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Multi-Objective Resources Allocation for OFDM-Based Cognitive Radio Systems

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Abstract: In this study, we focus on multi-objective resources allocation for OFDM-based cognitive radio system considering the mutual interference. The mutual interference between primary user and secondary user is neglected by most research works in cognitive radio systems. To achieve the allocation, we use Genetic Algorithm (GA) with fitness function. The fitness function is a weighted sum of multiple objectives which can represent the Quality of Service (QoS) requirements of user. Experiment results show that the proposed multi-objective allocation method considering mutual interference based on GA successfully meets the user's QoS requirement.

Key words: Cognitive radio, QoS, resources allocation, genetic algorithm

INTRODUCTION

Spectrum is one of the most valuable resources for wireless communications while wide spectral ranges are underutilized. Cognitive radio is a promising technique for improving the spectrum efficiency by dynamically accessing unoccupied channels licensed to primary users and vacating the channels when the primary users active. According to the cognitive loop (Mitola, 2006), secondary users (cognitive users) need to continuously observe the environment, be oriented by the objectives of the users and decide upon the transmission parameters (power, frequency, modulation etc.) to improve the overall efficiency of the radio communications. Though the principal goal of cognitive radio is to improve spectrum utilization efficiency at first, Quality of Service (QoS) requirements such as minimizing the Bit-Error-Rate (BER), maximizing the data throughput, minimizing the power consumption and so on also need to be considered when the goal of cognitive radio becomes to improve performance optimization. Therefore, performance optimization of cognitive radio is a multi-objective optimization problem.

The problem of optimal allocation of sub-carriers, bits and transmission powers in an OFDM-based cognitive radio system is a NP-hard problem as its complexity grows exponentially with respect to the size of the input. Multi-carrier techniques, such as Orthogonal Frequency Division Multiplexing (OFDM), support huge data rates that are robust to channel impairments. OFDM is a good modulation candidate for cognitive radio system due to its flexibility in allocating resources among secondary users (Weiss and Jondral, 2004). Resources allocation algorithms for OFDM systems have been well studied (Shen *et al*., 2003; Jang and Lee, 2003; Wong *et al*., 1999). However, most of these algorithms are designed for OFDM system in which primary user doesn't exist. Since in cognitive radio system both secondary users and primary users may exist in side by side band and their access technologies may be different, the mutual interference is the limiting factor for performance of both networks (Weiss *et al*., 2004). Only a few studies have considered mutual interference in resources allocation for OFDM-based cognitive radio systems. The mutual interference in OFDM-based cognitive radio system has been considered when allocating resources according to single optimizing objective of maximizing the capacity of cognitive radio system (Zhao *et al*., 2008; Zhang and Leung, 2008; Qin and Leung, 2007). But these resources allocation algorithms have ignored the secondary user's QoS requirements.

In this study, we focus on the resources allocation to meet the QoS requirement of OFDM-based cognitive radio system. We suppose a downlink OFDM-based cognitive radio scenario, in which sub-carriers, bits and power are allocated to meet the secondary user's requirements with mutual interference considered. The resources allocation process is accomplished with multi-objective Genetic Algorithm (GA). GA is well suited to multi-dimensional optimization due to the parallel evolution in many dimensions. At the same time, GA also allows easy implementation of constraints about the problem (Srinivas and Patnaik, 1994).

SYSTEM MODEL

We consider the scenario that primary user and secondary user coexist which is depicted in Fig. 1. It is

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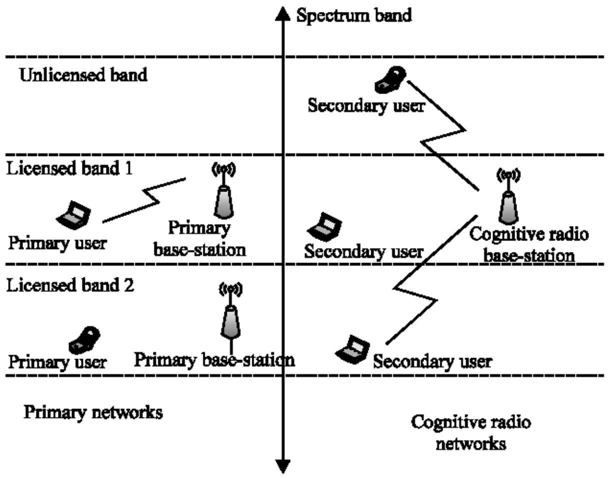

