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Power allocation in cognitive radio networks over Rayleigh-fading channels with hybrid intelligent algorithms

Feng Li · Kwok-Yan Lam · Li Wang

Abstract In this paper, we introduce a hybrid strategy containing pattern search (PS) optimization and genetic algorithm (GA) to address the problem of power allocation in cognitive radio networks. Considering the fluctuating interference thresholds in cognitive networks, an approach for promoting the coexistence between licensed users and cognitive users is designed first. Then, based on the analysis of transmission outage probability, a corresponding objective function with regard to the power allocation over Rayleigh fading channels is obtained. Due to the nonlinearity and complexity of the optimization problem, it is uneasy to figure it out directly by using traditional methods, such as common mathematical deduction or linear programming. Inspired by the concept of intelligent algorithms, we try to employ the scheme of combining PS optimization and GA method, which are both efficient intelligent algorithms to resolve this difficulty. The reason why we apply a combined algorithm is it can overcome the instability of GA and the local convergency of PS method. Thus, the hybrid intelligent method can attain a global and steady outcome. We improve the performance of power allocation strategy with an acceptable increase of computation burden. The numerical results are encouraging and show the proposed approach is worthy of consideration in finding complicated power optimization. Thus, we achieve steady and rational outcomes by ap-

Feng Li and Li Wang are with College of Information Engineering, Zhejiang University of Technology, Hangzhou, Zhejiang, 310023, China.

Kwok-Yan Lam is with School of Computer Science and Engineering, Nanyang Technological University, 639798, Singapore.

F. Li
E-mail: barackli@yeah.net

K. Y. Lam
E-mail: kwokyan.lam@ntu.edu.sg

Li Wang
E-mail: lwanghit@yeah.net

plying the proposed combined strategy when traditional method is uneasy to address the nonlinear objective.

Keywords Cognitive radio (CR) · intelligent algorithm · power allocation · outage probability

1 Introduction

With the rapid development of wireless services and applications, the currently deployed radio spectrum is becoming more and more crowded. Cognitive radio (CR) is widely considered as a promising technology to deal with the spectrum shortage problem [1-2].

To make full use of the spectrum resources, transmit power control and dynamic spectrum management are essential for CR [3]. Through effective power control, secondary users are allowed to share the licensed spectrum on condition that the resultant interference at the primary receiver is below a prescribed threshold, known as spectrum underlay in [4] or spectrum sharing in [5]. In addition, appropriate power control strategies are indispensable for guaranteeing quality of service (QoS) and system capacity objectives.

Many endeavors have been paid to resolve the problem of power control involved in the CR networks. To protect primary transmission, a common method is to impose an interference power constraint to secondary transmission. It thus requires the interference power to be below a prescribed threshold, known as the interference temperature constraint [5]. Motivated by this idea, a great deal of valuable scholarly work has been done on the design of optimal power control strategies for CR networks [6-8].

In recent years, the power allocation schemes for different communication networks with CR functionality received growing attention [9]-[11]. In [9], a power allocation strategy is designed for green cognitive radio networks to maximize energy-efficient fractional objective in terms of bits per Joule per Hertz. In [10], optimal beamforming and power allocation solution for secondary transmitter based on the sensing results on primary state in a multi-antenna CR networks is raised. According to the characteristics of wideband CR networks employing SC-FDMA, [11] proposes a power allocation method for secondary transmitter with the constraint of protecting the link of primary user.

Besides, based on many new network models and research perspectives, appropriate resource allocation solutions are unremittingly explored to optimize CR networks [12]-[14]. Reference [12] studies the power allocation in CR by considering the nonlinear effects of the power amplifier on received signal-to-noise ratio (SNR) at the secondary receiver and the adjacent channel interference to the primary receiver. Reference [13] considers a CR system with N secondary user pairs sharing a spectrum with a pair of primary users, then formulates the secondary user's power allocation problem as a capacity maximization problem under primary and secondary QoS and secondary peak

power constraints. Reference [14] proposes an energy-efficient joint relay selection and power allocation scheme in which the state of a relay is characterized by the channel condition of all relate links and its residual energy.

