Cognitive radio adaptation for power consumption minimization using biogeography-based optimization*

Pei-Han Qi(齐佩汉)[1], Shi-Lian Zheng(郑仕链)[1,2,†], Xiao-Niu Yang(杨小牛)[1,2], and Zhi-Jin Zhao(赵知劲)[3]

[1] *School of Telecommunications Engineering, Xidian University, Xi'an* 710071, *China*
[2] *Science and Technology on Communication Information Security Control Laboratory, Jiaxing* 314033, *China*
[3] *School of Telecommunications, Hangzhou Dianzi University, Hangzhou* 310018, *China*

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Adaptation is one of the key capabilities of cognitive radio, which focuses on how to adjust the radio parameters to optimize the system performance based on the knowledge of the radio environment and its capability and characteristics. In this paper, we consider the cognitive radio adaptation problem for power consumption minimization. The problem is formulated as a constrained power consumption minimization problem, and the biogeography-based optimization (BBO) is introduced to solve this optimization problem. A novel habitat suitability index (HSI) evaluation mechanism is proposed, in which both the power consumption minimization objective and the quality of services (QoS) constraints are taken into account. The results show that under different QoS requirement settings corresponding to different types of services, the algorithm can minimize power consumption while still maintaining the QoS requirements. Comparison with particle swarm optimization (PSO) and cat swarm optimization (CSO) reveals that BBO works better, especially at the early stage of the search, which means that the BBO is a better choice for real-time applications.

Keywords: cognitive radio, power consumption, adaptation, optimization

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1. Introduction

Cognitive radio has been regarded as a promising technique for solving the spectrum scarcity problem as well as improving the communication efficiency.[1] In general, cognitive radio has three basic parts that make it cognitive: the ability to sense the environment, the capability to learn from past experiences and the ability to adapt to the outside world.[2] Adaptation is one of these three key capabilities of cognitive radio, which focuses on how to adjust/reconfigure the radio parameters to optimize the system performance based on the knowledge of the radio environment and its capability and characteristics.

The adaptation problem in cognitive radio has been investigated in Refs. [3]–[16]. As pointed out in Ref. [3], the goal of adaptation in cognitive radio involves most of the time jointly maximizing spectral efficiency, maximizing data throughput, minimizing interference to other cognitive radios, maximizing battery energy efficiency, etc. To solve this multi-objective optimization problem, a lot of methods have been proposed, among which evolutionary algorithm-based methods are very popular. Specifically, in Refs. [3]–[9] genetic algorithms (GAs) have been proposed for cognitive radio adaptation. They revealed that GAs could solve the problem as expected. However, GAs may have the problem of slow convergence and may be stuck in a local maximum. In order to improve the performances of GAs, in our prior work,[10] we invoked particle swarm optimization (PSO) as an adaptation method for dealing with the cognitive radios. Performance gains over basic GAs have been observed in terms of convergence speed and converged fitness values. In Ref. [11], Chen and Wen used cross-entropy method to improve the adaptation performance, showing that cross-entropy method converged faster than PSO-based method. Finally, in Refs. [12] and [13], Pradhan *et al.* compared six evolutionary algorithms for cognitive radio adaptation, namely GAs, PSO, differential evolution, bacterial foraging optimization, artificial bee colony optimization, and cat swarm optimization algorithm. They pointed out that considering all the cases in the simulations, the cat swarm optimization (CSO) can be the best choice for solving the adaptation problem. The above work focused on solving the optimization problem in a specific environment, when the scenario changes, the problem changes and the optimization process needs to run again. This may be time-consuming. In this case, combining the learning in adaptation is beneficial as the techniques revealed in Refs. [14]–[16].

The above mentioned work discussed a general adaptation problem in cognitive radio, while in this paper, we consider the adaptation of cognitive radio for power consumption minimization. The motivation for this is due to the current

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†Corresponding author. E-mail: lianshizheng@126.com

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need for green communications. With green communications, optimizing the energy efficiency of wireless communications reduces not only environmental influence but also the overall network costs.[17,18] Some research of energy and power consumption minimization in cognitive radio has been conducted. Most investigations among these fall into the system level approach which focuses on system level energy consumption without considering power consumption of circuit, e.g., front-end mixers, filters, and amplifiers.[19,20] To overcome this, He *et al.*[21,22] combined system level approach and circuit level approach by considering the power consumption of the power amplifier (PA). The adaptation space in Refs. [21] and [22] was small, so the authors used the exhausted search to find the optimal parameters, thereby minimizing power consumption. In this paper, we formulate the problem of cognitive radio adaptation for power consumption minimization and consider a multicarrier system power minimization with a large search space for the adaptation. We introduce a biogeography-based optimization (BBO)-based method to solve this problem. A novel habitat suitability index (HSI) evaluation mechanism is proposed in which both the main power consumption minimization objective and the QoS constraints are taken into account. Simulations with different choices of parameters are conducted to evaluate the performance of the proposed method. Performance comparisons with other evolutionary algorithms, particle swarm optimization (PSO) and cat swarm optimization (CSO), are also given to show the advantage of BBO based method.

