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SUBCARRIER AND BIT ALLOCATION SCHEME FOR THE MA PROBLEM BASED ON THE ANT COLONY OPTIMIZATION TO MINIMIZE POWER CONSUMPTION IN OFDMA SYSTEMS

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Abstract. *Subcarrier and bit allocation for margin adaptive (MA) problem with goal of minimizing the transmit power consumption under a given requirement has become an important issue for providing efficient power saving design in downlink orthogonal frequency division multiplexing access (OFDMA) systems. However, the problem becomes NP-hard because it requires a great complex searching facility to find a bit and subcarrier combination which performs the best. To find the best combination without a full search, we propose an efficient subcarrier and bit allocation scheme for the MA problem based on the ant colony optimization (ACO) algorithm minimizing transmit power consumption with satisfaction of required bits. Simulation results show the proposed ACO based scheme provides better performance in terms of less transmit power consumption and faster convergence.*

Keywords: OFDMA system, Subcarrier and bit allocation, Ant colony optimization, Genetic algorithm, Transmit power minimization

1. **Introduction.** Subcarrier and bit allocation has been studied for a diversity of OFDM-based communication systems because of its benefit in terms of efficient use of the given frequency as well as power resources [1-3]. In particular, power-efficient design of a subcarrier and bit allocation algorithm with low transmit power while satisfying given throughput and fairness requirements is an important issue because, with low transmit power, the inter-cell interference (ICI) can be lowered in cellular OFDMA systems.

In the previous studies, there are optimal and suboptimal algorithms presented for downlink OFDMA systems that adaptively allocate the subcarriers and bits for multiple users [4-9]. Among them, [4, 5] formulated nonlinear optimization problems adopting integer variables, known as the margin adaptive (MA) and rate adaptive (RA) problems. The MA problem is to minimize the total transmission power under a given rate requirement, and the RA problem is the maximization of the data rate under a given maximum transmit power requirement. Since solving the optimization problem requires extremely high computational complexity because of the search space exponentially increasing with the number of subcarriers and users, suboptimal algorithms were also proposed, including the greedy algorithm for multi-user multicarrier systems [6-9]. Particularly, the subcarrier and bit allocation scheme for the RA problem based on the ant colony optimization (ACO) algorithm was introduced in [10].

This paper proposes a novel subcarrier and bit allocation scheme for the MA problem based on the ant colony optimization (ACO) algorithm to minimize power consumption in OFDMA systems. An important contribution of this paper is that the ACO algorithm is adapted to subcarrier and bit allocation of an OFDMA system for the MA problem,

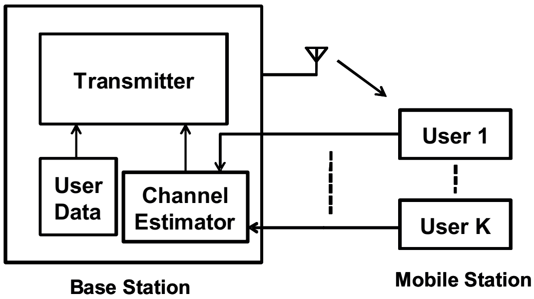

FIGURE 1. System model

which is the first time to the authors' knowledge. In the previous researches for the MA problem, the subcarrier and bit allocation scheme based on the genetic algorithm (GA) was presented by [4]. In addition to the Wang's GA based scheme, the improved genetic algorithm (IGA) based scheme for the MA problem proposed by [11] adopts some routines such as the repair function, and the generation of random immigrants and the modified mutation rate adaptation are adapted to accelerate the convergence speed as well as guarantee the quality of service (QoS) requirements. On the other hand, in the proposed ACO based scheme, the subcarriers are iteratively allocated to users by following the ACO procedure. The proposed ACO based scheme is expected to converge faster than the conventional GA based scheme and IGA based scheme, as well as require lower transmit power to achieve a certain throughput requirement. The advantages of the proposed ACO based scheme over the conventional suboptimal schemes are evaluated in terms of the amount of transmit power consumption through computer simulation.

