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GENETIC ALGORITHM-BASED ADAPTIVE CHANNEL ALLOCATION FOR BEST-EFFORT TRAFFIC USERS IN MICROCELLULAR SYSTEMS

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Abstract. *Previously proposed adaptive channel allocation schemes in cellular systems have mainly focused on the case in which a dedicated channel is exclusively allocated to each user. Thus, it is important to assign the infrequently used channels in adjacent cells among all available channels to reduce the probabilities of call drop and call block. Even when best-effort traffic users are supported by sharing multiple channels through time-domain scheduling, a similar approach (i.e., the conventional scheme) has utilized channels experiencing the lowest interference at each basestation. However, it is unlikely that the best-effort users are fairly supported using the channels chosen by the conventional scheme regardless of location because the interference conditions on these channels tend to be quite different for users far from its serving basestation. In other words, a channel experiencing low interference at the serving basestation does not guarantee adequate performance for a user who is far away. In this paper, we propose an adaptive channel allocation scheme in which the best-effort users are fairly supported regardless of distance to the serving basestation. Specifically, using genetic algorithm, the channel set that maximizes the sum of the far users' throughputs is found while allowing a pre-specified loss in the sum of all users' throughputs compared with that of the conventional scheme. Using computer simulations, it is shown that the throughput performance of the 10th percentile throughput users improves up to 38% in some cases, when the overall throughput performance loss was allowed to be less than 5% compared with that of the conventional scheme. In addition, only some of the link-gains can be measured in practice, because it is very difficult for a user to measure the link-gain of a distant basestation. Even when only some link-gains can be measured, performance degradation is negligible.*
Keywords: Genetic algorithm, Adaptive channel allocation, Radio resource management, Cochannel interference, Best effort traffic

1. **Introduction.** Efficient support of best-effort traffic (e.g., web browsing and data downloading) has recently attracted much attention as data demands are exponentially increasing [1]. Because best-effort traffic is relatively insensitive to QoS such as jitter, packet loss, and latency, it has been shown that best-effort traffic can be well supported if pre-allocated radio channels are shared via a time domain scheduling method such as proportional fair (PF) scheduling [1]. When best-effort traffic is supported in cellular systems, it is important to appropriately choose a set of the shared channels experiencing less cochannel interference (CCI) among all available channels.

In a macrocellular system employing a frequency reuse factor of one, the throughput performance of the users in the cell edge area is severely degraded due to high CCI from adjacent cells. To mitigate this problem, various channel allocation schemes have been proposed. For example, multiple frequency reuse factors are employed at each cell according to the distance from the basestation [2, 3]. In particular, the channels with a low frequency reuse factor are allocated to cell edge users, while the channels with a frequency reuse factor of one are allocated to the users in the cell interior. However, this approach inefficiently uses radio resources because the spectral efficiency of the channels allocated to the cell edge users is low. For this reason, dynamic channel allocation schemes have been proposed to avoid assigning channels with high CCI to adjacent cells [4, 5]. To achieve this, each cell is allowed to exchange information on the channel that is experiencing high CCI between adjacent cells.

Note that these approaches have been developed under the assumption that the basestations are regularly distributed over the service area. For instance, in a hexagonal cellular structure, each cell is surrounded by 6 adjacent cells. For this reason, the channel assignment at each cell should consider the CCI effect only on these adjacent cells. However, a spectral efficiency per unit area obtained from macro-cellular systems is not sufficient to support the exponentially increasing demand for wireless data service because the area covered by one macro-cell is too large [6]. To aggressively spatially reuse radio resource, a macro-cellular system needs to be employed by dividing the service area into a large number of small cells. However, as the cell size decreases in a macro-cellular system, the basestations become irregularly distributed because radio propagation becomes severely irregular. This may result in various types of interference. Consequently, the channels need to be adaptively allocated considering these complicated interference conditions.

1.1. **Previous works and motivations.** Several works on adaptive channel allocation for microcellular systems have been performed under the assumption that each channel is exclusively dedicated to each user in a distributed manner [7, 8]. The main purpose of these schemes is to assign a channel to each arrival call while reducing the call drop rate and/or block rate. In particular, each basestation identifies the channels which are infrequently used by adjacent cells and sorts them according to CCI level. Then, each of the chosen channels is sequentially assigned when needed. However, it is unlikely that these approaches are suitable to support best-effort users because the assigned channels need to be shared through PF scheduling as mentioned previously.