The rest of the paper is organized as follows. In Section 2, the problem of cognitive radio adaptation for power consumption minimization is formulated. In Section 3, our proposed BBO-based method is discussed in detail. In Section 4, simulation results are provided. Concluding remarks are provided in Section 5.

2. Problem formulation

2.1. General problem formulation

The main objective of a cognitive radio adaptation for saving energy is to minimize power consumption as much as possible. However, if basic QoS requirements cannot be maintained, then minimizing power consumption alone makes no sense because basic communications may not be possible as the transmit power may be too low. The general adaptation problem in cognitive radio for power consumption minimization can be formulated as a constrained optimization problem

$$\min P_{\mathrm{c}}(\boldsymbol{a}), \tag{1}$$

with constraints defined by QoS requirements, regulatory limitation, hardware restrictions, etc. In Eq. (1), $a = [a_1, a_2, \ldots, a_n]$ denotes adjustable parameters such as carrier frequency, transmit power, modulation type, and index, and symbol rate, and $P_{\mathrm{c}}(a)$ is the system power consumption under a specific choice of a. Examples of QoS requirements in Eq. (1) include maximum bit error rate (BER), minimum data rate, and minimum latency. They are usually functions of a. These QoS requirements usually relate to specific applications. For instance, the user who needs to transmit a large number of videos cares more about data rate, while a text messaging user cares more about BER. Transferring an email does not require high data rate, but transferring large digital files needs high throughput. Besides QoS requirements, cognitive radio must respect any local regulatory restrictions. Devices operating in different frequency bands will be subjected to different constraints. Certain bands would have strong restrictions against certain power level transmission (GPS), locations (TV broadcast), or time (public safety).[5] Furthermore, the hardware also provides constraints for decisions that cognitive radios can make. For example, even though orthogonal frequency division multiplexing (OFDM) waveform is a suitable choice for a cognitive radio in a certain circumstance, it may not be used because the radio front end may not support such a wide bandwidth.

Regulatory limitations and hardware restrictions usually remain there for a given cognitive radio system, a given spectrum band, and a given location. However, QoS requirements may change over time as the user needs change. When QoS requirements change, the cognitive radio should optimize the parameters to keep the power consumption as low as possible while still maintaining QoS requirements and other constraints.

2.2. Multicarrier system problem formulation

The problem formulated above is a general cognitive radio adaptation problem for power consumption minimization. Here we consider an example of a multicarrier system with N subcarriers which will be used for the rest of the paper. The adjustable parameters considered are the transmit power, the modulation type and the modulation index of each subcarrier. The QoS requirements considered are the target BER and the target data rate. The adaptation problem in this multicarrier cognitive radio system can be formulated as choosing the transmit power and modulation type for each subcarrier to solve the following problem:

$$\begin{aligned} &\min \ P_{\mathrm{c}}, \\ &\text{s.t. } \mathrm{BER} \le \mathrm{BER}_{\mathrm{tar}}, \ \ \mathrm{DR} \ge \mathrm{DR}_{\mathrm{tar}}, \end{aligned} \tag{2}$$

where P_{c} is the power consumption of the system, $\mathrm{BER}_{\mathrm{tar}}$ is the target BER, DR denotes the data rate, and $\mathrm{DR}_{\mathrm{tar}}$ is the target data rate. For different applications or services, $\mathrm{BER}_{\mathrm{tar}}$ and $\mathrm{DR}_{\mathrm{tar}}$ are different.

As in Ref. [22], we consider that the power amplifier (PA) dominates the system power consumption. Denote P_i as the transmit power of subcarrier i, then the total transmit power (radiated power) of the system will be $\sum_{i=1}^{N} P_i$. If class B PA is used, the power consumption of the system can be represented as[22]

$$P_{\mathrm{c}} = \frac{P_{\max}^{1/2}}{0.785}\left(\sum_{i=1}^{N} P_i\right)^{1/2}, \tag{3}$$

where $P_{\max}$ is the maximum output power of the PA. Note that in this paper, when choosing the value of P_i for each subcarrier, null subcarrier is allowed which means that cognitive radio can choose not to transmit power on some subcarriers to save energy. If dynamic spectrum access is considered, another constraint can be easily introduced by using null subcarriers: $P_i = 0$ if $s_i = 1$, where s_i denotes the spectrum sensing result of the subchannel corresponding to subcarrier i. Spectrum sensing can be performed by using existing methods.[23,24] If there is a primary signal in subchannel i, then $s_i = 1$; otherwise, $s_i = 0$.