Fig. 1: System model for cognitive radio

assumed that the primary user occupies the spectrum in the middle and the spectrum holes can be used for transmission to secondary user are located on each side of the licensed band 1. Secondary user employs OFDM modulation scheme and the available frequency is divided into N sub-carriers, N/2 sub-carriers on each side. The base station allocates the transmission power and bits to sub-carriers of the secondary user dynamically. It is assumed that each sub-carrier goes under frequency flat fading and the channel state information is perfectly known at the transmitter.

Multi-objective function: The wireless resources should be allocated according to the objective function. The objectives need to be optimized can be transmission power, bandwidth, BER, throughput, interference etc. These objectives often compete with each other, for example, when maximizing throughput and minimizing power at the same time. Resources allocation optimization requires joint optimization of many objectives. The optimization of the multiple objectives is a Pareto optimal problem. The solutions are trade-offs between the multiple objectives.

In the user's QoS requirements, all of above objectives are included. The relative importance of the objectives depends on the service being used. For example, service in emergency mode cares most about BER, while service in multimedia mode cares most about throughput. As a result, BER in emergency mode service has a bigger weight, while throughput has a bigger weight in multimedia mode service (Newman *et al*., 2007) gave the method using linear weighted sum to represent multiple objectives.

The combination of various kinds of objectives can be used to contribute to different services as below:

$$f = \sum_{k=1}^{K} \omega_k f_k \tag{1}$$

in which f_k is an objective, the weight of the objective f_k is ω_k, $0 \le \omega_k \le \omega_k$.

$$\sum_{k=1}^{K} \omega_k = 1 \tag{2}$$

Each objective f_k is weighted by its importance and f_k is normalized to one. The maximum value of Eq. 1 is 1. According to the user's QoS requirements, there are several desirable objectives to be achieved. In this study, we mainly consider three objectives: minimizing the power consumed by the system, maximizing the overall data throughput by the radio and minimizing the bit error rate by the radio.

The objective functions are defined as follows (Newman *et al*., 2007):

$$f_{min\_power} = 1 - \frac{\sum_{n=1}^{N} P_n}{P_{Max}} \tag{3}$$

$$f_{max\_throughput} = \frac{\sum_{n=1}^{N} b_n}{2^{M_{Max}} \times N} \tag{4}$$

$$f_{min\_BER} = 1 - \frac{\log_{10}(0.5)}{\log_{10} \bar{p}_e} \tag{5}$$

where, P_n denotes the transmission power allocated to nth sub-carrier, P_{MAX} denotes total secondary user power budget, b_n denotes the number of bits allocated to nth sub-carrier, M_{MAX} denotes the maximum modulation order, p_{en} denotes the bit error probability in nth sub-carrier, $\bar{p}_e$ is average bit error probability.

$$\bar{p}_e = \frac{\sum_{n=1}^{N} b_n p_{en}}{\sum_{n=1}^{N} b_n} \tag{6}$$

From the definition of the objectives we concerned, we can get $f_{min\_power} \le 1$, $f_{max\_throuput} \le 1$ and $f_{min\_BER} \le 1$. The value of these objectives is closer to 1 when the better performance it achieves. We combine the multiple objective functions into a function using the weighted sum approach as below:

$$\max(f) = \max\left(\omega_1 \times f_{min\_power} + \omega_2 \times f_{max\_throughput} + \omega_3 \times f_{min\_BER}\right) \tag{7}$$

subjected to:

$$\sum_{n=1}^{N} P_n \le P_{Max} \tag{8}$$

$$\sum_{n=1}^{N} I_n(d_n, P_n) \le I_{th} \tag{9}$$

in which I_{th} is the primary user's maximum tolerable interference power which is given next. According to the multi-objective function in Eq. 7, the resources allocation attempts to meet the user's QoS requirement while considering two constraints in Eq. 8 and 9: (1) a total transmission power constraint for secondary user and (2) a maximum tolerable interference power which can be tolerated by primary user.

