An Elitist Selection Adaptive Genetic Algorithm for Resource Allocation in Multiuser Packet-based OFDM Systems

Zhihua Tang, Youtuan Zhu, Guo Wei, Jinkang Zhu
Wireless Information Network Lab
University of Science and Technology of China
Email: {zhtang, ytzhu}@mail.ustc.edu.cn; {wei, jkzhu}@ustc.edu.cn

***Abstract*— This paper presents a new cross-layer resource allocation model for multiuser packet-based Orthogonal Frequency Division Multiplexing (OFDM) systems, where the packet arrival process, delay QoS in the application layer and the subcarrier conditions for all users in the physical layer are considered in the MAC layer design. The objective of the proposed cross-layer resource allocation is formulated into a constrained optimization problem, which incorporates the three layers into an integrated framework. To solve the problem effectively, we propose an elitist selection adaptive genetic algorithm (ESAGA), in which the probabilities of crossover and mutation are varied depending on the diversity of population. Numerical examples demonstrate the effectiveness of our proposed algorithm. Due to its low computational complexity, our proposed algorithm is very suitable for implementation in a practical system.**

***Index Terms*— OFDM, cross-layer, packet-based, resource allocation, adaptive genetic algorithm (AGA)**

I. Introduction

Broadband wireless networks providing QoS guarantees require efficient resource management schemes. OFDM is a promising modulation technique used in wireless LANs, and can support high-rate data transmission. Therefore, resource management in the OFDM systems, including a variety of subcarrier allocation, power allocation, and bit-loading algorithms, has drawn enormous attention in recent years [1]–[3].

In most of the existing resource allocation algorithms for OFDM systems, it is assumed that all users are delay-insensitive and always have backlogs in their infinite queues. The stochastic traffic arrivals to each user and the delay QoS in the application layer are seldom considered in the MAC layer design [2] [3]. These algorithms are concentrated on exploiting the dynamics of physical layer and optimizing the physical and MAC layers jointly. On the other hand, in the traditional MAC scheduling design such as packet scheduling, the physical layer is modeled as a simple abstract pipeline to carry information with a fixed level of reliability [4]. The analysis is focused on the abstract physical layer resource allocation among stochastic traffic arrivals to each user and the delay analysis from the queuing perspective. It only exploits the source statistics of the application layer. This motivates us to consider a new cross-layer approach in the packet-based environment with bursty arrival of packets, where the application, MAC and physical layers are jointly optimized to achieve good QoS of the whole system.

The genetic algorithm is a family of computational models inspired by the evolution and is used to find true or approximate solutions to optimization problems [5]. It has been proposed to resolve the adaptive resource allocation problem in the OFDM systems [6] and the packet scheduling problem in the High-Speed Downlink Packet Access (HSDPA) systems [7]. Moreover, it has been proved to be very suitable for the optimization of the subcarrier and bit allocation problem in multiuser OFDM systems. Elitist selection is a variant of the general process of constructing a new population in the genetic algorithm. It allows some of the better organisms from the current generation to carry over to the next, unaltered. Elitist selection improves the convergence of the genetic algorithm.

In [8], the MAC layer has been designed to be adaptive to the physical layer and the source statistics of the application layer, and a solution based on the elitist selection genetic algorithm (ESGA) is proposed. In this paper, we extend the idea of [8] to use the adaptive genetic algorithm. In our proposed elitist selection adaptive genetic algorithm (ESAGA), the probabilities of crossover and mutation are varied depending on the population diversity. Moreover, the complexity of ESAGA is analyzed. Numerical examples demonstrate that our proposed algorithm can further improve the performances of ESGA in terms of packet delay distribution and average throughput.

The rest of the paper is organized as follows. In Section II, the system model of cross-layer resource allocation for multiuser packet-based OFDM systems is given, and the optimization problem is formulated. In Section III, the complexity-reduced ESAGA is proposed and its computational complexity is analyzed. Numerical examples are given and discussed in Section IV. Finally, conclusions are drawn in Section V.

