GENETIC ALGORITHM BASED CROSS-LAYER RESOURCE ALLOCATION FOR WIRELESS OFDM NETWORKS WITH HETEROGENEOUS TRAFFIC

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ABSTRACT

We propose the genetic algorithm (GA) based cross-layer resource allocation for the downlink multiuser wireless orthogonal frequency division multiplexing (OFDM) system with heterogeneous traffic. The GA is used to maximize the sum of weighted capacities of multiple traffic queues at the physical (PHY) layer, where the weights are determined by the medium access control (MAC) layer. Simulation results demonstrate that the GA significantly outperforms the existing algorithm in terms of the system bandwidth efficiency, best-effort (BE) traffic throughput and quality of service (QoS) traffic delay.

1. INTRODUCTION

Conventional network architectures, where each layer is designed to operate independently, do not utilize resources effectively. With the rapid increase of demands for high speed multi-media services of wireless networks, which are confronted with fading channels, limited bandwidth and competition of limited air resources among multiple users, a cross-layer design to meet the required quality of service (QoS) is desirable [1].

In [2], a cross-layer scheduling scheme for the medium access control (MAC) layer was proposed, which assigns priorities of connections according to the channel quality, QoS satisfaction and service priority across layers. In [3], a so-called modified largest weighted delay first (M-LWDF) scheduling scheme was proposed, based on the head-of-line (HoL) packet delay, relative data rate and QoS requirement. However, [2] and [3] assumed single carrier systems.

Orthogonal frequency division multiplexing (OFDM) [1] is effective to combat frequency selective fading channels and support high data rate services, which has been widely used in WLAN (IEEE 802.11a & 11g), WiMAX (IEEE 802.16) and 3GPP LTE downlink systems [4]. In [5], a scheduling scheme was proposed for OFDM systems, which serves the QoS traffic and best-effort (BE) traffic together if the delays of the QoS packets do not approach the maximum allowable delay. In [6], an urgency and efficiency based packet scheduling (UEPS) scheme, which utilizes the HOL delay and channel quality, was proposed for OFDM systems. However, [5] and [6] only considered scheduling for the MAC layer, but did not consider adaptive resource allocation for the physical (PHY) layer. To exploit the synergy between scheduling and resource allocation at the PHY layer, a so-called maximum delay utility (MDU) cross-layer resource allocation and scheduling scheme was proposed in [7], which maximizes the utility function of the delay. However, the work in [7] is based on the sequential linear approximation algorithm (SLAA) [8], which may generate a local optimal solution instead of a global optimal solution.

The genetic algorithm (GA) is a family of computational models, which was first proposed in [9]. Since the GA is an effective search technique, it has been applied to wireless communications recently [10][11]. However, in most previous work, GA was used for channel equalization [10], multiuser detection [11], etc., rather than resource allocation.

In this paper, we propose the genetic algorithm (GA) based cross-layer resource allocation for the downlink multiuser OFDM system with heterogeneous traffic. The GA is applied to maximize the sum of weighted capacities of the OFDM system at the physical (PHY) layer, where the weights are determined by scheduling results of the medium access control (MAC) layer. Simulation results show that the proposed GA based cross-layer resource allocation scheme significantly outperforms the SLAA based resource allocation scheme [7], with a wide range of the number of users, in terms of the system bandwidth efficiency, BE traffic throughput and QoS traffic delay.

In Section II, we describe the system model and the maximum weighted capacity (MWC) based cross-layer design. The SLAA and GA based cross-layer resource allocation algorithms are presented in Sections III and IV, respectively. Simulation results are shown in Section IV, and the conclusion is drawn in Section V.

2. SYSTEM MODEL AND THE MAXIMUM WEIGHTED CAPACITY BASED CROSS-LAYER DESIGN

We consider a downlink OFDM system with K users, where each user obtains three heterogeneous queues: voice over IP (VoIP) traffic queue, variable bit rate (VBR) video traffic queue and best effort (BE) traffic queue. Without loss of generality and for simplicity, we assume that each subcarrier is occupied by only one queue [12]. With cross-layer optimization, the QoS information is transferred from the traffic controller to the subcarrier and power controller for resource allocation, and the resource allocation results are fed back to the traffic controller for scheduling.