A number of mathematical languages and tools, including game theory [15][16] and intelligent algorithms [17][18], have been used in the study of resource allocation in CR networks. In [17], a localized variation of the island genetic algorithm (GA) has been applied to solve a distributed cross layer channel allocation-power control problem for an ad-hoc CR networks in dynamic spectrum access. And in [18], a modified GA method was used to solve the problem of spectrum allocation in traditional cellular networks. The introduction of intelligent algorithms can help address the resource allocation problem of CR networks, which is non-linear, non-differentiable and with multiple objectives. For resource allocation in CR networks, the objective function which needs to be fixed is always nonlinear and complex. Therefore, the traditional methods, such as linear programming and complicated mathematical deduction, are found unsuitable to be employed in this case after many attempts. Inspired by the concept of intelligent algorithm, we thus try to utilize unconventional optimization method to solve such kind of difficulty.

In this paper, we propose a hybrid strategy by coupling pattern search (PS) optimization with GA method in order to optimize power allocation in CR networks. We use the GA first, which is an intelligent algorithm for searching the optimal point in global region, then adopt the PS method to refine the result. The hybrid strategy aims to make full use of the GA and PS solutions to achieve a global and steady optimum. The main reason behind the use of GA approach is its robustness and ability to fix the optimal solutions in the whole region. On the other hand, its defects mainly lie in the unstable results and relatively low speed. The PS method is a nonrandom method for searching minima of a function. Due to its ability to perform steady and fast search, it can remedy some deficiencies of the GA approach. However, the outcome of PS method is likely to be affected by the selection of the initial point which may lead PS to a local optimal solution sometimes. Our hybrid approach aims to adopt the GA method to find an optimal region which will be used by the PS method as an initial point to identify the global optimum. To our knowledge, there are few research applying intelligent algorithms to solve the resource allocation problem in CR networks.

The rest of this paper is organized as follows: Section II describes the model of power control under the constraint of interference temperature in CR networks. Section III introduces the PS optimization and GA, respectively. Section IV presents the simulation results. Finally, Section V concludes this paper.

2 System model

In this paper, it is assumed that the channel usage pattern of users is fairly static over time so that the CR network can deploy power control strategy

Fig. 1 Cognitive users and primary users work together in the networks. *PU*, *SU*, *CBS* and *BS* represent primary user, secondary user, cognitive base station and base station, respectively.

to avoid interfering to the primary users severely. First of all, cognitive users should sense channels and detect whether primary users are close or not. This can be done with different spectrum sensing techniques such as matched filter, energy detector, and cyclostationary feature detector [19-21].

A CR network is considered to consist of a single cognitive base station, several cognitive users and primary users as depicted in Fig. 1. In the figure, BS (Base Station) serves the primary users and CBS is the base station of the cognitive network. SUs are cognitive terminals. PU1 and PU2 are primary terminals. We will concentrate this paper on the uplink power control problem, and we assume that the cognitive network can work in the mode of Code Division Multiple Access whose main intention is to economize spectrum in maximum.

In this paper, we consider the model of signal-to-interference-plus-noise ratio SINR over Rayleigh fading environments. The power received from transmitter j at receiver i is given by

$$P = G_{ij}F_{ij}P_j. \quad (1)$$

The parameter G_{ij} , which is positive, represents the path gain (not including fading) from the j th transmitter to the i th receiver. It can be described as $G_{ij} = h_{ij}c_{ij}$, where $h_{ij} = A/r^\alpha$ and c_{ij} is the correlation coefficient [22]. A is a constant gain and α is usually between 2 and 6. In the analysis below, we assume that G_{ij} is constant, and does not change much with time.