The remainder of this paper is organized as follows: Section 2 describes the system model considered in this paper; Section 3 introduces the conventional GA based schemes for the MA problem and Section 4 presents the proposed ACO based scheme for the MA problem; the simulation results are shown in Section 5; finally, Section 6 contains the conclusions.

2. **Problem Description.** Figure 1 shows the system model considered in this paper. A base station (BS) is capable of serving K users at a time. At the BS, we assume that N subcarriers is available and the channel response for each user is used. User data are allocated on subcarriers and transmitted. For an allocation, eNBs need to consider numerous bit and subcarrier combinations. Possible combinations increase exponentially as users are added and more subcarriers are used. Because of the relation between subcarriers and users, the allocation has the great complexity, represented as $O(n^k)$ if expressed by O-notation. In addition, allocation should be completed because of time limit for QoS requirements of user data. It is impractical to search all possible combinations for the best performance. Therefore, bit and subcarrier allocation must be controlled and issued.

Let $r_{k,n}$ and $\alpha_{k,n}$ denote the number of bits and the channel gain of subcarrier n for user k when user k is allocated on subcarrier n. The transmit power $p_{k,n}$, satisfying the target bit error rate (BER), P_b, can be represented by

$$p_{k,n} = \frac{f(r_{k,n})}{\alpha_{k,n}^2}$$

where $f(r_{k,n}) = \frac{N_o}{3}\left[Q^{-1}\left(P_b/4\right)\right]^2 \left(2^{r_{k,n}} - 1\right)$, $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{\frac{-t}{2}}dt$, and N_o is additive white Gaussian noise (AWGN).

The system assumed in this paper is not a single user network system but a multiuser system. $\rho_{k,n}$ is needed to concern multiuser diversity. $\rho_{k,n}$ is drawn as:

$$\rho_{k,n} = \begin{cases} 1, & \text{if subcarrier } n \text{ is allocated to user } k \\ 0, & \text{otherwise} \end{cases}$$

The allocated bits for user k, r_k, has to be larger than the required minimum bits, R_k, as:

$$r_k = \sum_{n=1}^{N} r_{k,n}\rho_{k,n} \geq R_k \tag{1}$$

Also, the transmit power P_k is calculated as:

$$P_k = \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n}\rho_{k,n} = \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{f(r_{k,n})}{\alpha_{k,n}^2}\rho_{k,n}$$

Because it is our objective to minimize transmit power consumption satisfying the required minimum bits, our fitness function is formulated as follows:

$$\min_{R_k} \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n}\rho_{k,n} \tag{2}$$

$$\text{Subject to } \sum_{n=1}^{N} r_{k,n}\rho_{k,n} \geq R_k, \quad \forall k \in \{1, 2, \cdots, K\}.$$

3. **Conventional Genetic Algorithm Based Schemes for the MA Problem.** The genetic algorithm (GA) [12, 13] is one of the evolutionary algorithms inspired by the theory called natural selection in which strongers are more likely to survive by defeating the others in competition. The GA has been applied because searching faster. The primary procedure of GA includes the following steps: population initialization, recombination, mutation evaluation and selection. In the conventional GA based scheme by [4], the GA was applied to subcarrier and bit allocation for the MA problem due to a convex problem, where the authors inserted an additional step for adaptation of the mutation rate to improve the convergence speed, but with only three different preset constant rates. Also, [11] introduced another improved genetic algorithm (IGA) whose performance is further improved by adding the following operations: i.e., repair function, generation of random immigrants, as well as the modified mutation rate adaptation. The detail of the conventional IGA based scheme for the MA problem is as follows:

Population Initialization: In this step, W chromosomes are generated. Here, a chromosome denotes a group of user-to-subcarrier set combinations; in other words, W chromosomes are W different instances of subcarrier allocation to the K users. In generating a chromosome, one or more subcarriers are randomly selected for each user. The mapping between a user and the set of subcarriers allocated to the user is referred to as a *gene*. Thus, there are K different genes in a chromosome.