Mutual interference: From the system model depicted above, we assume that both secondary user and primary user exist in side by side band. There are interactions between primary user and secondary user due to the non-orthogonality of their respective signals (Weiss *et al*., 2004). Both secondary user and primary user will be influenced by the mutual interference.

The Power Spectral Density (PSD) of the nth sub-carrier signal is denoted as:

$$\phi_n(f) = P_n T_s \left(\frac{\sin \pi (f - f_n) T_s}{\pi (f - f_n) T_s} \right)^2 \tag{10}$$

where, T_s is the symbol duration, f_n is the intermediate frequency of the nth sub-carrier signal.

The interference introduced by nth sub-carrier into primary user band is given as below (Weiss *et al*., 2004):

$$I_n(d_n, P_n) = \int_{d_n - B/2}^{d_n + B/2} |g_n|^2 \phi_n(f)\, df \tag{11}$$

where, g_n is the nth sub-carrier channel gain from base station to the primary user, d_n is the spectral distance between the nth sub-carrier and the center frequency of the primary user band.

The interference introduced into the nth sub-carrier by the signal of primary user is denoted as below:

$$J_n(d_n) = \int_{d_n - \Delta f/2}^{d_n + \Delta f/2} |h_n|^2 \phi_{PU}(e^{j\omega})\, d\omega \tag{12}$$

where, $\phi_{PU}(e^{j\omega})$ is the PSD of the primary user signal.

GA BASED RESOURCES ALLOCATION

GA simulates the biology evolution scheme and can be used to solve both constrained and unconstrained optimization problems (Srinivas and Patnaik, 1994). In GA, basic operations such as encoding, fitness function calculating, selection, crossover and mutation etc are included.

Sub-carrier 1		Sub-carrier 2		......	Sub-carrier N	
Power	Bits	Power	Bits	......	Power	Bits

Fig. 2: The structure of the chromosome

In encoding, the solutions to a problem are encoded into a chromosome. The chromosome is represented by binary string. The length of the binary string is decided by the solutions' value range and precision needs. A collection of chromosomes called the population is allowed to act in a manner similar to genetic growth.

In this study, we generate a population of 100 chromosomes for the experiment. The chromosome is made up of N elements. Each element in the chromosome represents the transmission power and bits allocated to the specific sub-carrier, the chromosome can be depicted in Fig. 2.

Fitness function is established based on the specific goals to evaluate the current population and direct the evolution of population. In this study, we use the multi-objective function which is depicted in Eq. 7 as the fitness function in GA. As evaluating the chromosome with the fitness function f, the value of f which is closer to 1 means the allocation is better fulfilling the QoS of the secondary user.

The GA uses three main rules to create a new generation from the current population:

- **Selection:** Select the individual parent chromosomes that have higher scores when evaluated by fitness function for a new generation
- **Crossover:** Combine two parent chromosomes to form children
- **Mutation:** Apply random changes to individual parent chromosomes at random positions to form children

This generational cycle repeats until a desired termination criterion is met (For example, a predefined number of generations are processed). The above discussion shows that GA is suitable for the optimization of transmission power and bits allocation in an OFDM-based cognitive radio system. The processing steps are as shown in Fig. 3.

