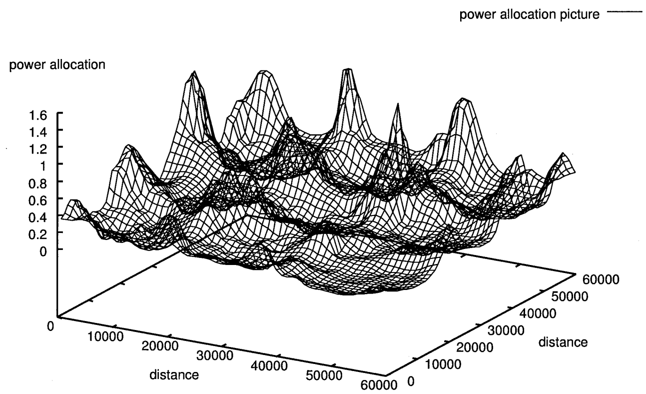

Fig. 16 Allocation of transmitted power for Fig. 11 in the entire coverage area.

by CPC. The simulation results showed that GAs are robust for the power allocation problems, especially for solving large-scale DS-CDMA cellular systems which will be a main approach used in IMT-2000.

In our model, the search vector of the power are presented as numeric strings using the real number encoding. In the investigation, three general genetic operators are employed. In order to speed up the convergence rate, three types of nonlinear decreasing functions and APMX algorithm with FIFO stacks have been defined. The control parameters of those functions can be determined either by a sophisticated techniques or by experience. In our investigation, the control parameters have been used, and they may not be optimal, yet they are still feasible at least for resolving the CPC problem that has been left as a difficulty in the vast literature.

In summary, according to the simulation results, the advantages and limitations in using GAs for solving the power control problem in DS-CDMA cellular systems, in particular for the large-scale DS-CDMA cellular system are listed as follows.

1. *Simplicity:* Genetic algorithms do not have so many mathematical requirements about the optimization problem; they only depend on the evolutionary nature of the solutions regardless to the specific inner structure or behaviors. Then, it is very suitable for some problems which could not be formulated theoretically. Throughout the CPC issue, we can see this point.

2. *Effectiveness:* The ergodicity of evolution operators make GAs very effective for searching a global solution. It proceeds very well for setting the CPC problem, has been successful to find the unique optimal solution from our simulation results.

3. *Flexibility:* GAs are flexible for introducing other techniques in the searching process. For example, in our model we introduced the nonlinear decreasing functions and FIFO stacks to speed up the convergence rate.

4. *Practicality:* In spite of some literature about the CPC problem, because of its complication, there are no reports to deal with a large-scale DS-CDMA cellular system with a practical user distribution. We solved this real time problem using GAs with the nonlinear decreasing functions and FIFO stacks in our model. This may lead to its beginning to define practical system problems encountered in real systems.

5. *Convergence:* In order to make a success in setting problem, GAs must be guaranteed to converge. It may be trapped a illegal solutions because of its blind search, which can be its limitation in solving some problems. Thus, when we use GAs, illegal solutions must be carefully processed. By introducing some better strategies and by adjusting control parameters of penalty functions, we are always able to obtain a legal solution. Based on this experience, better results could be obtained. It is the difficult point to settle a problem by GAs.

6. *Robustness:* Although we have been successful in CPC problem statement using GAs and all the results show the convergence with a targeted SIR, the processing delay time has not yet been studied in this paper, because it is not realistic to get an exact model. According to the results, if the convergence rate is slower, the longer processing delay time will be required. In the future works, many search techniques for global optimization, such as simulated annealing (SA) [15], tabu search (TS) [16] and so forth can be used for the CPC problem and the investigation on the processing delay time will become an important topic since the processing delay time depends on the CPU speed and the computer system load. The processing delay time will be an important parameter for determining which approach is the best when we adopt GAs, SA and TS approaches.

5. Conclusions

In this paper, we reformulated the power control problem in DS-CDMA cellular systems as a target optimization problem and solved this problem using GAs. According to the simulation results, it has been shown that genetic algorithms are robust for optimal power allocation.

In this investigation, to speed up the convergence rate and to filter out the illegal solutions, we introduced nonlinear decreasing functions and FIFO stacks. Then we have effectively simulated the centralized power control in a large-scale DS-CDMA cellular system and obtained better results.

The main benefit of these simulation results is, therefore, that they provide an estimate of CPC and it can be developed as some basics for the design of DPC in the system. Furthermore, they provide the reference results when we design the burst admission algorithms or a DS-CDMA cellular system with varying processing gains.

Further studies should, therefore, be devoted to be the algorithms used in GAs and the other approaches for solving the CPC problem. Of special interest are the DPC problems in which whether genetic algorithms, simulated annealing and tabu search could be adopted and their efficiency should be studied.

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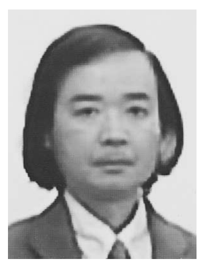

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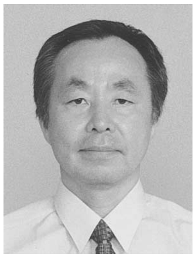

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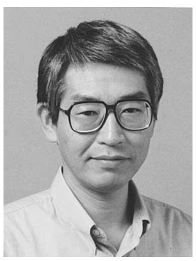

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