The best-effort users can be supported in a distributed manner using a set of channels with low CCIs at each basestation [9, 10, 11]. Particularly, in this conventional scheme, at a predetermined or a randomly selected instant, each basestation measures the CCI power of each channel from all other basestations and chooses channels with the lowest CCIs. Even though these channels are shared among the best-effort users through PF scheduling, it is unlikely that the best-effort users will be fairly supported. The reason is explained as follows. First, the CCI power of a user near its serving basestation is very similar to that of its serving basestation. Thus, the signal-to-interference power ratios (SIRs) measured at these channels will be improved with high probability. As a result, we expect that the throughput performance of the near user will improve. On the other hand, the CCI power measured at a user far from its serving basestation is quite different from that of its serving basestation because its adjacent cells are quite different from those of its serving basestation. This implies that another channel which is not chosen by the conventional scheme may provide sufficient throughput performance to this user. Thus, the conventional scheme is not a good solution to fairly support the best-effort users. This motivated us to develop a channel allocation scheme that fairly supports the best-effort user regardless of its distance to the serving basestation.

However, it is known that this channel allocation problem is non-deterministic polynomial-time (NP) hard, since it requires a search space which exponentially increases in order to identify the best channel combination among the cells as the numbers of the basestations and the users increase [12, 13, 14, 15]. Although there are neural network- or genetic algorithm (GA)-based approaches to solve this channel allocation problem due to its low computational complexity, they do not consider the case in which the assigned channels are shared through a PF scheduler to support the best-effort users.

1.2. **Contributions.** In this paper, we propose a GA-based channel allocation scheme to fairly support the best-effort users in microcellular systems. Specifically, using GA, the channel set that maximizes the aggregate throughput of the low percentile throughput users (i.e., the far users) is identified, while allowing a pre-specified amount of loss in overall throughput performance compared with that of the conventional scheme. In addition, the proposed scheme is performed under the assumption that each user measures the link-gains from all basestations and reports them to the central controller. However, this assumption is impractical because each user does not measure the link-gains of the basestations far from it. Using computer simulations, it is demonstrated that the proposed scheme shows robust performance even when each user can measure the link-gains of its nearby basestations.

The contributions of this paper are summarized as follows.

- It is shown that the conventional scheme which selects a set of channels with the lowest CCI is not a good solution to fairly support the best-effort users. More precisely, it tends to provide more improved performance to a user near the serving basestation.
- It is shown that the proposed scheme can identify a set of used channels at each basestation that maximize the low-percentile throughput performance, while mitigating the overall performance loss. Specifically, computer simulations demonstrate that the throughput of the 10th percentile users improves by up to 38% in some cases, while allowing an overall throughput performance loss less than 5% compared with that of the conventional scheme.
- The proposed scheme works very well even when only some of the link-gains are available.

This paper is organized as follows. Section 2 describes the system model. In Section 3, the conventional scheme in which each basestation selects a set of channels infrequently used by its adjacent basestations is described. Section 4 describes the GA used to improve low throughput user performance while mitigating the overall throughput performance loss. The simulation results are presented in Section 5. Finally, the conclusions are drawn in Section 6.

2. System Model.

Consider a microcellular system consisting of B basestations, each of which uses M channels among all available K channels. When the system is assumed to ignore the effect of noise (i.e., interference-limited), the instantaneous SIR of user n using channel j of basestation i at frame m is

$$\gamma_{i,n}^{(j)}(m) = \left|\rho_{i,n}^{(j)}(m)\right|^2 \overline{\gamma}_{i,n}^{(j)}, \tag{1}$$

where $\rho_{i,n}^{(j)}(m)$ is a Rayleigh fading process with unit variance sampled at frame m, which is assumed to be independent at each channel, each frame, and each user, and $\overline{\gamma}_{i,n}^{(j)}$ is the average SIR as

$$\overline{\gamma}_{i,n}^{(j)} = \frac{(1-\phi)PG_{i,n}}{\phi PG_{i,n} + \sum_{i' \in \mathcal{S}_j, i' \neq i} PG_{i',n}}. \tag{2}$$

In (2), P, $\mathcal{S}_j$, $G_{i,n}$, and ϕ denote the transmit power per channel, a set of the basestations using channel j, a link-gain between basestation i and user n including the effects of path loss and shadowing, and an orthogonality factor, respectively. Assume that the value of $\phi = 0.001$ is employed such that the average SIR cannot exceed 30dB. When channel j is assigned to user n at basestation i at frame m, its spectral efficiency is assumed to be

$$r_{i,n}^{(j)}(m) = \log_2\left(1 + \gamma_{i,n}^{(j)}(m)\right) \text{ (bps/Hz)}. \tag{3}$$