We assume a total bandwidth of B shared by N subcarriers, and the OFDM signaling is time slotted where the duration of each slot is T_{slot}. Let Ω_i denote the index set of subcarriers allocated to queue i ($i = \{1, \ldots, 3K\}$). Let $p_{i,n}$ be the power allocated to queue i on subcarrier $n \in \Omega_i$, $h_{i,n}$ the corresponding channel gain, and N_0 the power spectral density of additive white Gaussian noise (AWGN). Assuming perfect channel estimation, the achievable instantaneous data rate of queue i on subcarrier n is expressed as:

$$R_{i,n} = \frac{B}{N}\log_2(1 + p_{i,n}\gamma_{i,n}) \tag{1}$$

where $\gamma_{i,n} = \frac{|h_{i,n}|^2}{N_0 B/N}$ is the channel-to-noise power ratio for queue i on subcarrier n. Thus, the total instantaneous data rate of queue i is given by:

$$R_i = \sum_{n\in\Omega_i} R_{i,n} \tag{2}$$

We employ a MWC based cross-layer optimization scheme. Letting W_i denote the weight for queue i which contains the QoS information, our scheme is to maximize the sum of weighted capacities, *i.e.*, to maximize

$$J = \sum_{i=1}^{3K} W_i R_i \tag{3}$$

subject to $p_{i,n} \geq 0$, $\sum_{i=1}^{3K}\sum_{n\in\Omega_i} p_{i,n} \leq p_T$, $\Omega_i \bigcap \Omega_j = \emptyset$ ($i \neq j$), and $\Omega_1 \bigcup \ldots \bigcup \Omega_i \subseteq \{1, 2, \ldots, N\}$, where p_T is the total transmit power.

The weights of the MWC based cross-layer optimization contain the QoS information and are obtained from scheduling at the MAC layer. We define S_i and λ_i as the average waiting time and the average data arrival rate for queue i, respectively. We use the weights employed in [7], where the weight W_i in (3) for VoIP traffic is

$$W_i^{\text{VoIP}} = \begin{cases} \frac{S_i}{\lambda_i} & S_i \leq 25ms \\ \frac{S_i^{1.5} - 25^{1.5} + 25}{\lambda_i} & S_i > 25ms \end{cases}, \tag{4}$$

the weight for VBR video traffic is expressed as

$$W_i^{\text{VBR}} = \begin{cases} \frac{S_i^{0.6}}{\lambda_i} & S_i \leq 100ms \\ \frac{S_i - 100 + 100^{0.6}}{\lambda_i} & S_i > 100ms \end{cases}, \tag{5}$$

the weight for BE traffic is given by

$$W_i^{\text{BE}} = \begin{cases} \frac{S_i^{0.5}}{\lambda_i} & S_i \leq 100ms \\ \frac{100^{0.5}}{\lambda_i} & S_i > 100ms \end{cases} \tag{6}$$

3. SEQUENTIAL LINEAR APPROXIMATION ALGORITHM BASED CROSS-LAYER RESOURCE ALLOCATION

In this section, we review the sequential linear approximation algorithm (SLAA) based cross-layer resource allocation. In [13], when the subcarrier allocation is fixed, the optimal power allocation is given as

$$p_{i,n} = \left[\frac{W_i}{\sum_{m=1}^{3K}(W_m|\Omega_m|)}\left(p_T + \sum_{m=1}^{3K}\sum_{q\in\Omega_m}\frac{1}{\gamma_{m,q}}\right) - \frac{1}{\gamma_{i,n}}\right]^+ \tag{7}$$

where $[x]^+ = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases}$, and $|\Omega_m|$ denotes the number of elements in set Ω_m, *i.e.*, the number of subcarriers allocated to queue m.