EXPERIMENT RESULTS

Experiment design: In the experiment, we have a primary user and secondary user with three different services. The

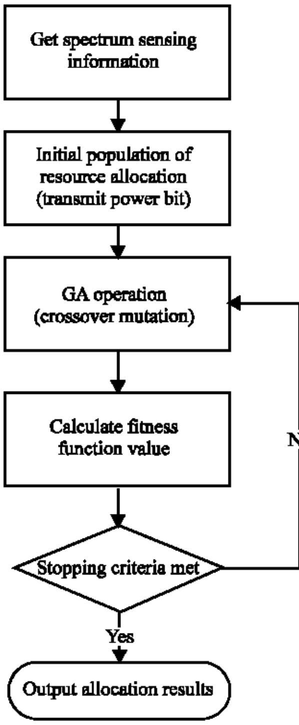

Fig. 3: The block diagram of GA based resources allocation

Table 1: Objective function weight settings

Service (important objective)	Weight vector [ω_1, ω_2, ω_3]
1 (minimizing power)	[0.8, 0.1, 0.1]
2 (maximizing throughput)	[0.1, 0.8, 0.1]
3 (minimizing BER)	[0.1, 0.1, 0.8]

band of primary user is 5 MHz and the bands available for secondary user are on each side of the primary user. The bandwidth of secondary user is also 5 MHz. We divide the secondary user bands into 16 sub-carriers, while each sub-carrier takes a bandwidth 312.5 kHz. The primary user intermediate frequency is 650 MHz and the OFDM symbol duration is T_s = 100 μs. The channel fading is Rayleigh distributed random with mean of one and the PSD of additive Gaussian noise is 10^{-8} W/Hz.

In service 1, power plays an important role, so we set the biggest weight to minimizing power in its objective function. Similarly, we set the biggest weight to the maximizing throughput in its objective function in service 2 in which the throughput is more important. Service 3 belongs to an emergency mode, so we put the biggest weight in minimizing the BER. The weight settings to different services respectively are shown in Table 1.

The number of bits allocated to sub-carrier can take 0 bit (no modulation), 2 bits (BPSK), 4 bits (QPSK), 8 bits (8QAM), 16 bits (16QAM), 32 bits (32QAM), 64 bits (64QAM) and 128 bits (128QAM) in this work. The target

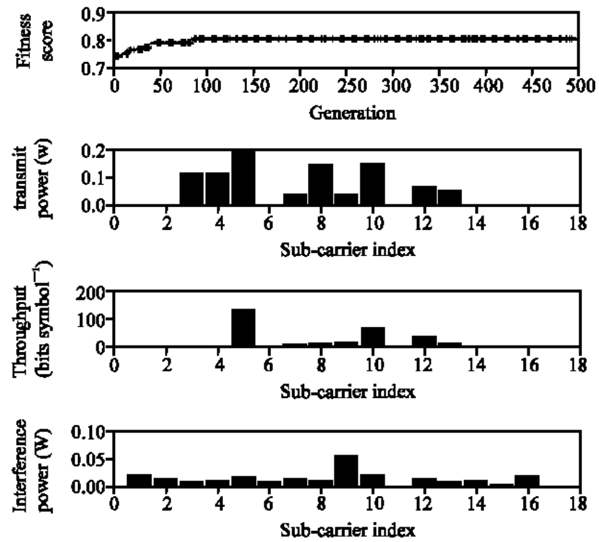

Fig. 4: Resources allocation of service 1 based on GA

BER is set to 0.05. We set the GA parameters as follows: crossover parameter is 0.6, mutation parameter is 0.03, the number of population is 100, the number of generation is 500. We set the Maximum power transmitted to secondary user is 5 W, the maximum interference introduced to primary user is 0.01W.

Experiment results: Multi-objective function depicted in Eq. 7 is employed as the fitness function when we allocate resources based on GA. The fitness functions are different in different services due to different weight settings which have been described in section 4.1. In the experiment, resources including transmission power and bits have been allocated for three kinds of services considering two constraints: total transmission power of secondary user and maximum tolerable interference power of primary user. Two groups of figures have been shown.