Based on this, assume that a full buffer traffic model is employed in which each user always has packets to be received from its serving basestation. Also, because M channels are available at each basestation, assume that a multichannel PF scheduler is employed to assign these channels to its serviced users [16]. In particular, channel j is assigned to user n^* served by basestation i at frame m if

$$n^* = \arg\max_{n \in \mathcal{U}_i} \frac{\gamma_{i,n}^{(j)}(m)}{\overline{\gamma}_{i,n}^{(j)}} \tag{4}$$

where $\mathcal{U}_i$ denotes a set of users at basestation i [17]. In this case, it is known that the long-term average throughput of user n at channel j of basestation i is [17]

$$R_{i,n}^{(j)} = \frac{1}{N_i}\int_0^\infty \log_2\left(1 + x\overline{\gamma}_{i,n}^{(j)}\right) e^{-x}\left(1 - e^{-x}\right)^{N_i - 1} dx \tag{5}$$

where N_i is the number of users served by basestation i. We see that the throughput of (5) can be evaluated if N_i and $\overline{\gamma}_{i,n}^{(j)}$ are available.

3. **Description of Conventional Scheme.** In this section, we describe the conventional channel assignment scheme used to improve the overall throughput performance compared with that of the random assignment scheme in which each basestation randomly selects M of K channels [9, 10, 11]. In the conventional scheme, each basestation chooses a set of the channels infrequently used in the adjacent basestations. From these channels, the users near the serving basestation will receive CCI powers similar to those of the serving basestations. This means that these channels' average SIRs at the near users can be improved compared with that of the random channel assignment scheme. As a result, the overall throughput performance can be improved because their performance is dominated by the performances of the near users.

The conventional scheme is performed as follows. At first, each basestation randomly chooses M channels among all available K channels. Then, at randomly chosen frames, each basestation repeatedly chooses M channels with the lowest CCI powers. To achieve this, it turns off its transmitter and measures the average CCI powers of all channels from all basestations. In this case, the average CCI power of channel j at basestation i is

$$I_i(j) = P \cdot \textstyle\sum_{i' \in \mathcal{S}_j, i' \neq i} \tilde{G}_{i,i'}, \tag{6}$$

where $\tilde{G}_{i,i'}$ denotes a link-gain between basestations i and i' including the effects of path loss and shadowing. From these measurements, basestation i chooses M channels with the lowest average CCI powers. Particularly, channel j is chosen if

$$I_i(j) \leq I_i(\pi_M) \tag{7}$$

where π denotes a permutation such that $I_i(\pi_1) \leq \cdots \leq I_i(\pi_K)$. The process is completed when all basestations update their chosen channels. Then, this process is iterated multiple times, after which it is expected that each cell selects the channels which are infrequently used at its adjacent cells [9].

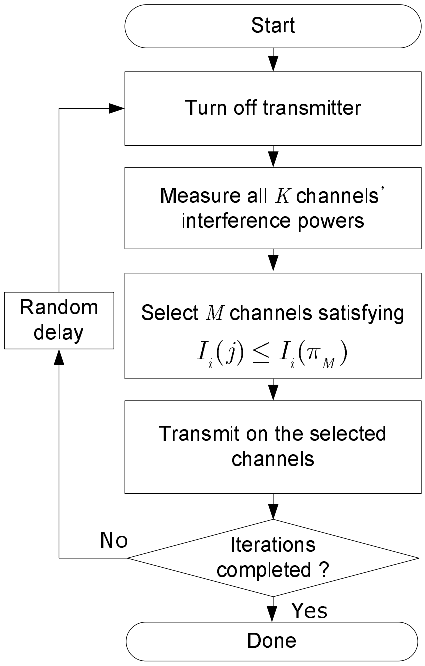

Figure 1. Flow chart of the conventional scheme

To avoid the case when more than two basestations update their channel sets simultaneously, assume that a sequence of updated basestations is pre-determined at each iteration. Under this assumption, only one basestation is allowed to update the channel set at each frame. The flowchart of the conventional scheme is shown in Figure 1.