Recombination: In this step, the genes are exchanged between the chromosomes. For this, two chromosomes are randomly selected and recombined through the mechanism called crossover, which is a replacement operation in which some genes in the two chromosomes are swapped. Both free and allocated subcarriers are candidates for crossover so that infeasible combinations which violate the requirements are frequently generated.

Mutation: In this step, one of the genes in each chromosome is substituted by a randomly generated gene. If the modified chromosome, called *offspring*, is better, then the original one (i.e., *parent*) is replaced by the new chromosome.

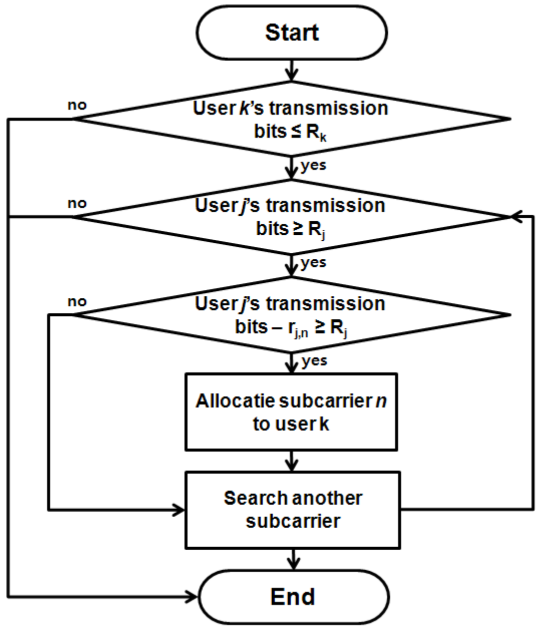

FIGURE 2. The flow chart of repair function

Repair Function: The new chromosome generated by recombination and mutation operations may violate the given requirement in (1). If a chromosome violates the requirement that the number of transmit bits for user k should not be less than R_k, the repair function [14] is performed to reallocate new subcarriers by following the flow chart shown in Figure 2. First, a user is randomly selected, and then check if the requirement for the user is satisfied even when one of the subcarriers assigned to the user is retracted. In this case, the subcarrier n is relocated to the other user. This repeats until the requirement for all users are satisfied.

Evaluation and Selection: After an offspring chromosomes are generated, the offspring and parent chromosomes are evaluated based on a fitness criterion which means the cost function for the MA problem in (2). Each chromosome is evaluated to select the best one as a parent for the next generation, discarding the others.

Random Immigrant: Since it is possible that a combination having poor fitness at present generation can evolve into a better chromosome, an infeasible combination is selected as a member for next generation. This random immigrant gives the infeasible combination a chance to evolve a better combination by extending the search space. This mechanism is also called the pluck operation [15].

Adaptation of the Mutation Rate: The mutation rate adaptation [16] is a mechanism in which the mutation rate at the m-th generation is determined as:

$$\mu_m = 0.3 - 0.15 \times \frac{e^{6P_{div}-3} - 1}{e^{6P_{div}-3} + 1} \tag{3}$$

where P_{div} is the parent diversity given by [14]

$$P_{div} = 1 - \frac{\text{the number of repeated parent}}{\text{the number of selected parent}}.$$

A realization of the mutation rate according to (3) is shown in Figure 3. The adaptation of the mutation rate not only increases the possibility of finding the global optimum but also accelerates the convergence time [16].