3. BBO-based solution

In this section, we use BBO to solve problem (2). BBO is a new evolutionary algorithm proposed by Simon[25] who was motivated by natural biogeography. Using BBO for problem (2) needs several key processes which will be discussed in detail in the following subsections.

3.1. Mapping parameters to habitats

The first step to use BBO for power consumption minimization in cognitive radio is to map the adjustable radio parameters into the suitability index variables (SIVs) of the habitats in BBO. For the adaptation problem in this paper, we use binary SIVs. This means that each parameter a_j is encoded by a binary string. The number of bits used to encode a parameter is determined by the range and the expected precision of the parameter. Take the multicarrier system for example. Assume that the transmit power ranges from 0.4 dBm to 25.2 dBm in steps of 0.4 dBm, then the number of bits to represent the transmit power for each subcarrier will be 6. However, if the step of the transmit power is 0.1 dBm, then the number of bits representing the transmit power for each subcarrier increases to 8.

3.2. Habitat suitability index evaluation

In BBO, habitat suitability index (HSI) is used to reflect how good the solution is. HSI is analogous to "fitness" in other evolutionary algorithms. In most applications, the objective function serves as the function to calculate the fitness of each individual. However, in our problem (2), two additional constraints need to be satisfied. In this paper, we propose the following HSI evaluation method:

$$h = (P_{c,\max} + 1 - P_{\mathrm{c}})\, f\left(\mathrm{BER}_{\mathrm{tar}} \Big/ \left(\frac{1}{N}\sum_{i=1}^{N}\mathrm{BER}_i\right)\right) \times f\left(\left(\frac{1}{N}\sum_{i=1}^{N}\mathrm{DR}_i\right) \Big/ \mathrm{DR}_{\mathrm{tar}}\right), \tag{4}$$

where h denotes the HSI value, $P_{\mathrm{c,max}}$ is the possible maximum power consumption of the system, i.e., $P_{\mathrm{c,max}} = P_{\max}/0.785$, and $f(\cdot)$ is a function defined as

$$f(x) = \frac{1}{1+\exp\left(-a\left(\log(x)-b\right)\right)}, \tag{5}$$

where a and b are two real-valued numbers chosen to ensure the following conditions are met: $f(1) = \xi$ and $f(1/2) = \eta$, where ξ is smaller than but close to 1 and η is larger than but close to 0. We refer to $f(\cdot)$ as punishment function in the rest of the paper. Figure 1 shows several curves of $f(x)$ when ξ and η take different values. It can be seen that when $x > 1$, $f(x)$ is very close to $f(1)$, while when $x < 1$, $f(x)$ is far less than $f(1)$.

So, when using Eq. (4) to calculate the HSI, if the mean BER is higher than the target BER or if the data rate is lower than the target data rate, there will be punishment to this solution. Furthermore, when the obtained power consumption is smaller, the HSI computed from Eq. (4) will be higher. As the evolution of the BBO is toward the direction of higher HSI, the solution obtained would be a solution which meets the requirements of QoS and has a small value of power consumption. This HSI evaluation mechanism is the core of our proposed method in which both the power consumption optimization and the two QoS constraints are taken into account.

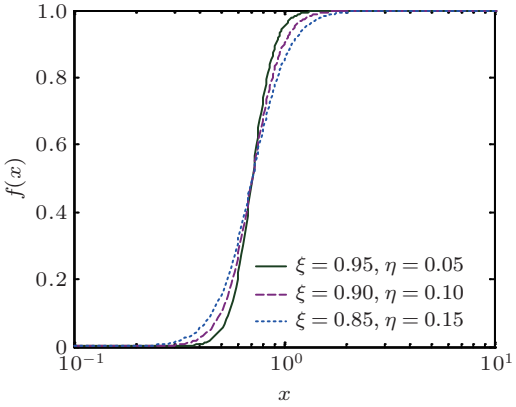


Fig. 1. (color online) Curves of $f(x)$.

3.3. Migration

BBO uses emigration and immigration rates of each solution to probabilistically share information between habitats. A habitat with higher HSI has higher emigration rate and lower immigration rate. We use the basic migration scheme of the BBO in our adaptation method. The process of migration can be described as Algorithm 1.[26]

Algorithm 1. Pseudo-code of Migration in BBO.