Figure 4-6 show the transmission power and bits allocation of different services based on GA. There are 4 sub-figures in all figures from Fig. 4-6. The first sub-figure shows the GA converging situation according to the fitness function. The process for GA converging is an optimization process for transmission parameters (power and bits) allocation. The convergence happens at about the 200th generation which shows that GA could quickly find a good solution. It is especially crucial for a time-variant wireless environment. The fourth sub-figure shows the interferences introduced to the sub-carriers by primary user. The second and third sub-figure shows the transmission power and bits allocation at the final generation. Mutual interference between primary user and secondary user has been considered. From the

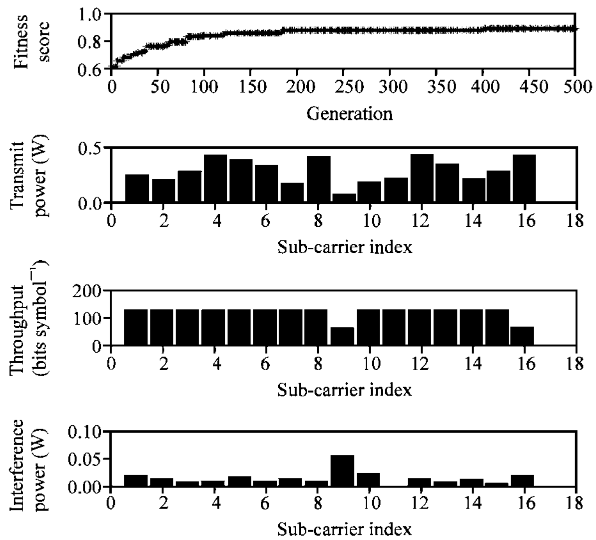

Fig. 5: Resources allocation of service 2 based on GA

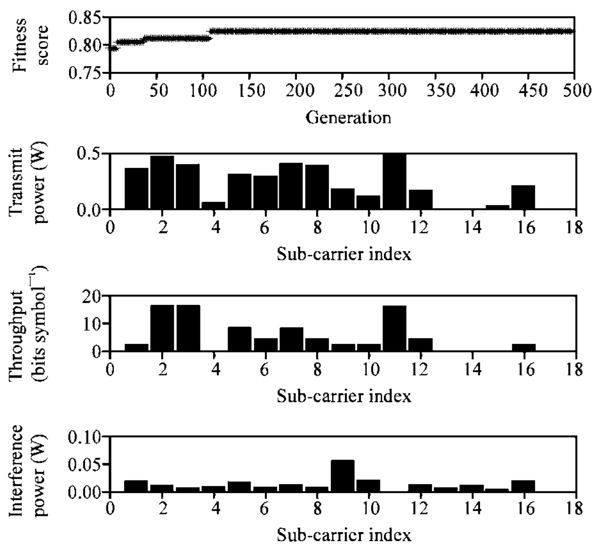

Fig. 6: Resources allocation of service 3 based on GA

figures, we can tell that the interference introduced by primary user influences the transmission power and bits allocation. Transmission power and bits allocated to the sub-carriers with bigger interference are smaller. In Fig. 4, we can get that all transmission powers on the sub-carriers are below 0.2 W which means that the requirement of minimizing transmission power has been met in service 1. Similarly, Fig. 5 and 6 show that the objective of maximizing the throughput and the objective of minimizing the BER have also been met. The fitness function directs the evolution of the GA to optimize the given objectives for each service.