4. Description of the Proposed Scheme.

4.1. **Motivations.** As mentioned previously, it is expected that the conventional scheme improves the overall throughput performance because it is dominated by the performance of the near users. On the other hand, it is unlikely that the conventional scheme will improve the performance of the users far from their serving basestation because the received average CCI powers at these users are quite different from those of the basestation. To fairly support these users, we need to improve their performances.

To achieve such fair support, the proposed scheme replaces some used channels with the unused channels which enhance the far users' performances. However, when a used channel is replaced with an unused channel with large CCI, the performance of the near users (i.e., the high throughput users) may be severely degraded. To mitigate this problem, unused channels with relatively low CCI must be chosen. One major issue with this task is that the search space to identify such channels exponentially increases as the numbers of basestations and users increase. Thus, the heuristic GA algorithm is employed to mitigate this complexity problem. Specifically, GA is used to find the channel set that maximizes the aggregate throughput of low throughput users while allowing a pre-specified amount of loss in the aggregate throughput of all users as compared with that of the conventional scheme.

In the following section, we define the low throughput users as those whose throughput values are below some specified percentile throughput value. For instance, when the 10th percentile throughput users are defined as the low throughput users, their throughput values are less than the threshold of the lowest 10% of all users' throughput values in the system.

In the followings, we describe the proposed scheme's flow in a more detail.

4.2. **Flow of the proposed scheme.**

4.2.1. *Evaluation function.* GA is one of the search algorithms which originate from an evolutionary algorithm [18, 19, 20, 21]. In this paper, a chromosome represents a set of channels chosen by all basestations in the system. Each chromosome is represented as a B by K matrix in which each row represents the channel allocation at each basestation. Particularly, the (i, j)th element of the chromosome is 1 (0) if channel j at basestation i is used (unused). The number of 1's in each row is M, while the number of 0's is $(K - M)$, because M channels are assumed to be used at each basestation.

Under this set-up, the proposed scheme identifies the set of used channels (i.e., the chromosome) maximizing the aggregate throughput of the low throughput users while allowing a pre-specified amount of loss ϵ in the aggregate throughput of all users. The detailed process is described as follows. The evaluation function, i.e., the aggregate low throughput user performance for a given chromosome c at generation g is

$$F(g, c) = \begin{cases} \phi(g, c), \text{ if } \Phi(g, c) \geq (1 - \epsilon) \cdot \Phi_{conv} \\ 0, \qquad \text{otherwise.} \end{cases} \tag{8}$$

In (8), $\phi(g, c)$ is the aggregate throughput of low throughput users of chromosome c at generation g as

$$\phi(g, c) = \sum_i \sum_{j \in \mathcal{C}_i(g,c)} \sum_{n \in \mathcal{L}_i(g,c)} R_{i,n}^{(j)} \tag{9}$$

where $\mathcal{C}_i(g, c)$ and $\mathcal{L}_i(g, c)$ denote the set of chosen channels at basestation i and a set of low throughput users at basestation i of chromosome c at generation g, respectively, $\Phi(g, c)$ is the corresponding aggregate throughput of all users and is defined as

$$\Phi(g, c) = \sum_i \sum_{j \in \mathcal{C}_i(g,c)} \sum_{n \in \mathcal{U}_i} R_{i,n}^{(j)} \tag{10}$$

where $\mathcal{U}_i$ denotes the set of all users at basestation i, Φ_{conv} is the aggregate throughput of all users using the channel sets determined by the conventional scheme, and ϵ (for $0 < \epsilon < 1$) is the maximum allowed loss rate of the overall user throughput.

From these definitions, we can see that the evaluation function (8) returns the aggregate throughput of the low throughput users if the overall throughput loss is less than ϵ compared with that of the conventional scheme. Otherwise, it returns zero. Using this, therefore, GA finds the chromosome (i.e., the channel allocation pattern of all basestations) maximizing the aggregate low throughput user performance, while maintaining the overall performance loss rate, which is less than ϵ.

4.2.2. *Initial population generation.* To perform GA, we need to generate an initial population (i.e., a set of chromosomes). However, when initial population is randomly generated, it is difficult to find suitable chromosomes to satisfy the overall performance loss requirement according to (8) because the overall throughput performance of a randomly selected channel set will likely be too low compared with that of the conventional scheme.