Pseudo-code of Migration in BBO:
$y \leftarrow z$ (i.e., create a temporary population)
For each habitat y_k
  For each SIV s
    Use the immigration rate of y_k to probabilistically decide whether to immigrate to y_k.
    If immigrating **then**
      Use the emigration rates to probabilistically select the emigrating habitat z_j.
      $y_k(s) \leftarrow z_j(s)$.
    End if
  next SIV
next habitat
$z \leftarrow y$

The migration decision requires that the habitats be sorted in the ascending order of HSI. The immigration rate and emigration rate of each habitat are determined according to the index of its HSI in the sorted sequence. Figure 2 illustrates the emigration curves used in this paper, which have been shown with the best performance among the six different emigration modes investigated in Ref. [27]. Analytically, the migration rate and immigration rate are

$$\lambda_k = \frac{1}{2}\left(\cos\left(\frac{k\pi}{K}\right)+1\right), \tag{6}$$

$$\mu_k = \frac{1}{2}\left(-\cos\left(\frac{k\pi}{K}\right)+1\right), \tag{7}$$

where λ_k and μ_k respectively denote the migration rate and the immigration rate of the habitat with the number of species k, and K denotes the maximum number of species of a habitat. In this paper, we determine the value of k with a specific habitat as the index of its HSI in the sorted sequence. In this case, K equals the number of habitats in the population (i.e., population size).

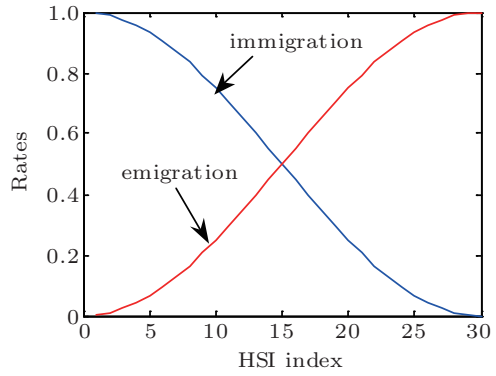


Fig. 2. (color online) Illustrations of emigration curves. The population size is 30.

3.4. Mutation

After migration, BBO uses mutation to simulate sudden change of species count due to random events. Very high HSI solutions and very low HSI solutions are equally improbable and they are given higher mutation rates. The solutions that are averaged are given lower mutation rates. So, in the basic BBO, before mutation, fitness (HSI) evaluation needs to be carried out for each habitat after migration. Note that in the vast majority of real-world applications including our adaptation problem in this paper, the fitness function evaluation dominates the computation complexity of the algorithm. In order to make the computation complexity of the algorithm as low as possible, in practice, this mutation mechanism is usually not adopted. In our proposed method, we use a traditional mutation mechanism utilized in genetic algorithms[28] by assigning a predefined equal mutation rate to each SIV in each habitat. So fitness evaluation is avoided in the mutation process.

3.5. Termination

After migration and mutation, a new generation of habitats is obtained. The process repeats until the termination criterion is met. As with other evolutionary algorithms, BBO also incorporates some sort of elitism in order to retain the best solutions in the population of all iterations. The habitat with the highest HSI when the algorithm is terminated is the solution obtained. In our BBO-based method, we use the maximum number of iterations as the criterion for terminating the algorithm.

4. Simulation results

4.1. Simulation settings

We consider a multicarrier system with 32 subcarriers in the simulations. The noise floor is assumed to be -90 dBm. The path loss due to the distance between the transmitter and the receiver is assumed to be 72 dB. In addition, each subcarrier is assigned to a random attenuation value which ranges from 0 to 1 to simulate a dynamic channel situation. The transmit power ranges from 0.4 dBm to 25.2 dBm in steps of 0.4 dBm. When the transmit power takes the value 0, it means that the subcarrier is null. The modulation types considered in the simulation are BPSK, QPSK, 16 QAM and 64 QAM. In this case the total search space is $(64\times 4)^{32} \approx 1.158\times 10^{77}$ and it needs 256 bits to represent a potential solution. The symbol rate is assumed to be 10 KSPS. To verify the perfor-

mance, three modes with different QoS requirements are used as shown in Table 1. These QoS settings correspond to different types of services. For instance, mode 1 is for voice communication, mode 2 is for video communication, and mode 3 is for low rate data communication.

Table 1. QoS Requirements.

	Mode 1	Mode 2	Mode 3
Target BER	10^{-2}	10^{-3}	10^{-6}
Target data rate	10 kbps	100 kbps	200 kbps

It is important to note that although this simulation setting is used to test the performance of the proposed algorithm, it can be tailored to be applied to practical systems such as IEEE 802.22.[29] The OFDMA is used as the multiplexing scheme of IEEE 802.22. The base station (BS) and the customer premise equipment (CPE) nodes can adapt their modulations (QPSK, 16 QAM or 64 QAM), transmission powers (up to 4 watts) and uplink and downlink subcarriers (4–256) to accommodate specific application requests and QoS requirements. So the same problem (2) can be formulated and the technique proposed in this paper can be used to minimize the power consumptions of BSs and/or CPEs of IEEE 802.22.