In (3), both the subcarrier and power allocation can be changed. Thus, the iterative subcarrier allocation, power allocation in the SLAA based cross-layer resource allocation algorithm is given by:

1. Initialize $p_{i,n}^0 = p_T/N$ ($\forall n \in \{1, ..., N\}$ and $\forall i \in \{1, ..., 3K\}$); allocate subcarrier n ($\forall n \in \{1, ..., N\}$) to queue $i^0 = \arg\max\{\gamma_{i,n}\}$; obtain R_i^0 from the initial resource allocation;
2. Find $i^{l+1} = \arg\max\{W_i R_i\}$ ($\forall n \in \{1, \ldots, N\}$) for the $(l+1)$th iteration, and allocate subcarrier n to it;
3. Obtain $p_{i,n}^{l+1}$ for the $(l+1)$th iteration, according to (7);
4. Update R_i^{l+1} for the $(l+1)$th iteration, by using (1) and (2);
5. Repeat Steps 2, 3 and 4 until $\sum_{i=1}^{3K} W_i(R_i^{i+1} - R_i^i) < \varepsilon$.

4. GENETIC ALGORITHM BASED CROSS-LAYER RESOURCE ALLOCATION

The genetic algorithm [9] based cross-layer resource allocation is presented in this section. In the GA based cross-layer resource allocation, we define a chromosome is a string of N elements, where each element represents a queue index which the corresponding subcarrier is allocated to, *i.e.*, if the nth ($\forall n \in \{1, ..., N\}$) element is valued i ($i \in \{1, ..., 3K\}$), it means the subcarrier n is allocated to queue i. Therefore, each chromosome represents a sort of subcarrier allocation results, and is associated with a fitness value indicating how good the chromosome is with respect to the optimization problem. During the evolution, chromosomes with higher fitness values, which are also called elites, have a higher chance to survive. Fig. 1 shows the flow chart of the GA based cross-layer resource allocation.

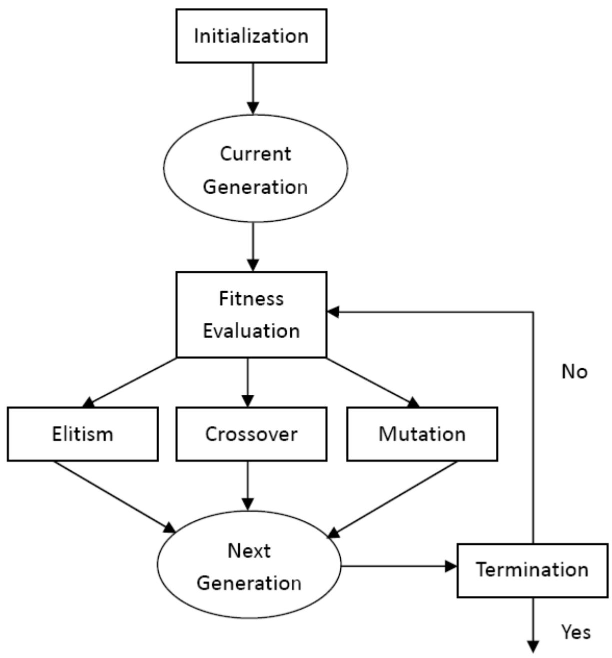

Figure 1: Block diagram of the GA

The procedure of the GA based resource allocation is described as follows:

1. Initialization: generate a population N_{pop} of chromosomes, where each bit of all the chromosomes is randomly picked from $\{1,...,3K\}$.
2. Fitness evaluation: update power allocation for each chromosome by using the subcarrier allocation presented by the chromosome and (7); utilizing the corresponding power and subcarrier allocation of each chromosome, obtain the fitness value of each chromosome, which is the value of (3).
3. Elitism: find N_{elite} chromosomes with the highest fitness values, copy them into the next generation directly.
4. Crossover: pick two chromosome parents from the current generation to create chromosome children for the next generation; parents can be chosen with equal probability; randomly obtain a crossover point for the parents; the parents are split into two parts, one child chromosome consists of the first part of the first parent and the second part of the other, while the other child chromosome consisting of the second part of the first parent and the first of the other; generate N_{cross} crossover children chromosomes for the next generation.
5. Mutation: randomly pick a chromosome from the current generation, each bit of it can be changed with a chance of P_{mu}; generate N_{mu} mutation children chromosomes for the next generation.
6. Repeat Steps 2, 3, 4 and 5 until reaching the maximum generation limit N_{gen}.