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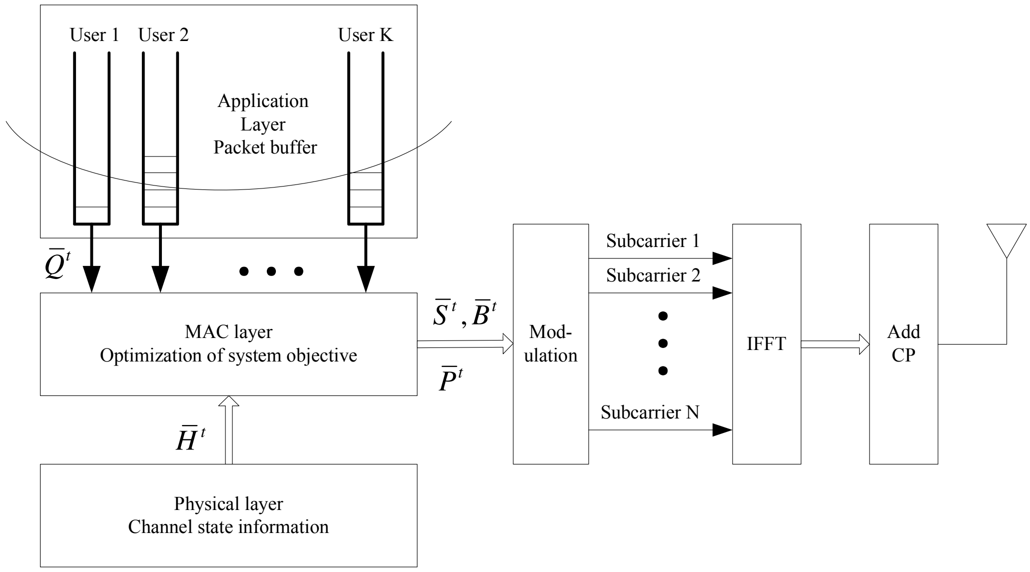


Figure 1. Cross-layer resource allocation model for multiuser OFDM systems

II. System Model and Problem Formulation

Fig.1 illustrates the cross-layer resource allocation model for multiuser packet-based OFDM systems, where the packet arrival process in the application layer and the subcarrier conditions for all users are considered in the MAC layer resource allocation design. Assume that there are N subcarriers, K users in the system. It is advisable to assign only one user to a subcarrier [9]. Let $\bar{\mathbf{S}}^t = (s_1^t, \ldots, s_N^t)$ represent the subcarrier allocation, which is a vector of the indices of users scheduled over all subcarriers. Likewise, we define $\bar{\mathbf{B}}^t = (b_1^t, \ldots, b_N^t)$ and $\bar{\mathbf{P}}^t = (p_1^t, \ldots, p_N^t)$ to be the bit and power allocation vectors. At every time slot, the resource allocation module has to generate $\bar{\mathbf{S}}^t$, $\bar{\mathbf{B}}^t$ and $\bar{\mathbf{P}}^t$ based on the observation of current channel state information (CSI) $\bar{\mathbf{H}}^t$ in the physical layer and queue state information (QSI) $\bar{\mathbf{Q}}^t = (q_1^t, \ldots, q_K^t)$ from the application layer. Assuming that perfect instantaneous CSI is available, the channel gain matrix can be expressed as follows:

$$\bar{\mathbf{H}}^t = \begin{pmatrix} h_{1,1}^t, & \ldots, & h_{1,K}^t \\ \ldots, & \ldots, & \ldots \\ h_{N,1}^t, & \ldots, & h_{N,K}^t \end{pmatrix}, \tag{1}$$

where $h_{n,k}^t$ is the channel fading for user k on subcarrier n at time slot t.

The number of bits allocated to user k at time slot t is:

$$r_k^t = \sum_{n=1}^{N} b_n^t \cdot \mathbf{1}_{\{s_n^t = k\}}, \tag{2}$$

where $\mathbf{1}_{\{\cdot\}}$ is an indicator function:

$$\mathbf{1}_{\{s_n^t = k\}} = \begin{cases} 1 & \text{if } s_n^t = k, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Assume a new packet with λ_k^t bits arriving during $(t-1, t]$, the queue length is updated as follows:

$$q_k^{t+1} = q_k^t - r_k^t + \lambda_k^t. \tag{4}$$

A more general framework for the cross-layer resource allocation is based on the utility functions [10]. The problem is formulated to find the optimal subcarrier allocation, bit allocation and power allocation policies so as to maximize a system utility function of the average user-specific variables:

$$U(\bar{R}_1, \ldots, \bar{R}_K; \bar{Q}_1, \ldots, \bar{Q}_K), \tag{5}$$

where $\bar{R}_k$ is the average data rate and $\bar{Q}_k$ is the average queue length of user k. It is challenging to convert the system utility function with respect to the average user-specific variables directly to an instantaneous optimization object with respect to the instantaneous variables which makes sense in practice. This problem has been widely studied in the single channel system such as CDMA [11]. However, the same idea no longer performs well in the multi-channel system like OFDM directly, due to the multiple freedoms of resource management (e.g., subcarrier, bit, power). But the same effect can be pursued if we optimize a predefined instantaneous utility function firstly, then figure out the relationship between them.

It is reasonable to predefine an instantaneous utility function U^t with respect to the instantaneous queue sizes $\{q_k^t, k = 1, \ldots, K\}$ and the instantaneous achievable rates $\{r_k^t, k = 1, \ldots, K\}$ as follows:

$$U^t = \sum_{k=1}^{K} V_k(r_k^t, q_k^t), \tag{6}$$

where $V_k(r, q)$ is the instantaneous utility function of user k. The sum throughput maximization rule is a special case when $V_k(r, q) = c \cdot r + d$, where $c > 0$ and d are constants for all k. In the following, we define $V_k(r,q) = q{\cdot}r$ for analysis convenience, then (6) can be rewritten as:

$$U^t = \sum_{k=1}^{K} r_k^t{\cdot}q_k^t = \sum_{k=1}^{K}\sum_{n=1}^{N} b_n^t{\cdot}\mathbf{1}_{\{s_n^t=k\}}{\cdot}q_k^t. \qquad (7)$$

Let P_{tol} be the overall power offered for an OFDM symbol. $f_k(c)$ represents the needed SNR to guarantee BER constraint of user k with 2^c-ary modulation. $f_k(b_{n,k}^t)/|h_{n,k}^t|^2$ is the transmission power of user k on subcarrier n. Let $\rho_{n,k}^t$ be an indicator variable. $\rho_{n,k}^t = 1$ means that the subcarrier n is allocated to user k at time slot t, otherwise $\rho_{n,k}^t = 0$. Our problem can be described as follows:

$$\max_{(b_{n,k}^t,\rho_{n,k}^t)} \quad U^t = \textstyle\sum_{k=1}^K q_k^t \sum_{n=1}^N b_{n,k}^t{\cdot}\rho_{n,k}^t$$
$$\text{for} \quad \rho_{n,k}^t \in \{0,1\}, b_{n,k}^t \in \{1,2,\cdots,C\} \qquad (8)$$
$$\begin{aligned} s.t.\quad & 1)\ \textstyle\sum_{n=1}^N \sum_{k=1}^K f_k(b_{n,k}^t)/|h_{n,k}^t|^2{\cdot}\rho_{n,k}^t \le P_{tol},\\ & 2)\ \textstyle\sum_{k=1}^K \rho_{n,k}^t \le 1,\\ & 3)\ \textstyle\sum_{n=1}^N b_{n,k}^t{\cdot}\rho_{n,k}^t \le q_k^t. \end{aligned}$$

The number of bits that can be transmitted by each subcarrier is bounded to C. Constraint 1) is to guarantee the total allocated power is not more than the supportable power. Constraint 2) is to ensure that one subcarrier is allocated to at most one user at a time. Constraint 3) comes from the fact that the scheduler should not waste service rate at users whose queues are empty.

The problem of (8) is a combinatorial optimization problem. The exhaustive search for the optimal solution requires $O((KC)^N)$ complexity and is prohibitive. In the following section, we propose an ESAGA to solve the problem efficiently.

III. Elitist Selection Adaptive Genetic Algorithm

Without power adaption, the problem (8) can be solved using the largest weighted delay first (LWDF) algorithm easily but at the cost of performance degradation. The LWDF algorithm is a widely used scheduling algorithm proposed by the Bell Labs [12].

In the general genetic algorithm, the crossover probability p_c and the mutation probability p_m are set to fixed values. Recently, many researchers realize that these parameters need to variate with the genetic evolution [13], [14]. So we propose an adaptive genetic algorithm with elitist strategy to solve (8).