4.2. Simulation results

4.2.1. Choices of ξ and η

We first evaluate the performances under different choices of ξ and η. A population size of 30 and an elitism parameter of 1 are used. The algorithm is run 1000 iterations. The mutation rates used in these simulations are all 0.005. Fifty Monte Carlo simulations are used. We illustrate convergence curves when choosing different values of ξ in Fig. 3. It can be observed that these choices of ξ have little influence on the convergence property at the early stage of the search of the algorithm but much on the converged value.

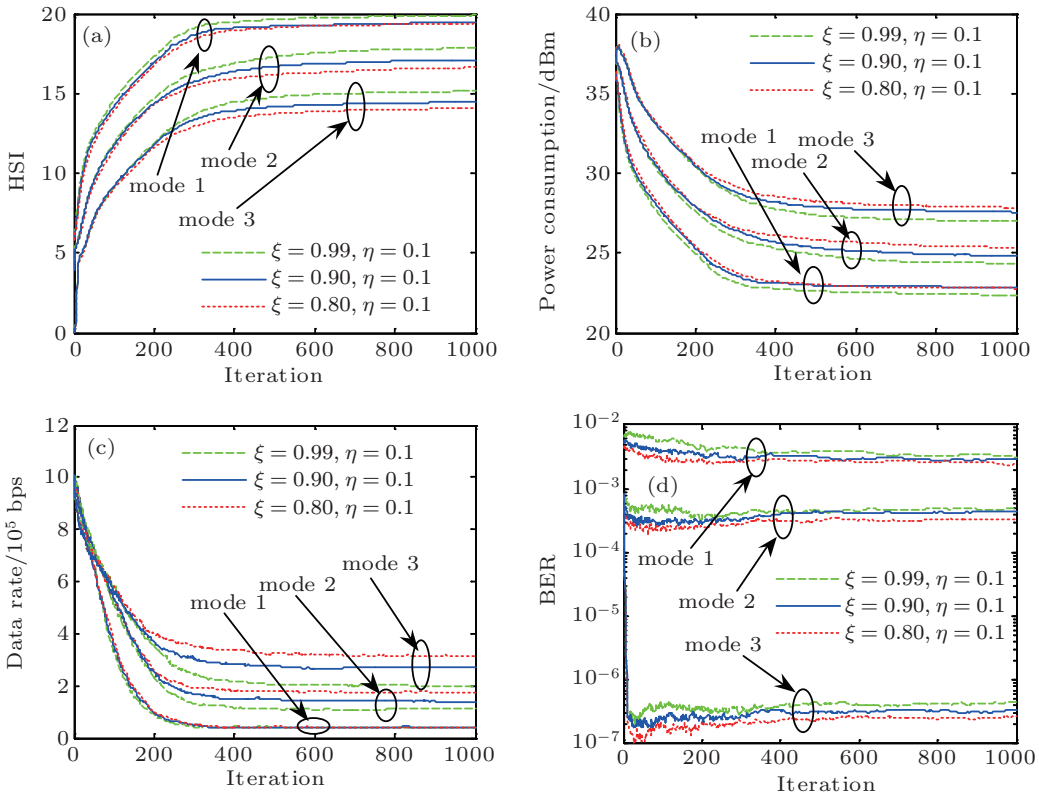


Fig. 3. (color online) Results when choosing different values of ξ, with η kept at the same value, i.e., 0.1. (a) HSI, (b) power consumption, (c) data rate, and (d) BER. The results shown correspond to the best habitat found by the algorithm in each iteration, averaged over 50 Monte Carlo simulations.

Table 2 further shows the converged results of each mode. From Table 2, we see that these choices of ξ and η result in close converged values in mode 1, while in modes 2 and 3 (especially mode 3), their influences on the converged values are quite obvious. A general observation is that when η keeps to be the same (say, 0.1), the larger the ξ is, the smaller the obtained power consumption is. However, when ξ is too large (for example, 0.99), the QoS requirements may not be satisfied (for instance, among these 50 simulations, there are 15 simulations where the obtained data rate is lower than 200 kbps in mode 3). So ξ should not be too large. As for η, when ξ keeps to be the same (say, 0.9), these choices of η ($0.01 \leq \eta \leq 0.3$) do not influence the performance much. In the rest of the paper, we will use $(0.9, 0.1)$ 0.9 and 0.1 for $(\xi, \eta)\xi$ and η. Observing results, when $(\xi, \eta) = (0.9, 0.1)\xi$ and η are 0.9 and 0.1 respectively, this reveals that in all of the three modes, vast power consumption is saved while QoS requirements are maintained.