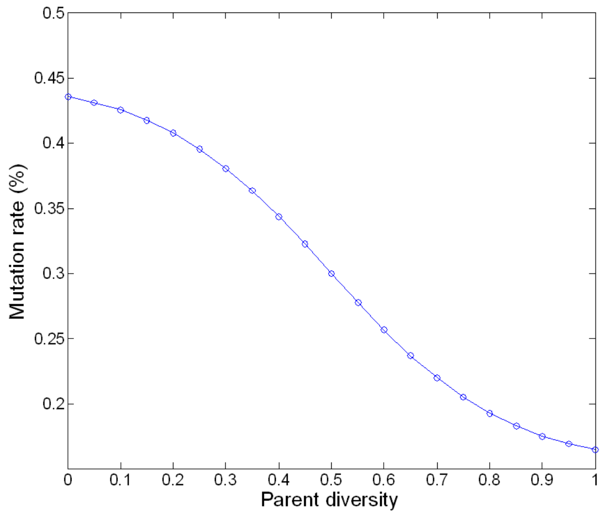

FIGURE 3. Mutation rate

4. **Proposed Ant Colony Optimization based Scheme for the MA Problem.** Although it can get an asymptotic solution of the global optimum, the GA has the disadvantage that it may find an infeasible combination does not guarantee the throughput requirement. In this section, we consider the ant colony optimization (ACO) algorithm to faster and more accurately find the global solution. Unlike the GA, the ACO algorithm does not generate infeasible combinations because it allocates subcarriers under the given requirement in (1), while converging to the optimum faster than the GA.

In the ACO algorithm, a number of blind ants collaborates to find the shortest path between food sources and their colony by sharing information by means of the *pheromone* [17-19]. In this algorithm, an ant lays a little amount of pheromone on the route it walks. An isolated ant, which first establishes a path, marks a trail at random because it cannot find any trail of other ants. However, as many ants move from their colony to the food source, a large amount of pheromone is accumulated on the trails on the shorter routes because the ants visit the short routes more frequently, but little pheromone remains on the other routes as the pheromone evaporates with time. Thus, the ants can choose shorter routes by deciding based on the amount of the pheromone laid on the trails. As a consequence, the shortest route is more likely to be chosen by most of the ants as time goes by.

TABLE 1. An example of Tabu list

Ant's decision	Tabu list	
8		available
1	8	available
3	1, 8	available
7	1, 3, 8	available
3	1, $\underline{\boldsymbol{3}}$, 7, 8	unavailable
4	1, 3, 7, 8	available

In the proposed subcarrier and bit allocation scheme for the MA problem based on the ACO algorithm considered in this paper, a subcarrier should not be allocated at the same time to more than two users. Therefore, this requirement can be maintained by using a Tabu list that contains the subcarrier information already allocated. When an ant tries to allocate subcarrier n to user k, the Tabu list is checked before allocation. If the subcarrier n was already allocated to the other user, the ant is supposed to find the other subcarrier. If the subcarrier n is not occupied by the others, the ant actually can allocate the subcarrier to the user k, and then register the subcarrier index n to the Tabu list. An example of the Tabu list is shown in Table 1. In the proposed ACO based scheme, the ant is characterized by the three main characteristics [17]. Firstly, the ant chooses the subcarrier and user combination based on the transition probability and the amount of feasible users should satisfy the given requirement in (1). Secondly, in order to enable the ant to search for proper combinations as optimization factor, selecting a subcarrier already allocated to another user is forbidden until the ant finishes the tentative selection. This is controlled by using the tabu list. Thirdly, after finishing the selection the ant lays a small amount of pheromone on the trail. The amount of pheromone is determined by the fitness function in (2) which is the cost function of the MA problem. After that the ant follows pheromone trail lay more pheromone. Beyond that, more detail on the proposed ACO based scheme is described as follows [17, 20]:

Selection: An ant becomes an agent which allocates the subcarriers to the users. The ant continues to allocate subcarriers to the user k until more than the required bits R_k are loaded as shown in (1).