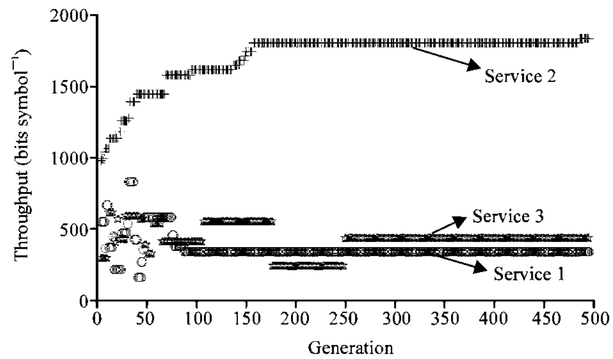

Fig. 7: Comparison of the throughput in different services

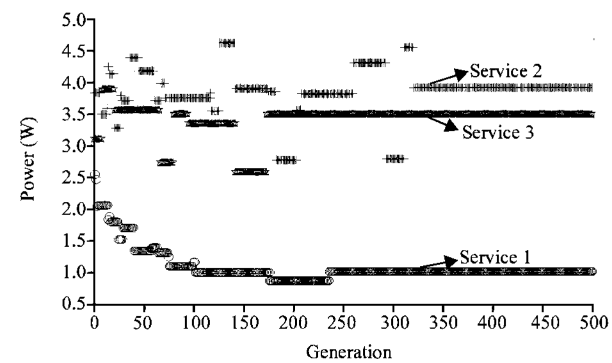

Fig. 8: Comparison of total power in different services

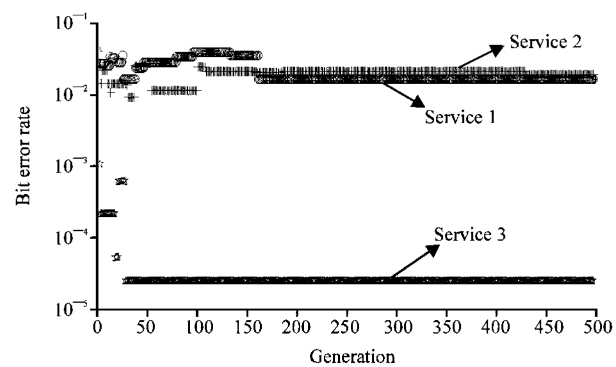

Fig. 9: Comparison of average bit error rate in different services

Figure 7 shows the comparison of throughput in different services. The throughputs of different services change as generation grows in different directions. The throughput of service 2 becomes larger and converges to a specific high value, while the throughputs of service 1 and service 3 become smaller and converge to low values. In service 2, the weight of maximizing throughput in fitness function is much bigger than the weight of minimizing power and the weight of minimizing BER which means that the primary objective of the service 2 is maximizing the throughput with sacrificing the power and BER. In service 1 and service 3, the weight of maximizing throughput is much smaller that maximizing throughput is not the most important objective and we can sacrifice it for other more important objectives. Figure 8 and 9 can give us the similarly situation. We can get the conclusion that the resources allocation based on GA with multi-objective fitness function can meet the user's QoS requirements.

DISCUSSION

The first group of figures shows the resources allocation of different services based on GA. The second group of figures shows the comparison of allocation results in different services.

These experiments on different services prove that GA can be used to optimize the constrained allocation problem and promptly converge to find a good solution. GA based optimization algorithm is competent for cognitive radio system which is a time-variant wireless environment.

The mutual interference influences the resources allocation. More resources (power and bits) are allocated to channels with better channel state in which less mutual interference is introduced by primary user. Mutual interference can not be ignored in OFDM-based cognitive radio system.

Fitness function with a weighted sum of multiple objectives can orient the direction of the evolution of the GA to optimize the resources allocation for each service. After resources allocation with different weighted in multiple objectives, service 1 which is in multimedia mode gains large throughput, service 2 which is in energy shortage mode gains small consuming power and service 3 which is in emergency mode gains small bit error rate. Resources allocation based on GA with multi-objective fitness function can meet the user's QoS requirements.

CONCLUSION

We have presented the transmission power and bits allocation for OFDM-based cognitive radio system. The allocation of transmission power and bits is restricted to the maximum transmission power and interference tolerance of primary user. Mutual interference between primary user and secondary user influences the transmission power and bits allocation. When the channel state is good, an appropriate power could be loaded to get a good SNR and high order modulation is adopted to reach a big bit rate and vice versa low order modulation is to guarantee the reliability of system if the channel state is bad. Resources allocation algorithm based on GA converges fast enough to adapt to the dynamic wireless environment. The fitness function used to direct the evolution of the GA makes the resources allocation successfully fulfill the QoS requirement of user.

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