Table 2. Converged results when different values for the punishment function are used. "Std Dev" means "standard deviation" and "No_D" refers to the number of simulations in which the obtained result satisfies neither the target BER nor the target data rate. Note that αe $-$ 7 represents $\alpha \cdot 10^{-7}$.

Mode	(ξ, η)	Power consumption/dBm		BER			Data rate/kbps		
		Mean	Std Dev	Mean	Std Dev	No_D	Mean	Std Dev	No_D
Mode 1	(0.99, 0.10)	22.366	1.494	0.0031	0.0040	0	39.600	11.058	0
	(0.95, 0.10)	22.799	1.686	0.0034	0.0036	0	37.800	9.957	0
	(0.90, 0.10)	22.788	1.792	0.0029	0.0032	0	41.000	10.350	0
	(0.85, 0.10)	22.656	1.699	0.0025	0.0029	0	38.600	7.001	0
	(0.80, 0.10)	22.778	1.781	0.0024	0.0027	0	40.800	13.223	0
	(0.90, 0.01)	22.527	1.722	0.0028	0.0034	0	38.800	12.229	0
	(0.90, 0.20)	22.562	1.699	0.0022	0.0028	0	40.600	9.127	0
	(0.90, 0.30)	22.455	1.545	0.0021	0.0027	0	38.600	7.827	0
Mode 2	(0.99, 0.10)	24.388	0.850	0.0005	0.0003	**1**	112.800	10.309	**1**
	(0.95, 0.10)	24.609	0.922	0.0004	0.0003	0	130.200	13.169	0
	(0.90, 0.10)	24.813	1.036	0.0004	0.0002	0	138.200	18.371	0
	(0.85, 0.10)	25.133	0.926	0.0004	0.0002	0	162.600	17.474	0
	(0.80, 0.10)	25.316	0.893	0.0003	0.0002	0	172.200	25.257	0
	(0.90, 0.01)	24.792	1.037	0.0005	0.0002	0	132.800	15.784	0
	(0.90, 0.20)	25.270	1.233	0.0004	0.0002	0	153.000	29.294	0
	(0.90, 030)	24.994	1.075	0.0004	0.0001	0	153.000	21.688	0
Mode 3	(0.99, 0.10)	26.989	0.630	4.464×10^{-7}	2.614×10^{-7}	0	199.800	9.792	**15**
	(0.95, 0.10)	27.413	0.677	3.720×10^{-7}	1.946×10^{-7}	0	239.400	14.344	0
	(0.90, 0.10)	27.559	0.529	3.446×10^{-7}	1.512×10^{-7}	0	269.400	13.311	0
	(0.85, 0.10)	27.755	0.535	3.276×10^{-7}	1.282×10^{-7}	0	290.600	16.214	0
	(0.80, 0.10)	27.816	0.457	2.676×10^{-7}	1.013×10^{-7}	0	313.400	19.017	0
	(0.90, 0.01)	27.382	0.526	3.432×10^{-7}	1.850×10^{-7}	0	252.200	12.501	0
	(0.90, 0.20)	27.540	0.481	3.064×10^{-7}	1.434×10^{-7}	0	271.600	18.223	0
	(0.90, 0.30)	27.563	0.510	2.784×10^{-7}	1.403×10^{-7}	0	280.800	22.753	0

4.2.2. Choice of mutation rate

Figure 4 and Table 3 show the obtained results when choosing different values of the mutation rate, denoted as p_m, of the algorithm $(\xi, \eta) = (0.9, 0.1)$, where ξ and η are 0.9 and 0.1 respectively. The other parameters of the BBO are the same as those