The parameter F_{ij} models Rayleigh fading which is assumed to be independent, exponentially distributed random variables, with unit mean [23]. In other words, the power received at receiver i from transmitter j is an exponentially distributed random variable, with mean value

$$E(G_{ij}F_{ij}P_j) = G_{ij}P_j. \quad (2)$$

Then, the SINR γ for the user i th can be defined as

$$\gamma_i = \frac{G_{ii}F_{ii}P_i}{\sum_{j \neq i} G_{ij}F_{ij}P_j + \sigma^2}, \quad (3)$$

where P_i is the transmitted power from the base station and σ^2 is the background noise which will be given in later simulation tests. One of the designing goals of communication in wireless networks is to ensure that no mobile's SINR γ_i falls below its threshold γ_i^{tar} to ensure adequate QoS. Thus, there is

$$\gamma_i \geq \gamma_i^{tar} \quad \forall i. \quad (4)$$

For individual mobiles, this threshold can be calculated to maintain a satisfactory frame error rate. Furthermore, we define the interference vector as I which can be represented as

$$I_i(P_{-i}) = \sum_{j \neq i} G_{ij}F_{ij}P_j + \sigma^2. \quad (5)$$

Sign $I_i(P_{-i})$ means that the interference vector of the i th mobile depends on all but the power vector itself. For Eq.(3), we regard P_i as the power of the primary user and P_j as the power of cognitive user. We assume that primary users can not interfere with each other when they use different spectrums, and we ignore the interference from other cells. The primary user needs to meet the requirement of QoS, as described in Eq.(4). When the power of primary user is constant, if we want to satisfy Eq.(4), we can acquire the following equation from Eq.(3)

$$\sum_{j \neq i} G_{ij}F_{ij}P_j \leq T = \frac{G_{ii}F_{ii}P_i}{\gamma_i^{tar}} - \sigma^2. \quad (6)$$

Equation (6) can be rewritten as follows

$$G_{il}F_{il}P_l + \sum_{\substack{j \neq i \\ j \neq l}} G_{ij}F_{ij}P_j \leq T, \quad (7)$$

where P_l is the power of a cognitive user and T is interference threshold which can be obtained from (6). Equation (7) can also be deduced to

$$P_l \leq (T - \sum_{\substack{j \neq i \\ j \neq l}} G_{ij}F_{ij}P_j) / G_{il}F_{il}. \quad (8)$$

The interference to the primary user cannot exceed the threshold, otherwise it will not ensure the QoS of the primary user. If the interference is too large, cognitive users need to decrease their powers or leave their present positions, or get away from the channels in the worst condition. For a single cognitive user, we can obtain that

$$P_l \leq P_l^{tar}, \quad (9)$$

where P_l^{tar} is derived from Eq.(8). Cognitive users need to satisfy both Eq.(4) and Eq.(9). If P^{max} represents the maximal power that mobile can use, and P^ψ means the power we can get from this work. Therefore, the power for a cognitive user that we should apply is

$$P = \min\{P^\psi, P^{tar}, P^{max}\}, \quad (10)$$

where P^{tar} is usually far less than P^{max} .

Then, for a cognitive user, in order to guarantee a rational QoS which means the SINR exceeds a given threshold γ^{tar} , the outage probability of the i th receiver/transmitter pair is given by

$$\begin{aligned} OP_i &= Pr(\gamma_i \leq \gamma^{tar}), \\ &= Pr(G_{ii}F_{ii}P_i \leq \gamma^{tar}(\sum_{j \neq i} G_{ij}F_{ij}P_j + \sigma^2)), \end{aligned} \quad (11)$$

where OP represents the outage probability. Suppose $f_{ii}, \dots, f_{in}$ are independent exponentially distributed random variables with unit means, there are $E(g_{ii}f_{ii}p_i) = g_{ii}p_i = 1/\lambda_{ii}$ and $E(\gamma^{tar}g_{ij}f_{ij}p_j) = 1/\lambda_{ij}$. Let $m = \gamma^{tar}\sigma^2$, there is the following equation