To avoid this problem, the initial population is generated as follows. First, for a given channel allocation set determined by the conventional scheme, some basestations are randomly chosen. Then, a chromosome is generated such that, at each chosen basestation, some used channels are randomly selected and replaced with unused channels. When the aggregate throughput of the low throughput users is not greater than that of the conventional scheme or it does not satisfy the loss requirement of (8), this chromosome is eliminated, and this process is repeated until a suitable chromosome is found. When such a chromosome is found, an other basestation is randomly selected, and the whole process is repeated until the initial population is formed. The overall process generating the initial population is shown in Figure 2.

4.2.3. *Crossover and mutation.* Crossover generates offspring chromosome by combining the two parent chromosomes that survived from the previous generation. Also, in this algorithm, the number of 1's in each row in the offspring chromosome should be the same as the number of used channels at each basestation, M. In this respect, the conventional crossover process does not seem to be suitable because the number of 1's in all of the rows of the offspring chromosome are not guaranteed to be the same.

To satisfy this condition, a modified crossover process should be employed as follows. First, the two parent chromosomes that survived from the previous generation are selected. Then, if the elements of the two chromosomes at the same position have the same value, this value is copied to the corresponding element position of the offspring chromosome. The remaining elements of the offspring are filled with the values randomly selected of the two parent chromosomes while ensuring that each row in the offspring contains M 1's.

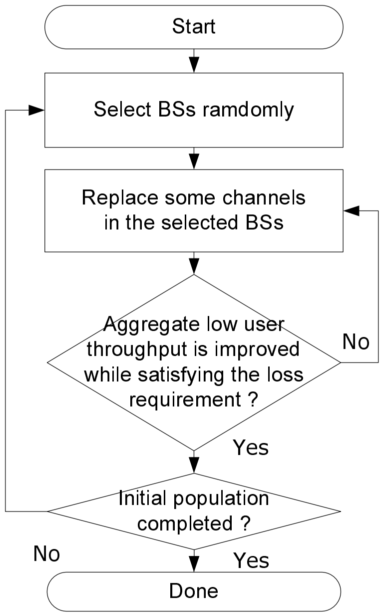

FIGURE 2. Flow chart of initial population generation

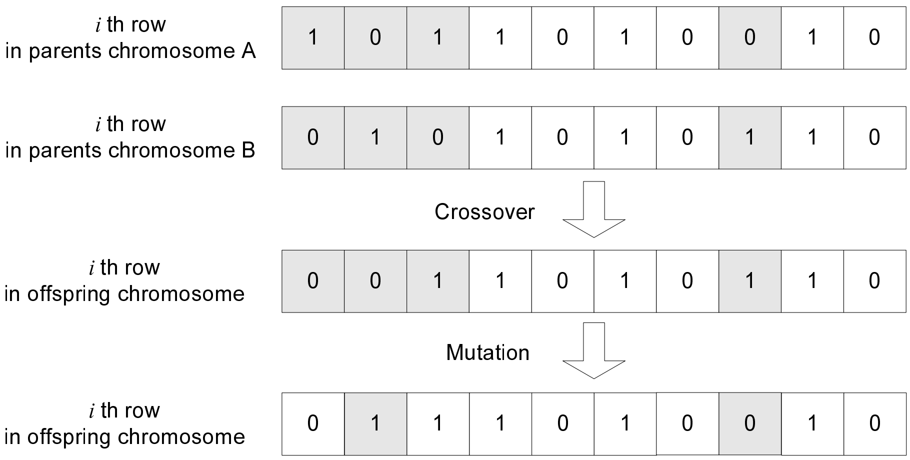

FIGURE 3. Example of crossover and mutation processes

TABLE 1. Summary of simulation conditions

Parameter	Value
no. of BSs (B)	20
no. of users	240
std. of shadowing	10 dB
corr. dist. of shadowing	50 meters
no. of total CHs per BS (K)	10
no. of used CHs per BS (M)	5
no. of populations	15
no. of offsprings	10
mutation probability (p_{mu})	0.05

As a result, this crossover process can generate a new offspring chromosome that contains M 1's in each row.

Figure 3 shows an example of crossover and mutation processes for $K = 10$ and $M = 5$. In this figure, we see that elements $4 \sim 7$, 9, and 10 at row i in parent chromosomes A and B are the same, respectively. They are copied to their corresponding positions in the offspring chromosome. The remaining elements in the offspring chromosome are filled with the randomly selected elements of the two parent chromosomes while ensuring that the number of 1's is M. In this example, elements 2 and 3 of parent chromosome A are copied to the offspring, as are elements 1 and 8 of parent chromosome B.