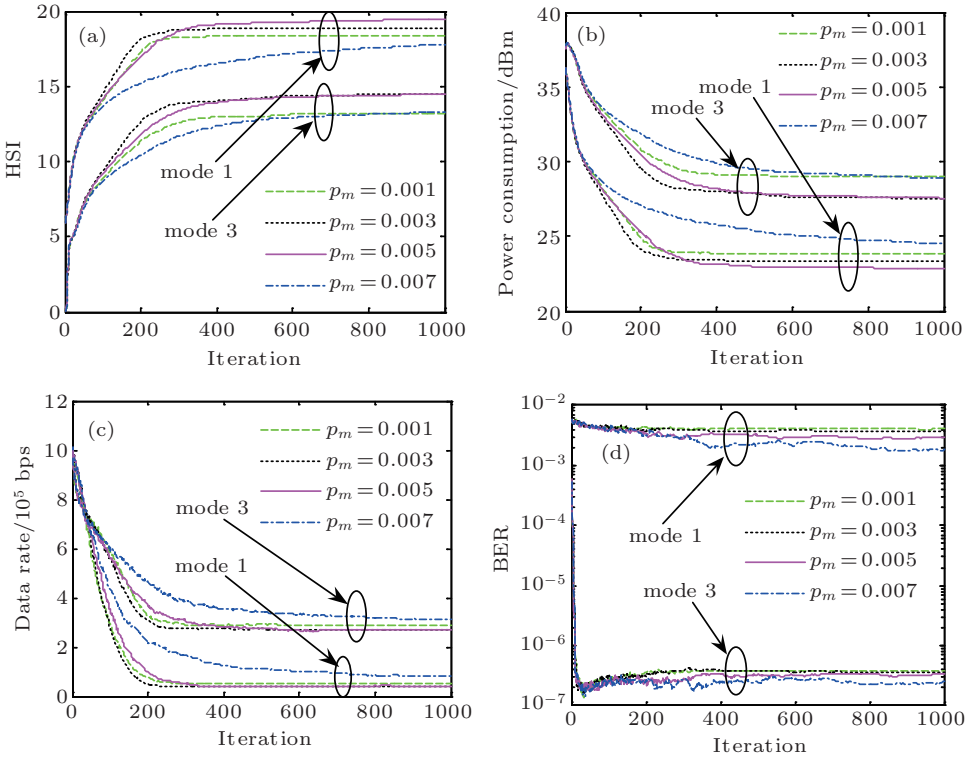


Fig. 4. (color online) Obtained results when choosing different mutation rates. (a) HSI, (b) power consumption, (c) data rate, and (d) BER. The results shown here correspond to the best habitat found by the algorithm in each iteration, averaged over 50 Monte Carlo simulations.

Table 3. Converged results when different mutation rates are used. Note that "Std Dev" means "Standard Deviation" and "No_D" refers to the number of simulations in which the obtained result satisfies neither the target BER nor the target data rate. Note that $\alpha e-7$ represents $\alpha \cdot 10^{-7}$.

Mode	p_m	Power consumption/dBm		BER			Data rate/kbps		
		Mean	Std Dev	Mean	Std Dev	No_D	Mean	Std Dev	No_D
Mode 1	0.001	23.803	2.066	0.0041	0.0032	0	49.000	25.092	0
	0.003	23.341	1.742	0.0038	0.0030	0	40.000	10.101	0
	0.005	22.788	1.792	0.0029	0.0032	0	41.000	10.350	0
	0.007	24.530	1.068	0.0018	0.0024	0	83.600	39.783	0
Mode 2	0.001	25.497	1.727	0.0005	0.0002	0	144.200	21.004	0
	0.003	24.704	1.177	0.0004	0.0002	0	136.200	22.121	0
	0.005	24.813	1.036	0.0004	0.0002	0	138.200	18.371	0
	0.007	26.919	0.517	0.0003	0.0002	0	190.000	26.263	0
Mode 3	0.001	28.955	1.872	3.839×10^{-7}	1.298×10^{-7}	0	289.200	30.466	0
	0.003	27.552	0.973	3.537×10^{-7}	1.337×10^{-7}	0	268.000	14.708	0
	0.005	27.559	0.529	3.446×10^{-7}	1.512×10^{-7}	0	269.400	13.311	0
	0.007	28.898	0.383	2.504×10^{-7}	1.906×10^{-7}	0	309.200	29.887	0

stated in previous Subsection 4.2.1. It can be seen that the target data rate and the target BER are met in all of these simulations. However, when p_m is too small (for example, 0.001) or too large (for example, 0.007), the algorithm performs poorly in the sense of the power consumption. On the other hand, when p_m is chosen to be some medium value (for example, 0.003 or 0.005), the converged power consumption values are smaller. Furthermore, when $p_m = 0.005$, as the obtained standard deviation of the power consumption is smaller, the algorithm is more stable. Taking all of these into account, $p_m = 0.005$ is a fairly good choice for the adaptation problem in the present paper.

4.2.3. Comparison with PSO and CSO

In our previous work,[9] binary PSO was utilized for the general adaptation problem of cognitive radio. Performance advantage over GA was observed.[9] Furthermore, in Ref. [13] the authors used CSO for solving the adaptation problem. By using the fitness (i.e., HSI) evaluation mechanism (i.e., Eq. (4)) proposed in this paper, binary PSO and CSO can also be used for solving problem (2). In this subsection, we compare the performances obtained from our proposed BBO-based method, binary PSO-based method and CSO-based method. For the sake of fairness, each of the algorithms has a population size of 30 and runs 1000 iterations.