5. SIMULATION RESULTS

We use simulation results to demonstrate performance of the proposed cross-layer design for a system with a total transmit power $p_T = 1$ W, a slot duration of $T_{\text{slot}} = 4$ ms, and a total bandwidth of $B = 5$ MHz which is divided into $N = 512$ subcarriers. The channel has six independent Rayleigh fading paths with an exponentially delay profile and a root-mean-square (RMS) delay spread of 0.5 μs. The maximum delay tolerances for VoIP, VBR video and BE traffic are 100 ms, 400 ms and 1000 ms, respectively. The VoIP traffic queue and BE traffic queue have a constant data rate of 64 Kbps and 500 Kbps, respectively. The data rate of the VBR video traffic follows a truncated exponential distribution [14] with a minimum of 120 Kbps, a maximum of 420 Kbps, and a mean of 239 Kbps. The duration for each data rate of the VBR video traffic follows an exponential distribution with a mean of 160 ms. The signal-to-noise ratio (SNR) is defined as the average received signal power to noise power ratio for each queue.

In the GA based cross-layer resource allocation, the population size is $N_{pop} = 30$, consisting of $N_{elite} = 10$ elites, $N_{cross} = 14$ crossover children and $N_{mu} = 6$ mutation children, where the mutation probability is $P_{mu} = 0.01$. The maximum generation is $N_{gen} = 100$. We set $\varepsilon = 0.01\sum_{i=1}^{K} W_i R_i^i$ in the SLAA based cross-layer resource allocation.

Figs. 2 to 5 demonstrate the impact of the number of users on performance of different searching algorithms for the cross-layer deign, with SNR=20 dB. The system capacity and the BE traffic throughput are shown in Fig. 2 and Fig. 3, respectively. The GA based cross-layer resource allocation scheme provides significant performance advantages over the SLAA based cross-layer resource allocation, with a wide range of the number of users (8 to 64 users), *i.e.*, The GA based cross-layer resource allocation achieves the system capacity which is up to 35% higher than that of the SLAA based one. Similar trends can be found in Fig. 3. This is because The SLAA based cross-layer resource allocation might stop searching when it finds a local optimal solution while the GA based resource allocation manages to approach the optimal solution during the evolution. Note that the BE traffic throughput decreases as the number of user increases. Since the number of QoS traffic queues augments as the number of user increases, the QoS queues occupy more resources, and the BE traffic throughput degrades.

Fig. 4 shows the impact of the number of users on the average voice traffic delay of different cross-layer designs. The GA based cross-layer resource allocation achieves a much lower delay than the SLAA based one, with a wide range of the number of users. For instance, the average voice delay for the SLAA based cross-layer resource allocation with 32 users is about 22 ms, while it is only 4 ms for the GA based one. A similar trend can be observed in Fig. 5 for the average video traffic delay. We notice that the gap between the performances of the GA and SLAA based cross-layer resource allocation algorithms is tiny when the number of users is 64. This is because when there are 64 users, which means there are 192 queues, the search space is 192^{512}, which is too large for a GA with a $N_{pop} = 30$ population size and a $N_{gen} = 100$ generation number.

6. CONCLUSION

In this paper, we have proposed the GA based cross-layer resource allocation for the downlink multiuser OFDM system with heterogeneous traffic. Through simulation results, we demonstrated that the GA based cross-layer resource allocation provides significant performance advantages over the SLAA [8] based cross-layer resource allocation, in terms of the system bandwidth efficiency, BE traffic throughput and QoS traffic delay, with a wide range (from small to moderate) of the number of users.