After the crossover process is complete, the mutation process starts with probability p_{mu} at each row of the offspring chromosome. Specifically, a randomly selected element of 1 is replaced with a randomly selected element of 0. In Figure 3, we see that elements 2 and 7 are replaced. When the offspring chromosome is the same as any parent chromosome or any previously generated offspring chromosome, a randomly chosen row of the corresponding offspring is replaced with the randomly generated row containing M 1's. This indicates that the channel set of a randomly chosen basestation is fully re-generated. After generating the offspring chromosomes, those satisfying the loss requirement in (8) along with their parent chromosomes are sorted in evaluation function value order. Finally, the chromosomes with the largest evaluation values survive as the populations of the next generation.

4.2.4. *Termination condition.* GA may be terminated if the maximum evaluation function value among the chromosomes is unchanged during pre-specified generations. However, even when a suitable chromosome is not found, this termination condition may be met.

To avoid this, we employ a termination condition in which the termination of GA is possible after the production of at least a pre-specified number of generations. This issue will be discussed in Section 5.1.

4.2.5. *Implementation issue.* Note that the value of $R_{i,n}^{(j)}$ can be estimated if N_i and $\overline{\gamma}_{i,n}^{(j)}$ as shown in (5) are available at the controller which performs GA. To have each user measure its average SIR $\{\overline{\gamma}_{i,n}^{(j)}\}$ for a given channel set (i.e., a given chromosome) and report them to the controller is a very time consuming task in the GA process.

Fortunately, the controller can estimate $\{\overline{\gamma}_{i,n}^{(j)}\}$ using (2), if link-gains $\{G_{i,n}\}$ between all users and all basestations are available. This allows the GA execution time to be as short as possible because no average SIR measurement is required. However, the requirement for the availability of all link-gains is not practically feasible because a user cannot measure the link-gain from far basestations. Thus, we investigate the performance loss when only some of the link-gains are available in Section 5.3.

5. **Simulation Results.** To evaluate the performance, assume that 20 basestations and 240 users are randomly distributed on a wrap-around structured rectangular area with width 1000 meters. In this case, the average number of users per basestation is 12. Assume that the basestations and the users are equipped with an omnidirectional antenna, and the number of all available channels K is 10. Also, the number of used channels per basestation M is 5. The path loss model for a given distance d is [22]

$$L(d)[\text{dB}] = \begin{cases} 39 + 20\log_{10} d, & 10m < d \leq 45m, \\ -39 + 67\log_{10} d, & d > 45m. \end{cases}$$

It is assumed that the shadowing is log-normal distributed with 10dB standard deviation and its decorrelation distance is 50 meters [9]. Each user selects a serving basestation with the largest link-gain.

In addition, assume that the population size is 15 at each generation. The offspring chromosomes are generated using the 5 parent chromosomes with the largest evaluation values. Because they are generated from all possible combinations of these 5 parent chromosomes, the number of the offspring chromosomes is $\binom{5}{2} = 10$. As discussed in Section 4.2.3, the parent chromosomes and the offspring chromosomes which satisfy the loss requirement in (8) are gathered, and the 15 chromosomes with the largest evaluation values among them are chosen as the population for the next generation. To determine the average performances, simulation results are obtained and averaged over 100 independent distributions of the basestations and users. Simulation conditions are summarized in Table 1.

5.1. **Convergence property.** Figure 4 shows the average 10th percentile user throughput performances with generation for the maximum allowed overall throughput loss rate