$$\begin{aligned} \rho_{out} &= Pr\{g_{ii}f_{ii}p_i \leq \sum_{j=1, j \neq i}^k \gamma^{tar}g_{ij}f_{ij}p_j + m\} \\ &= 1 - \int_{t_2=0}^{\infty} \dots \int_{t_n=0}^{\infty} e^{-\lambda_{ii}(t_2+\dots+t_n+m)} \times \prod_{j=1}^k \lambda_{ij} e^{-\lambda_{ij}t_j} dt_1 \dots dt_k \\ &= 1 - \int_{t_2=0}^{\infty} \dots \int_{t_n=0}^{\infty} Pr(g_{ii}f_{ii}p_i > \sum_{k=2}^n t_k) \times \prod_{k=2}^n \lambda_{ij} e^{-\lambda_{ij}t_k+m} dt_2 \dots dt_n \\ &= 1 - e^{-\lambda_{ii}m} \prod_{j=1}^k \int_{t_\tau=0}^{\infty} \lambda_{ij} e^{-(\lambda_{ii}+\lambda_{ij})t_\tau} dt_\tau \\ &= 1 - e^{-\lambda_{ii}m} \prod_{j=1}^k \frac{\lambda_{ij}}{\lambda_{ii} + \lambda_{ij}}. \end{aligned} \quad (12)$$

Therefore, we can obtain the following equation by applying Eq.(12) to Eq.(11)

$$OP_i = 1 - e^{-\frac{\gamma^{tar}\sigma^2}{G_{ii}P_i}} \prod_{i \neq j} \left(\frac{1}{1 + \frac{G_{ij}P_j\gamma^{tar}}{G_{ii}P_i}} \right). \quad (13)$$

In this situation, define the worst outage probability over all cognitive users as

$$OP = \max OP_i. \quad (14)$$

And this is also defined as the outage probability of the network. Then, our optimization problem can be described as

$$\begin{aligned} \min \max \{ & 1 - e^{-\frac{\gamma^{tar} \sigma^2}{G_{ii} P_i}} \prod_{i \neq j} \left(\frac{1}{1 + \frac{G_{ij} P_j \gamma^{tar}}{G_{ii} P_i}} \right) \}, \\ \text{subject to } & P_i > 0, \quad i = 1, \dots, n. \end{aligned} \quad (15)$$

In addition, in the cognitive system, we should follow the principle of protecting the primary communication described as Eq.(9). Due to the nonlinearity and complexity of this power allocation problem described in Eq.(15), traditional methods, such as linear programming and complicated mathematical deduction, are found to be unsuitable. Inspired by the concept of intelligent algorithm, we thus try to utilize unconventional optimization method to solve this difficulty.

3 Hybrid intelligent algorithms

3.1 Implementation of genetic algorithm

Developed by a Dutch research group in 1970's, GA has currently been used as a robust tool of optimization [24-25]. GA is superior to some traditional optimization techniques in the search of global optimal values of multi-model objective function instead of local ones. Extensive research have been performed exploiting the robust properties of the genetic algorithms and demonstrating their capabilities across a broad range of problems including multi-objective optimization [26], image and video processing [27], system control [28], and so on.

There are a number of significant differences between standard optimization methods and GAs. GAs search the solution space by using a population of potential solutions and treating them in parallel rather than following one potential solution to its best value. They only use the values of objective function but their derivatives or other auxiliary knowledge. Furthermore, they use probabilistic transition functions and not deterministic ones.

We use the function $f(P_i)$ defined in Eq.(15) as our fitness function. Many parameters involved in the fitness function should be set, including noise power σ^2 , fading coefficient A , fitness function $f(P_i)$, SINR threshold γ^{tar} , the constraint of power P^{min} and P^{max} . The values of these parameters will be given in the next section, and other parameters about the GA are listed in the Table 1. We further use the genetic routine of Houck [29] to achieve the optimal power distribution of cognitive users.

Table 1 Settings used in the GA

Parameter	Setting
Population size	30
Crossover fraction	0.6
Number of iteration	1000
Selection	Uniform
Mutation	Gaussian
Mutation probability	0.1
Crossover	Two-point

3.2 Process of pattern search optimization

The PS algorithms that were first defined and analyzed by Torczon [30] for derivative-free unconstrained optimization belong to the family of direct search methods. As opposed to more traditional optimization methods that use information about the gradient or higher derivatives to search for an optimal point, a PS algorithm searches a set of points around the current point, looking for one where the value of the fitness function is lower than the value at the current point. Due to this characteristic, the effects of the PS algorithms are likely influenced by the selection of initial point. Detailed discussion of the basic concepts of the PS algorithm can be found in [31-33]. The main purpose that we introduce the GA to the strategy is to solve this problem of unsuitable initial point effectively.