Pheromone Update: After the subcarrier selection, the pheromone is updated according to the fitness. Let $\tau_{k,n}(g)$ denote the amount of pheromone at generation g. Then, the allocation of the ants at generation g is affected by the value of $\tau_{k,n}(g)$ until the allocation of all the ants is completed. The pheromone is updated as:

$$\tau_{k,n}(g) = e \times \tau_{k,n}(g) + \Delta\tau_{k,n}$$

where e is the evaporation constant ranging (0, 1], and $\Delta\tau_{k,n}$ is the incremental amount of pheromone which is determined by the inverse of the required transmit power for the user k: i.e., $\Delta\tau_{k,n} = \frac{1}{P_k}$ where $P_k = \sum_n p_{k,n}$.

Elite Update Strategy: The elite update strategy is simply to update more pheromone to the best fit combination. This is accomplished by adopting $\Delta\tau$ defined by

$$\Delta\tau_{k,n} = \frac{E}{P_k}$$

where

$$E = \begin{cases} \varepsilon & \text{if } P_k \text{ is the least} \\ 1 & \text{otherwise} \end{cases}$$

and ε is an elite updating constant greater than 1.

Transition Probability: Ants combine the subcarriers and the users based on a transition probability denoted by $T_{k,n}$. At every time the pheromone has been updated, the transition probability is computed as:

$$T_{k,n} = \frac{\tau_{k,n}(g)}{\sum_{n=1}^{N} \tau_{k,n}(g)}.$$

Given the transition probabilities of the subcarriers for each user k, each ant randomly selects one subcarrier among the N subcarriers, so that the consequent selection probability of each subcarrier becomes equal to the transition probability corresponding to it. This selection is repeated until the required bits are satisfied for the user. As the transition probability involves the quantity of pheromone, it starts with the same probability value at first as Figure 4(a) but finishes with a differentiated probability value for each user at last as Figure 4(b).

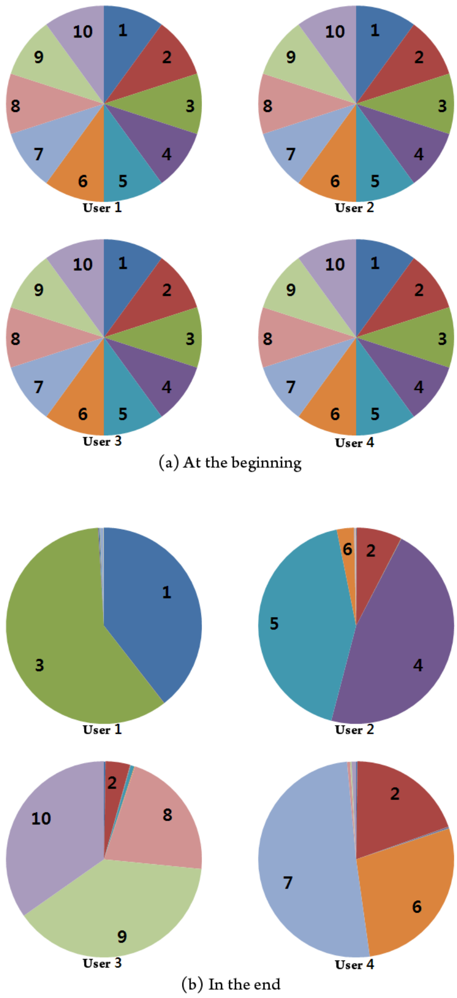

Figure 4. An instance of transition probability

5. **Simulation Results.** In this section, the performance of the proposed ACO based scheme is compared with the conventional schemes: the greedy based scheme, the GA based scheme proposed by Wang [4], and the IGA based scheme proposed by Song [10]. In the simulation, the number of subcarriers was 64; the number of users were from 4 to 9 users; the target BER was 10^{-3}; the minimum required bits was set to 24 bits per OFDM symbol; the modulation levels were QPSK, 16-QAM and 64-QAM. 10 parent and 100 offspring chromosomes were used for the conventional GA and IGA based schemes and 5 ants were employed for the proposed ACO based scheme. To simulate the conventional GA and IGA based schemes, the mutation rates were set to 0.1, 0.2, 0.4 and 0.5 depending on the number of iterations [4, 11]. For the simulation of the proposed ACO based scheme, the number of ants was set to 10, the evaporation constant was $e = 0.8$, and elite update constant was $\epsilon = 2.0$ [10].