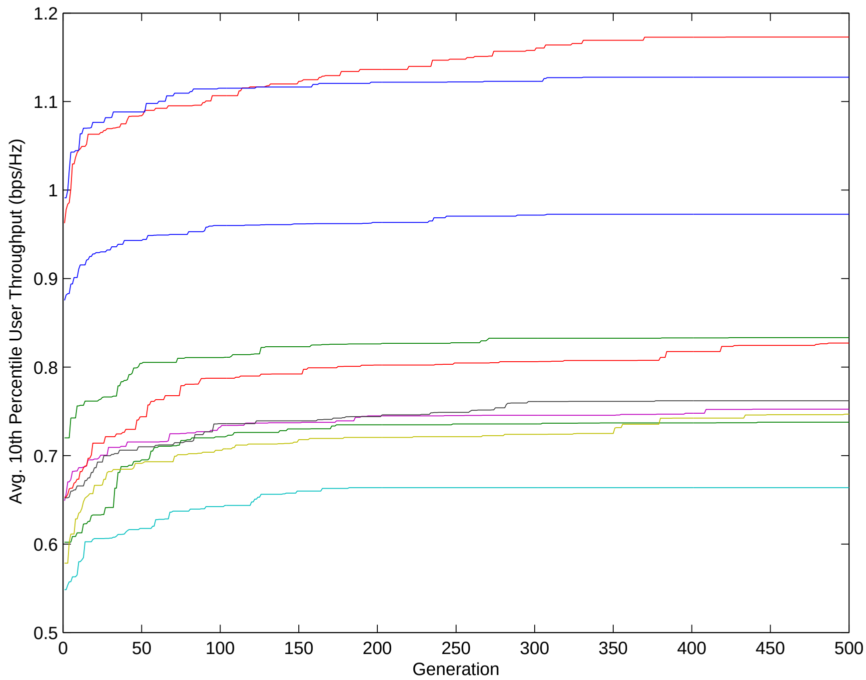

FIGURE 4. Convergence of the proposed scheme improving the performance of the 10th percentile user throughput for $\epsilon = 0.05$

$\epsilon = 0.05$. In this figure, each line represents one distribution of basestations and users. We see that the performance and the complexity are well compromised after a certain number of generations (more than about 150 generations in this figure). In this case, the aggregate number of chromosomes searched is about 10×150 because the number of offspring chromosomes generated at each generation is 10. On the other hand, the search space size is $\left(\binom{10}{5}\right)^{20} \approx 10^{48}$ because 5 of 10 channels are chosen at each of 20 basestations.

As discussed in Section 4.2.5, the execution time to generate 150 generations can be shortened under the assumptions that a suitable processor is employed and all link-gains are available at the controller. Also, because similar performance trends are observed in other cases which are not presented in this paper, the performance of the proposed scheme with 150 generations is presented in the following section.

5.2. **Low throughput performance improvement.** Figure 5 shows the comparison of low throughput user performances for $\epsilon = 0.05$ and 0.1. Particularly, we compare the performances of the 5th, 10th, 15th, and 20th percentile users. As expected, the low throughput user performance improvement increases when a large value of ϵ is allowed. In this example, the 10th percentile user throughput performances are improved by about 38% and 44% if the overall throughput performance loss rates of $\epsilon = 0.05$ and 0.1 compared with the conventional scheme are allowed, respectively.

In addition, we see that the improvement rate becomes large for low percentile values. The reason is that, at a low percentile value, the number of users whose throughputs need to be improved is relatively small. Thus, it is relatively easy to find a channel set to significantly improve these users' performances.

5.3. **Effect of available link-gains.** Previously, we have assumed that link-gains between all basestations and users are available at the controller. However, this assumption is not practically feasible because it is very hard for a user to measure the link-gains of distant basestations. When only some link-gains are available at the controller, each user's average SIR values for a given channel set will be estimated inaccurately. Thus, we