The main routine of our PS algorithm can be described as Table 2.

Table 2 Main routines of the PS optimization

Initialization

```

PSoptions = struct('MeshTolerance', 1e-6, ...
    'MaxIteration', 5000, ...
    'FunctionTolerance', 1e-6, ...
    'MaxFunEvals', '20000', ...
    'TimeLimit', Inf, ...
    'MeshContraction', 0.5, ...
    'MeshExpansion', 2.0, ...
    'MeshRotate', 'on', ...
    'StepSize', '2', ...
    'InitialMeshSize', 0.2, ...
    'ScaleMesh', 'on', ...
    'MaxMeshSize', inf, ...
    'CompletePoll', 'on', ...
    'PollingOrder', 'consecutive', ...
    'CompleteSearch', 'on', ...
    'PlotFun', 'on', ...);

```

```

PAoptions = struct('MaxPower', 1000, ...
    'MinPower', 0, ...
    'NoisePower', 2e-13, ...
    'FadingCoefficient', '1e-11', ...
    'FitnessFunction', f(x), ... % defined in (15)
    'SINRthreshold', 10, ...
    'FadingConstant', 4, ...
    'UserNumber', n, ...);
s=InitialMeshSize;
X(1)=[P1(1) P2(1) ... Pn(1)]; % initial point
for i=1:MaxIteration;
    if s ≥ MeshTolerance && ft ≥ FunctionTolerance
        && mfe ≤ MaxFunEvals && X(i) ≤ Ptar
        && X(i) ≥ MinPower &&  $\gamma_u \geq \text{SINRthreshold}$ 
        ComFit: if  $f(P1(i) \pm s, P2(i) \pm s, \dots, Pn(i) \pm s) < f(P1(i), P2(i), \dots, Pn(i))$ 
            X(i+1)=[P1(i)±s P2(i)±s Pn(i)±s];
            s=s*StepSize;
            break; % begin next iteration
        else
            s=s/StepSize;
            if s ≥ MeshTolerance
                break;
            else
                return; % exit loop
            end
        end
    end
end
end

```

The accuracy and convergence speed of the algorithm depend on the parameter settings. The algorithm parameters, such as MeshTolerance and FunctionTolerance, should be appropriately set to guarantee a global optimal solution. The pattern search method seeks optimal solution through the mode of mesh point, and the mesh size will be reduced by half when there does not exist a point whose objective function is smaller than current point. Detailed parameter settings is shown in simulation section.

4 Numerical results

In this section, we give the presentation of simulation results of the power allocation obtained by hybrid optimization solution including GA and PS method. As shown in Fig. 2, several cognitive users and one primary user distribute in the networks where we ignore the interference from other primary users or other cells due to their different spectrum bands. We further consider the Rayleigh

Fig. 2 Several cognitive terminals and one primary user distribute in the networks. SU, BS and PU represent secondary user, base station and primary user, respectively.

fading environment is modeled by F_i in an exponential distribution. The background noise power is supposed to be $\sigma^2 = 2 \times 10^{-13}$ mW. The channel gain is determined according to

$$h_i = \frac{A}{r^\alpha}. \quad (16)$$

We assume that $\alpha = 4$ and $A = 10^{-11}$.

4.1 Results of the genetic algorithm

In this test, we set the threshold of SINR as $\gamma^{tar} = 10$ dB. Cognitive users and one primary user randomly distribute in the networks as shown in Fig. 2. In this test, we fix the positions of cognitive users and primary users as shown in Table 3. The power level of the primary user is just required to satisfy its QoS.

We set several stop criterions in the GA, including maximum iteration times $\tau_{max} = 5000$ and minimal fitness function tolerance $\nu_{min} = 10^{-6}$. The minimum and maximum powers are set to be 0 mW and 1000 mW, respectively. The population size is fixed as 30 which means multiple seeds are searching the optimal results same time. Crossover fraction is 0.6 which locates at the range $[0, 1]$. High crossover fraction guarantees the full computation for every generation. Number of iteration is set to be 1000 which is relatively high as a stop criterion. An uniform selection method is to let the individual with highest fitness function have most opportunity to be selected. Furthermore, high mutation probability is to add stochastic effects into the computation process so as to avoid falling into local optimum.