Figure 5 shows the convergence property of the subcarrier and bit allocation schemes with 64 subcarriers, 8 users and the required bits of 28 bits. In the figure, it is observed that the transmit power by the allocation schemes decreases with the number of iterations, indicated by the word 'generation'. Specifically, the performance of the conventional GA based scheme outperformed the greedy based scheme at 45 generation. However, the dotted red line indicates that the performance of the conventional IGA based scheme exceeded the greedy based scheme at 20 generations while the black line shows that the

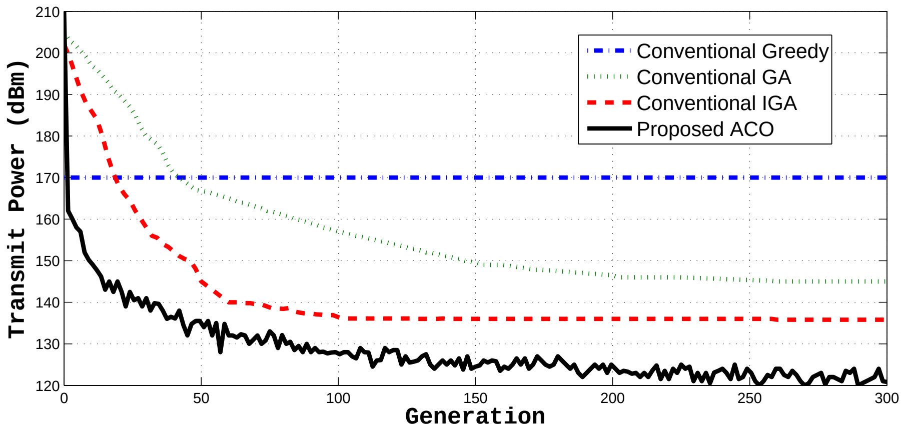

FIGURE 5. Convergence property (K = 8, N = 64, Required bits = 28bits, BER = 10^{-3})

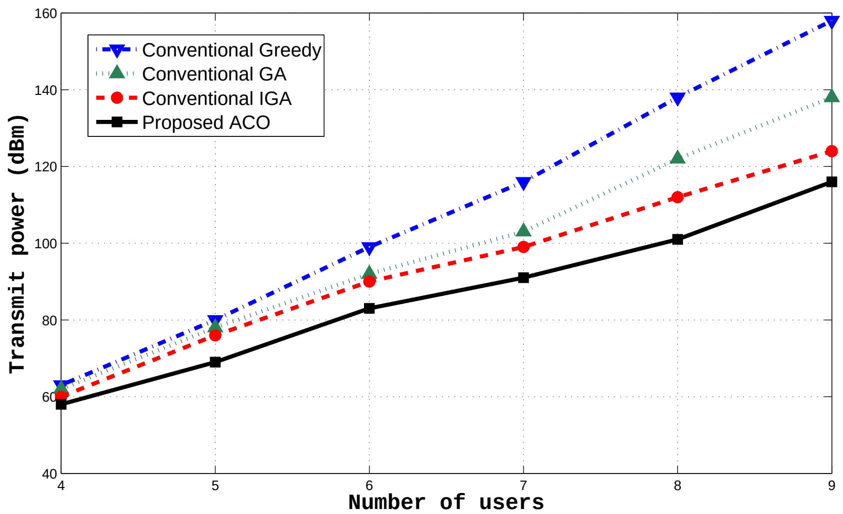

FIGURE 6. Transmit power versus number of users (N = 64, Required bits = 24bits, BER = 10^{-3})

performance of the proposed ACO based scheme was superior to the greedy based scheme within several generations. As a result, the proposed ACO based scheme at the lowest part outperforms the others within the smallest generation. From Figure 5, we find that the proposed ACO based scheme provides better performance than the conventional schemes in terms of convergence property.