The main idea of our proposed algorithm is to add the LWDF solution as a good individual to the initial population of the genetic algorithm and adopt elitist selection to guarantee that the ultimate solution of the genetic algorithm is at least not worse than the LWDF solution. Meanwhile, the population diversity in each generation is calculated, and the probabilities of crossover and mutation are adjusted to prevent premature convergence of genetic algorithm to a local optimum.

TABLE I.
Parameters for the adaptive genetic algorithm

Parameters	Value
Individuals number N_{ind}	20
Generations number N_{gen}	100
Generation gap p_g	0.9
Distance threshold D	5
Initial crossover probability p_c^0	0.8
Initial mutation probability p_m^0	0.2

A. The LWDF Algorithm

In (8), once the power allocation is determined, the $\{b_{n,k}^t\}$ can be estimated using $f_k(c)$. If the power is uniformly distributed on each subcarrier, then we have:

$$b_{n,k}^t = \lfloor f_k^{-1}(P_{tol}/N{\cdot}|h_{n,k}^t|^2)\rfloor, \qquad (9)$$

where $\lfloor\cdot\rfloor$ is the flooring operation.

The optimal subcarrier allocation $\{\rho_{n,k}^t\}$ is to select the user with the largest weighted bit rate $\{q_k^t{\cdot}b_{n,k}^t\}$, like the LWDF scheduling algorithm in a single channel system. Assuming that the user set selected at slot t on subcarrier n is ϕ_n^t, where $\phi_n^t \subset \{1,\ldots,K\}$, the problem (8) can be solved directly by the LWDF scheduling rule:

$$\rho_{n,k}^t = \begin{cases} 1 & q_k^t{\cdot}b_{n,k}^t \ge q_j^t{\cdot}b_{n,j}^t, j \in \phi_n^t \\ 0 & \text{otherwise.} \end{cases} \qquad (10)$$

After allocation, we update ϕ_n^t according to the constraint 3) in problem (8) by removing users whose queues are empty.

B. Design of adaptive p_c and p_m

Table I illustrates the parameters needed in the proposed algorithm. We adopt the adaptive genetic algorithm proposed in [14]. The heuristic updating principals are using large p_c and small p_m when the diversity of population in the current generation is large. The increase of p_c leads to rich information exchange between chromosomes, while the decrease of p_m avoids random search.

We regard a chromosome as a multidimensional vector and use the vector distance to measure the similarity of chromosomes. Chromosome i is expressed as $C_i = [g_i(1),\ldots,g_i(N)]$, and chromosome j is expressed as $C_j = [g_j(1),\ldots,g_j(N)]$. The distance between chromosomes i and j is

$$d(i,j) = \sqrt{(g_i(1)-g_j(1))^2+\cdots+(g_i(N)-g_j(N))^2}. \qquad (11)$$

If the distance is below a predefined threshold D, we think the two chromosomes are similar; else, the two chromosomes are dissimilar. We use the following equation to estimate the diversity of the population

$$div = \frac{\sum_{i=1}^{N_{ind}}\sum_{j=i+1}^{N_{ind}} \mathbf{1}_{\{d(i,j)>D\}}}{\binom{2}{N_{ind}}}. \qquad (12)$$

If all chromosomes in the population are similar, $div = 0$. On the other hand, if all chromosomes in the population are dissimilar, $div = 1$. So div is a variable in the range [0, 1].

p_c and p_m are adjusted according to the following:

$$p_c = p_c^0 + div \cdot (1 - p_c^0), \tag{13}$$

$$p_m = p_m^0 - div \cdot p_m^0, \tag{14}$$

where p_c^0 is the initial crossover probability and p_m^0 is the initial mutation probability. It is shown that if p_c^0 and p_m^0 are chosen in [0, 1], p_c and p_m can be guaranteed in [0, 1].