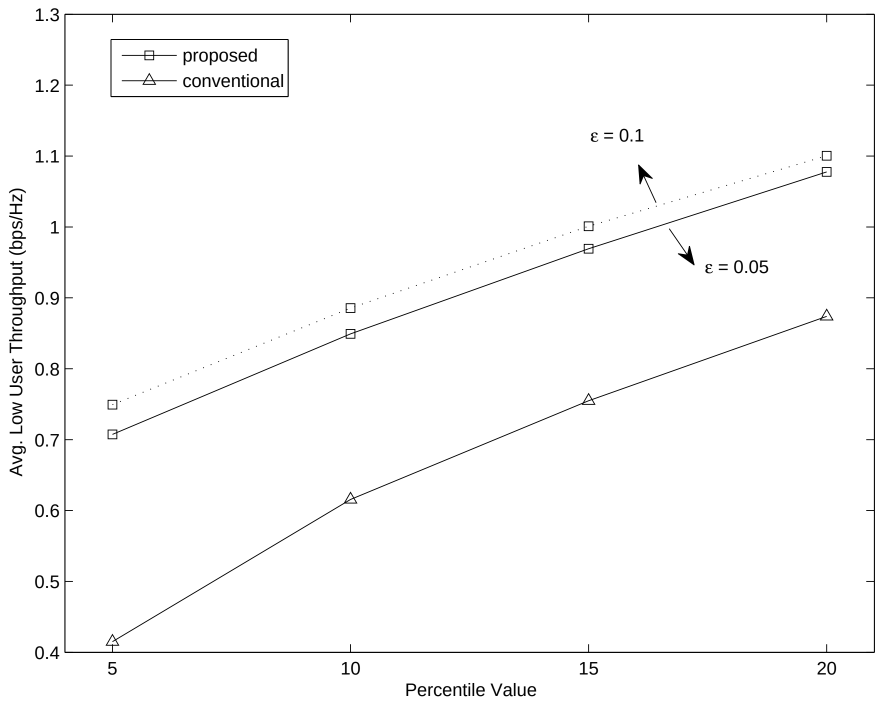

Figure 5. Comparison of the average low throughput user performances

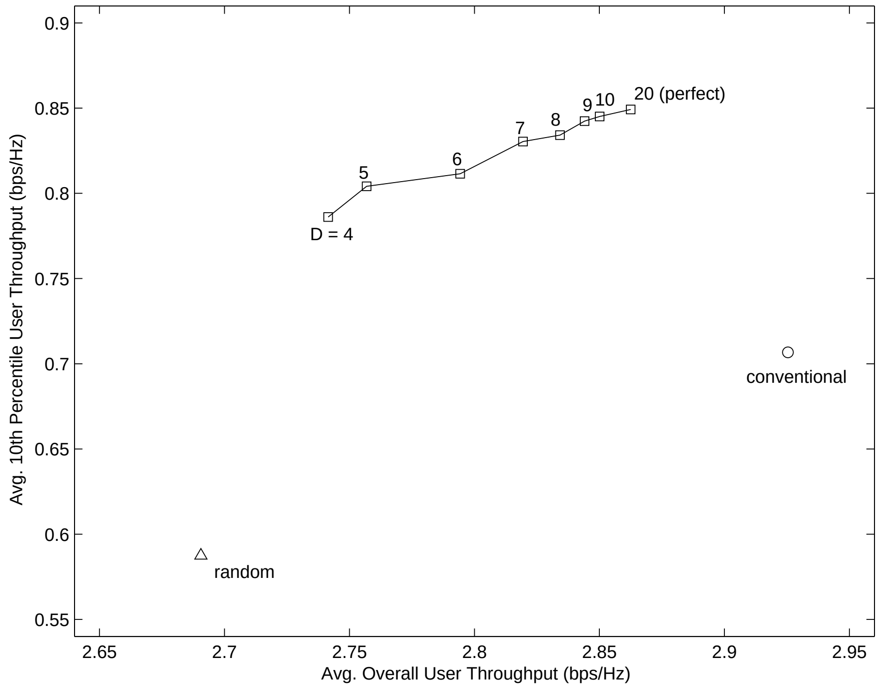

FIGURE 6. Average user throughput performance with the number of available link-gains for $\epsilon = 0.05$

investigate the effect of link-gain availability on the performance. In particular, consider the case when each user can measure the link-gains from D basestations whose link-gains are the largest.

Figure 6 shows the overall throughput performance versus the 10th percentile user throughput performance for the number of available link-gains per user D and $\epsilon = 0.05$. Also, the performances of the conventional and the random assignment schemes are plotted. As expected, the low throughput user performance and the overall throughput performance are degraded as D decreases because the average SIR value estimation becomes more inaccurate for low D. However, the low throughput user performances are still better than those of the conventional scheme and the random scheme.

In addition, the performance loss due to the unavailability of some link-gains is not significant when D is not excessively small. For example, at $D = 7$, the low and the overall throughput performances are degraded by about 1.8% and 1.5% compared with those of the case when all link-gains are available (i.e., $D = 20$), respectively. This implies that the proposed scheme can improve the low throughput user performance if a suitable number of link-gains are available.

6. **Conclusions.** In this paper, we propose a GA-based channel allocation scheme that fairly supports best-effort users in a microcellular system. The conventional scheme does not properly support the users far from the serving basestation, because it chooses the channels which improve the performance of the near users. To solve this problem, the proposed scheme finds the channel set maximizing the far users' performances while allowing a pre-specified loss of overall performance. Using computer simulations, we demonstrate that the proposed scheme improves the performance of the 10th percentile low throughput users up to 38% while allowing the overall performance loss to be less than 5% compared with that of the conventional scheme. Also, we show that the low percentile user performance improvement can be maintained even when only some basestations' link-gains are available to each user.

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