Figure 6 shows the transmit power needed to obtain the minimum required bits for different number of users. From the figure, it is observed that the proposed ACO based scheme requires the minimum transmit power compared to the others, and the conventional IGA based scheme shows worse performance than the proposed ACO based scheme, yet having better performance than the conventional greedy based scheme and GA based scheme.

Figure 7 shows the required transmit power by the candidate schemes to accommodate the required bits. This figure also shows that the proposed ACO based scheme exhibits the best performance among the candidates, and the conventional IGA based scheme has

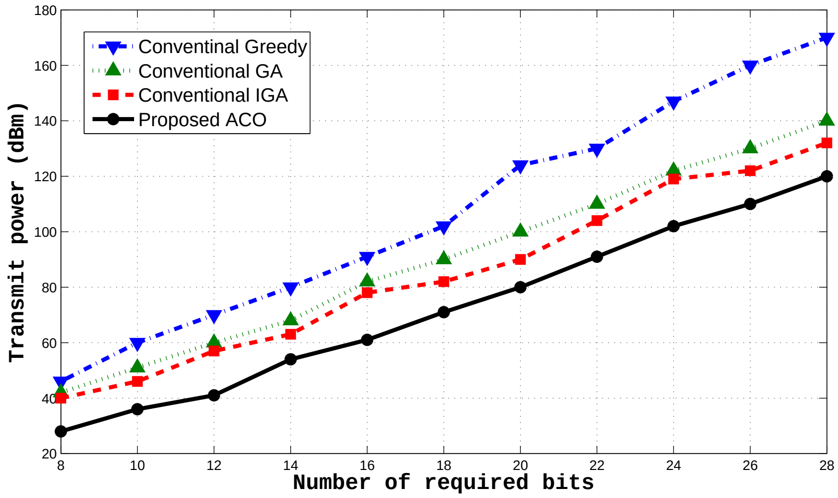

Figure 7. Transmit power versus number of required bits (K = 8, N = 64, BER = 10^{-3})

the second best performance compared to the conventional greedy based scheme and GA based scheme. From the simulation results, we find that the proposed ACO based scheme provides better performance than the conventional schemes in terms of less transmit power consumption and faster convergence.

6. **Conclusion.** In this paper, we have presented an efficient subcarrier and bit allocation scheme for the margin adaptive (MA) problem based on the ant colony optimization (ACO) algorithm in downlink OFDMA systems. The proposed ACO based scheme was compared to the conventional greedy based scheme, GA based scheme, and improved GA (IGA) based scheme that introduced three additional techniques such as the random immigrant, adaptive mutation rate, and repair function to accelerate the convergence speed and to exploit the multiuser diversity. From the simulation results, it is concluded that the proposed ACO based scheme shows better performance in terms of transmit power consumption and convergence property compared to the conventional schemes. In addition, it is helpful not only to allocate efficiently subcarrier and bit but also to reduce inter-cell interference (ICI). It is because the reduction of transmit power in a serving cell causes less ICI to adjacent cells. Therefore, the proposed ACO based scheme can contribute to reduce power consumption which is one of the big issues in wireless network design as energy efficiency technology.