C. Proposed ESAGA

The elitist selection adaptive genetic algorithm is described as follows:

1) **Initialization.** Pick the deterministic LWDF solution alongside with other randomly generated solutions to form the N_{ind} initial population. Each solution is mapped to a chromosome, which consists of N genes and each gene's value is confined to the integer from 1 to K that represents the user index.
2) **Updating.** Calculate the diversity of the current population according to (12). Then adjust p_c and p_m according to (13), (14), respectively.
3) **Selection.** Calculate the utility function as the fitness of each chromosome, applying water-filling power allocation. Select $(1 - p_g)N_{ind}$ individuals with the highest fitness as elitists and let them go to the next generation directly. The rest individuals are put into the mating pool for the next operation.
4) **Breeding.** The breeding process consists of two stages: crossover and mutation. Use a two-point crossover algorithm with crossover probability of p_c. For each bit in the chromosomes of the offspring, there is a mutation probability of p_m to chance the bit.
5) **Termination.** Replace the original population with $(1 - p_g)N_{ind}$ elitists to form the population of the new generation. Repeat steps 2), 3) and 4) until the predefined generation number N_{gen} is reached. The best individual in the last population is our needed solution.

D. Complexity Analysis

We quantify the complexity of our proposed algorithm in the form of the number of flops. A flop is defined to be a real floating point operation [15]. A real addition, multiplication, or division is counted as one flop. The number of flops used to compute the logarithm of a number is about 20 [16]. Although flop counting cannot characterize the true computational complexity, it captures the order of the computation load.

The computational complexity of our proposed ESAGA mainly comes from steps 2), 3) and 4). In step 2), calculating the distance between two chromosomes takes $2N$ real additions and N real multiplications, hence the calculation of population diversity requires $\frac{3}{2}N_{ind}(N_{ind}+1)N$ flops. In step 3), water-filling over N subcarriers takes up to $(N^2 + 3N)$ real additions, $\frac{1}{2}(N^2 + 3N)$ real multiplications, and $\frac{1}{2}(N^2 + 3N)$ real divisions. The flop count for water-filling is $2(N^2 + 3N)$. The complexity of calculating the fitness of chromosome is dependent on the utility function. Under (7), it takes $2N$ real additions, $2N$ real multiplications, and N logarithmic operations. So the flop count of calculating the fitness of N_{ind} chromosomes is $N_{ind}(2N^2 + 30N)$. The complexity of selecting $(1-p_g)N_{ind}$ elitists is $(1-p_g)N_{ind}^2$ flops. In step 4), the complexity of crossover operation can be ignored. Considering that the mutation is operated on each gene of the p_gN_{ind} individuals, its complexity can be expressed as $p_gN_{ind}N$ flops.

Hence, the flop count of our proposed ESAGA is

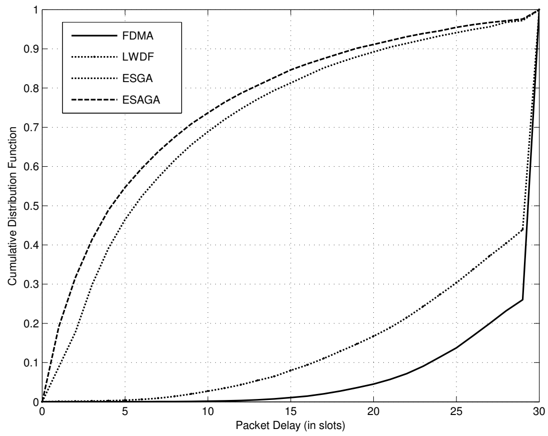
$$\begin{aligned} N_{gen}[\frac{3}{2}N_{ind}(N_{ind}+1)N + N_{ind}(2N^2 + 30N) \\ + (1 - p_g)N_{ind}^2 + p_gN_{ind}N], \end{aligned} \tag{15}$$

which is independent of K and C. Obviously, it is less than the exhaustive search mentioned above, especially when N, K, C become large, but N_{ind} and N_{gen} are not very large. Complexity in step 2) introduces the additional complexity compared to ESGA. Using the parameters in Table I, the complexity in step 2) is less than 25% of the whole algorithm. So it won't add too much computation burden.