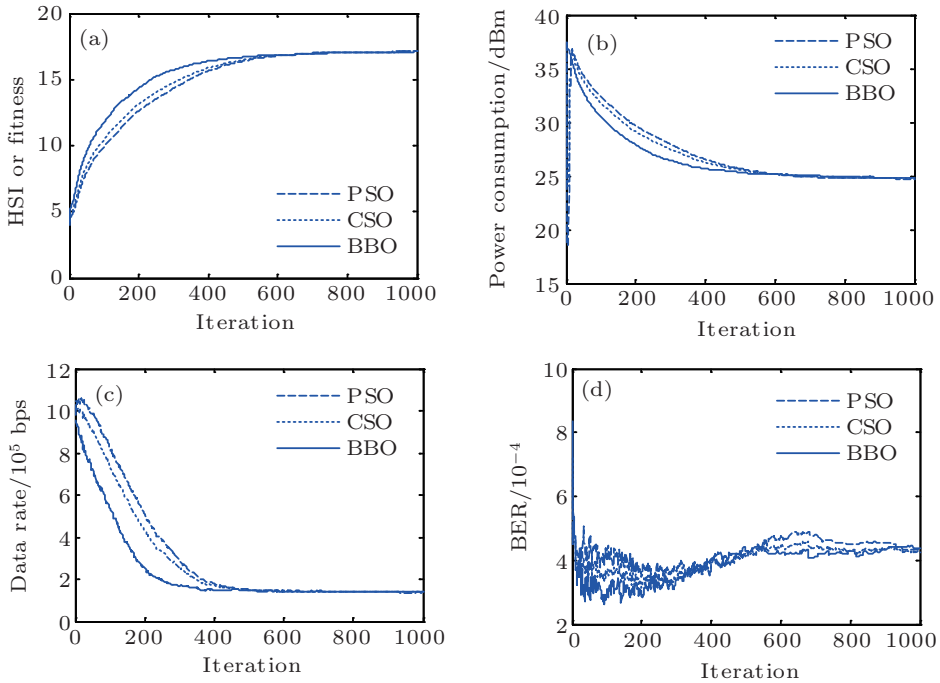


Fig. 5. (color online) Comparisons of BBO with PSO and CSO (mode 2). (a) HIS or fitness, (b) power consumption, (c) data rate, and (d) BER. The results shown here correspond to the best solutions found by the algorithms in each iteration, averaged over 50 Monte Carlo simulations.

In this case, the numbers of fitness evaluations are the same for all three algorithms. For BBO, $p_m = 0.005$. For binary PSO, an initial constant of 1, a cognitive constant of 2, a social constant of 2, and a maximum velocity of 4 are used as in Ref. [9]. For CSO, the inertia weight is maintained to be a constant of 1. The other parameters are chosen to be the same as those in Ref. [13]. Figure 5 shows the performances of these three algorithms in mode 2. Results in modes 1 and 3 are similar. It is obvious that in solving problem (2), BBO performs better than PSO and CSO in the sense of convergence rate. As we expect the adaptation process to take as little time as possible, BBO is a better choice for real-time applications.

To further illustrate the effectiveness of our proposed method in saving energy, we define the system power consumption reduction as

$$P_{\text{saving}} = \frac{P_{\text{c,max}} - P_{\text{c,obtained}}}{P_{\text{c,max}}} \cdot 100\%, \tag{8}$$

where $P_{\text{c,max}}$ is the maximum power consumption of the system (i.e., each subcarrier transmits with the maximum power), $P_{\text{c,obtained}}$ is the power consumption obtained with the algorithm. We illustrate power savings in Fig. 6. Vast power savings are observed. Another observation from this figure is that through several iterations BBO can save more than 50% power consumption, which further validates its effectiveness for cognitive radio adaptation problem for power consumption minimization formulated in this paper.

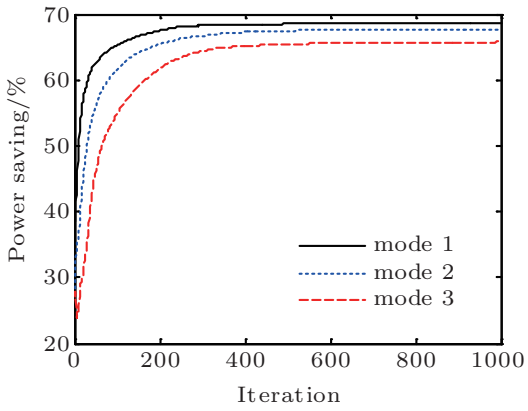


Fig. 6. (color online) Power saving.

5. Conclusions

In this paper, the adaptation problem in cognitive radio for power consumption minimization is formulated as a constrained optimization problem and the BBO method is introduced to solve this problem. A novel HSI evaluation mechanism with punishment to those solutions which do not satisfy QoS constraints is proposed. The performance of the proposed method is evaluated through simulations. Results show that the algorithm can optimize the system power consumption while maintaining the QoS requirements, thus saving energy. Comparison with PSO and CSO shows that BBO outperforms PSO and CSO at the early stage of the search, which indicates that BBO is a better choice for real-time applications.

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