REFERENCES

[1] H. Rohling and R. Grunheid, Performance of an OFDM-TDMA mobile communication system, *VTC'96*, vol.3, pp.1589-1593, 1996.
[2] A. Czylwik, Adaptive OFDM for wideband radio channels, *GLOBECOM'96*, vol.1, pp.713-718, 1996.
[3] H. Rohling and R. Gruneid, Performance comparison of different multiple access schemes for the downlink of an OFDM communication system, *VTC'97*, vol.3, pp.1365-1369, 1997.
[4] Y. Wang, F. Chen and G. Wei, Adaptive subcarrier and bit allocation for multiuser OFDM system based on genetic algorithm, *Communications, Circuits and Systems*, vol.1, pp.242-246, 2005.
[5] W. Rhee and J. M. Cioffi, Increase in capacity of multiuser OFDM system using dynamic subcarrier allocation, *VTC 2000-Spring Tokyo*, vol.2, pp.1085-1089, 2000.
[6] H. Yin and H. Liu, An efficient multiuser loading algorithm for OFDM-based broadband wireless systems, *GLOBECOM'00*, vol.1, pp.103-107, 2000.

[7] J. Jang and K. B. Lee, Transmit power adaptation for multiuser OFDM systems, *IEEE J. Sel. Areas in Commun.*, vol.21, pp.171-178, 2003.

[8] E. Bakhtiari and B. H. Khalaj, A new joint power and subcarrier allocation scheme for multiuser OFDM systems, *PIMRC'03*, vol.2, pp.1959-1963, 2003.

[9] J. Lee, R. V. Sonalkar and J. M. Cioffi, Multiuser bit loading for multicarrier systems, *IEEE Trans. on Commun.*, vol.54, no.7, pp.1170-1174, 2006.

[10] J. Song and D. H. Kim, Dynamic subcarrier and bit allocation for throughput maximization in multiuser OFDM systems using ant colony optimal algorithm, *International Journal of Innovative Computing, Information and Control*, vol.6, no.10, pp.4705-4718, 2010.

[11] J. Song, S.-S. Kim, K. Chang and D. H. Kim, Improved genetic algorithm based bit and subcarrier allocation scheme for efficient resource use in multiuser OFDM systems, *The Journal of Korea Information and Communications Society*, vol.33, no.11, pp.1095-1103, 2008.

[12] K. F. Man, K. S. Tang and S. Kwong, Genetic algorithms: Concepts and applications, *IEEE Trans. on Industrial Electronics*, vol.43, pp.519-534, 1996.

[13] S. N. Sivanandam and S. N. Deepa, *Introduction to Genetic Algorithm*, Springer, New York, 2008.

[14] A. K. Tripathi, D. P. Vidyarthi and A. N. Mantri, A genetic task allocation algorithm for distributed computing system incorporating problem specific knowledge, *Int. J. High Speed Computing*, vol.8, pp.363-370, 1996.

[15] S. S. M. Patra, K. Roy, S. Banerjee and D. P. Vidyarthi, Improved genetic algorithm for channel allocation with channel borrowing in mobile computing, *IEEE Trans. on Mobile Computing*, vol.5, pp.884-892, 2006.

[16] M. A. C. Lima, A. F. R. Araujo and A. C. Cesar, Adaptive genetic algorithms for dynamic channel assignment in mobile cellular communication systems, *IEEE Trans. on Veh. Technol.*, pp.2685-2696, 2007.

[17] M. Dorigo, V. Maniezzo and A. Colorni, Ant system: Optimization by a colony of cooperating agents, *IEEE Trans. on Systems, Man, and Cybernetics*, vol.26, pp.29-41, 1996.

[18] S. S. Kim, I.-H. Kim, V. Mani and H. J. Kim, Ant colony optimization for reporting cell planning in mobile computing using selective paging strategy, *International Journal of Innovative Computing, Information and Control*, vol.5, no.6, pp.1587-1598, 2009.

[19] H. Zhang, X. Li, L. Dong, X. Ren and J. Guo, Study of emergency resource distribution based on ant colony algorithm, *ICIC Express Letters*, vol.4, no.3(A), pp.751-756, 2010.

[20] M. Dorigo and G. D. Caro, Ant colony optimization: A new meta-heuristic, *Proc. of the Congress on Evolutionary Computation*, vol.2, pp.1470-1477, 1999.