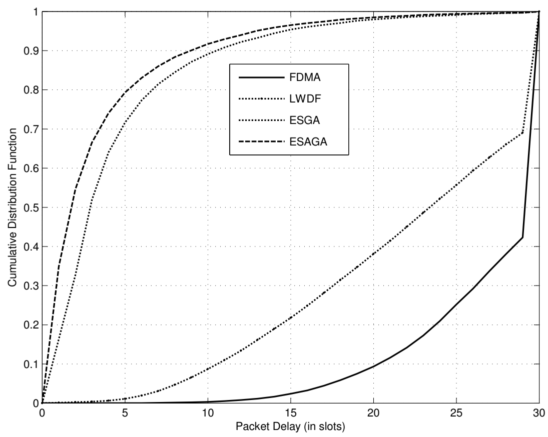
IV. NUMERICAL EXAMPLES

An OFDM system with 32 subcarriers and 4 users is considered in our simulation. The channel model is a 6-path Rayleigh fading channel with 10 μs delay spread. The length of cyclic prefix is 8 and the normalized doppler spread is 0.01. Each time slot comprises one OFDM symbol. We assume $\text{BER}_k = 10^{-3}$ for all users and $\text{SNR}_k = (10 + 3k)$(dB). When uncoded 2^c-ary QAM is employed, the required SNR function can be approximated as $f_k^c = \frac{1-2^c}{1.5}\log(5\cdot\text{BER}_k)$ [17]. The queuing system is modeled the same as [18]. The data sources generate packets with poisson arrivals and exponentially distributed packet lengths. The average packet length is 100 bits. User k's average arrival rate in bits is given by $\lambda_k = 15$. Packets with delay up to 30 slots will be dropped.

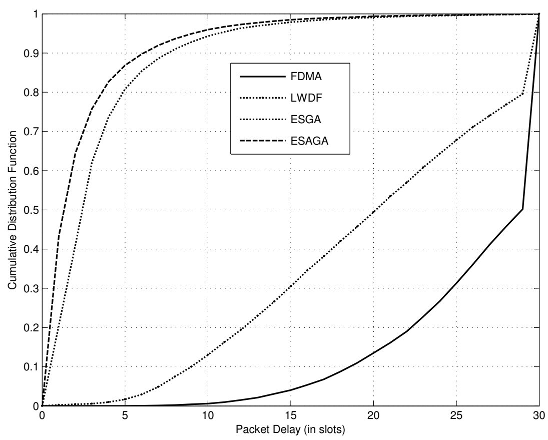
We compare the performance of four algorithms: FDMA, LWDF, ESGA in [8] and our proposed ESAGA. In the FDMA allocation algorithm, subcarriers are allocated in proportion to the user's queue length. It only takes the QSI in the application layer into consideration. The FDMA algorithm is served as a benchmark to measure how much gain results from exploiting CSI. For comparison, we use the packet delay distribution and average throughput as performance metrics. The cumulative distribution curve of packet delay is an easy way to illustrate the delay performance. If a packet is dropped due to the delay bound, its delay will be considered as 30 slots for statistical convenience. The average throughput is defined as the number of bits sent successfully per slot averaged over time.



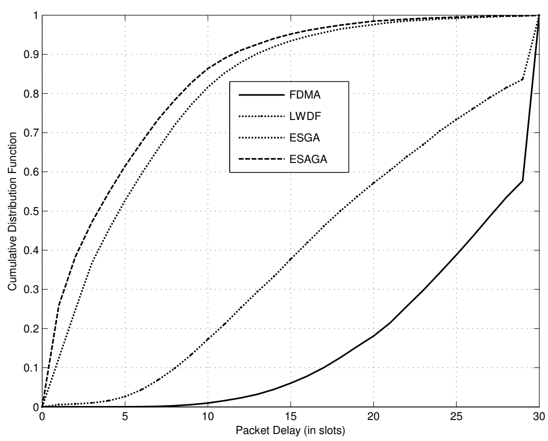
(a) User 1



(b) User 2



(c) User 3



(d) User 4

Figure 2. The CDFs of packet delay for all users

The cumulative distribution of packet delay for all users are plotted in Fig.2. For each algorithm, user 1 with the lowest SNR corresponds to the worst user case, while user 4 with the highest SNR corresponds to the best user case. It is shown that for each user, our proposed ESAGA achieves the best delay performance. Our proposed ESAGA outperforms ESGA due to the adaptive crossover probability and mutation probability in the advanced adaptive genetic algorithm. The delay performance of FDMA is the worst because it only exploits QSI. For the worst user case, more than 70% packets are dropped due to the delay bound. Even for the best user case, the drop rate of FDMA can be as high as 42%. So it is essential to make use of the physical layer dynamics. Both our proposed ESAGA and the ESGA can achieve much better delay performance than the LWDF algorithm due to the full use of resource allocation freedoms.