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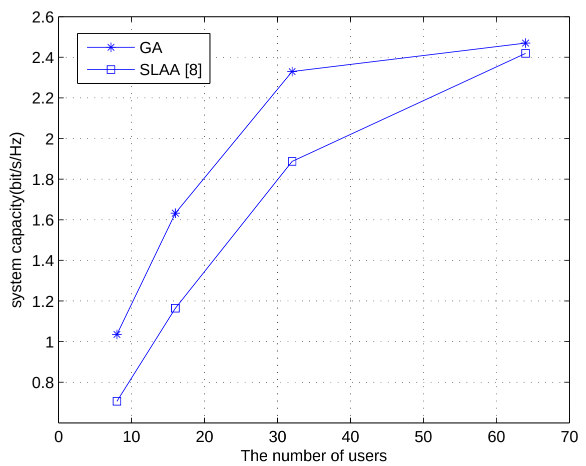

Figure 2: Impact of the number of users on system capacities (SNR=20 dB)

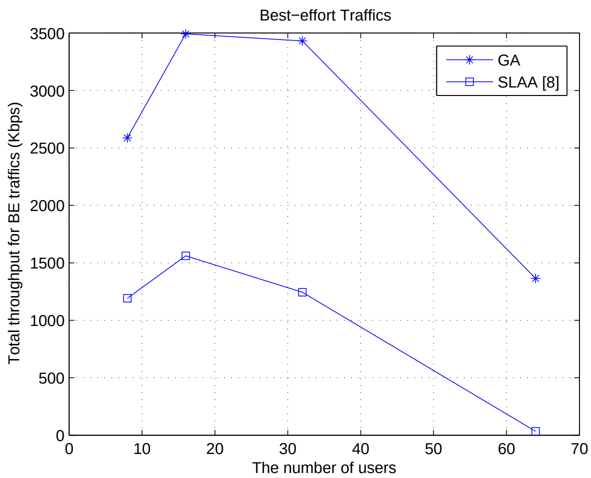

Figure 3: Impact of the number of users on BE traffic throughputs (SNR=20 dB)

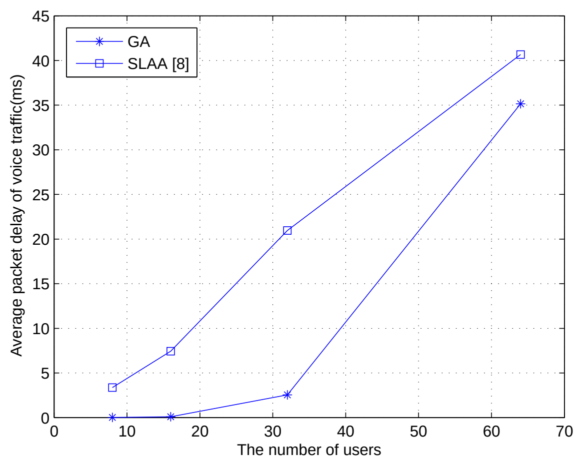

Figure 4: Impact of the number of users on average voice traffic delays (SNR=20 dB)

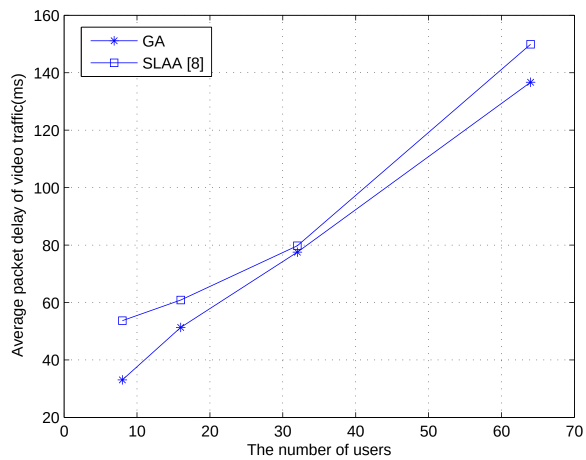

Figure 5: Impact of the number of users on average video traffic delays (SNR=20 dB)