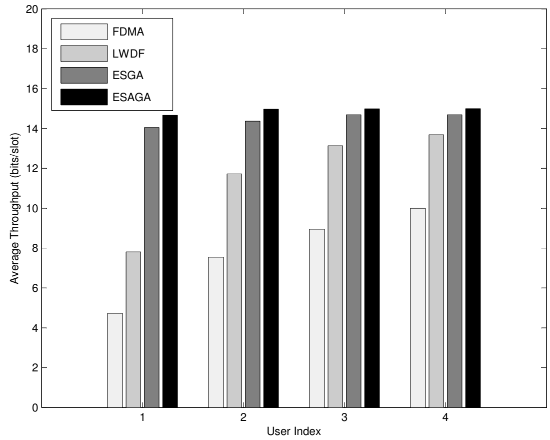


Figure 3. Each user's average throughput

In Fig.3, the average throughputs are illustrated for all users for the four algorithms. The average throughput of ESAGA is very close to the upper bound (the packet arrival rate). Our proposed ESAGA can achieve about 3% gains over ESGA. For each user, our proposed ESAGA retains high throughput even for the worst user case, while the average throughput in others algorithms decreases for the low SNR users. The FDMA algorithm has the worst performance for each user. So it is not enough to only exploit the application layer dynamics in the cross-layer design.

V. Conclusions

In this paper, a new cross-layer resource allocation model for multiuser packet-based OFDM systems has been proposed. In this model, the application, MAC and physical layers are jointly optimized. Then the cross-layer resource allocation problem is formulated into a constrained optimization problem. In order to solve the problem effectively, we extend the idea of ESGA in [8] to use the adaptive genetic algorithm. The probabilities of crossover and mutation are varied depending on the population diversity. The numerical examples demonstrate the good performances of our proposed ESAGA in forms of packet delay distribution and average throughput. Our proposed ESAGA can improve the performances of ESGA further at the cost of minor increase in complexity. So it is very suitable to a practical system.

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Zhihua Tang is currently a Ph.D. candidate at University of Science and Technology of China (USTC). She received her MS degree in Electrical Engineering (EE) from USTC in 2004.

She is a member of Personal Communication Network and Spread Spectrum Lab (PCNSS Lab). Her current research is at the cross-layer resource allocation design for OFDM system, including scheduling algorithms, multiuser diversity, limited feedback, cooperative communications, cognitive radio, etc.

Youtuan Zhu was born in Fujian, China, on 6 November 1979. He received his BS and MS degrees from USTC, in 2003 and 2005, all in EE. He is now a Ph.D. candidate at USTC. His research interests are in the area of wireless communications, especially in multiuser CDMA and MIMO communications.

Guo Wei was born in 1959. He received his B.S. degree in EE from USTC in 1983, and M.S., Ph.D degrees in EE from Chinese academy of Science in 1986 and 1991 respectively. He is a professor and the dean of School of Information Science and Technology, USTC. His current research interests are wireless and mobile communications, wireless multimedia communications, Ultra Wide Band communication system.

Jinkang Zhu is a professor of Department of Electronic Engineering and Information Science of USTC. Now he is director of PCNSS Lab of USTC.

His research area is Wireless and Mobile Communications, CDMA and Spread Spectrum Communications, Signal Process of Communications, and Wireless Networks. He got two awards of Ministry of Science and Technology of China, three awards of Chinese Academy of Science. He published five books and 100 papers, where synchronous CDMA method proposed is used in TD-SCDMA Standard of 3G as basic technology.

Prof. Zhu was Permanent V-President of School of Information Science and Technology of USTC, Chairman of PCN Experts Group of Communication Project of National R&D on High-Technology Programme of China, Member of Information Technology Expert Group of the Chinese Academy of Sciences, Member (Representation of China Mainland) of Technical Forum on Wireless Communications of Asia Pacific Region, Member of Technical Advisory Committee of IEEE VTC'99 Fall, Member of Technical Program Committee of IEEE VTC'2000, Member of Technical Program Committee of SCI'2001.