Due to the instability of GA, we perform five simulation tests in order to obtain ideal results. The data obtained by the GA is listed in Table 4. The user

being closer to the base station saves more powers because of lower path loss. Another reason for the relatively low power distribution lies in the constraint that the cognitive users should limit their interference in order to protect the primary communication. In Table 4, it should be noted that several power values of the secondary users are negative which is not rational and should be discarded. We can also get from the table that the data obtained from the GA is not very steady and should be further improved. Hence, it is worth of considering to introduce the PS optimization to achieve more steady and more rational final solutions. In this case, we choose the average powers listed in Table 4 as appropriate initial point for the following PS method, and the negative values are substituted by zero.

Table 3 User positions

SU1	SU2	SU3	SU4	SU5	Primary	Cognitive BS
(2.3,1.1)	(2.6,0.4)	(2.6,2.1)	(2.7,2.1)	(2.5,3)	(1,3.1)	(3.5,0.5)

Table 4 Data obtained by the GA

	SU1	SU2	SU3	SU4	SU5	Primary
1	-0.051	-0.182	1.277	6.398	12.958	3.699
2	0.305	-0.317	1.730	6.292	13.155	3.989
3	0.641	0.155	2.080	6.299	13.005	3.893
4	0.900	-0.776	1.711	6.249	13.225	3.809
5	-0.083	-0.144	1.813	5.825	13.288	3.912
Average	0.342	-0.253	1.722	6.213	13.126	3.860

4.2 Refined by the pattern search optimization

Similar parameter settings are applied to this test, including SINR and power threshold. We utilize the initial point obtained from the GA method, and then achieve the final results by pattern search method as shown in Fig. 3. In this test, the powers of the secondary users are [0.86, 0.169, 2.118, 6.68, 13.442]mW as described in Fig. 3, which is slightly higher than those gotten by the GA as shown in Table 4. Whereas, the results obtained by the PS method are very steady and have no unreasonable values as well, which solve the problems appearing in the process of the GA. In this case, the power of the primary user is 3.965mW. Furthermore, the fitness function which represents the system outage probability is also very steady. This outage probability can be interpreted as the fraction of time one transmission experiences an outage due to fading.

On the other hand, we give the analysis of the computation complexity for both GA and PS method to testify the algorithms' performance. For GA method, its computation complexity mainly depends on the following aspects: population size, modes of reproduction, crossover and mutation. In our tests, we set initial population size to be 30. For GA method, more initial population

Fig. 3 Numerical results obtained by the PS method. (a) Power allocation of the five cognitive users (b) Outage probabilities of the five cognitive users.

can better guarantee the characteristics of global convergency rather than local convergency. When you are looking for a prey in forest, it would be better to let out more hunters randomly. Nevertheless, too large population size will cost high computation resources. Furthermore, we set the elite count of reproduction as 2, and the mode of mutation to be Gaussian. Crossover mode is arranged to be scattered to make sure the global optimum. The convergency performance of the GA method is given in Fig. 4. We can obtain from the figure that the convergency speed is relatively fast. The steady outcome of GA method can be always attained within 100 iterations and the computation time lasts not more than one minute which is very acceptable.

In addition, we further give the iteration performance of PS method as shown in Fig. 5. Similar conclusions can be fit to PS method that the convergency speed and computation complexity for solving the proposed resource

allocation problem is rational and acceptable in condition of common personal computer equipped with Core i3 processor and 4G bytes memory. In general, the PS method is easier to get convergent than GA since there is only ‘one initial seed’ for the PS to launch the searching of global optimum. As a result, it will likely to converge at a local optimum. The key factor influencing the effects of PS method is the selection of initial point. In this paper, we obtain the initial points from the outcomes of GA which are close to each other, hence the results received by PS method become steady and unchanged.

Besides, it should be noted that the outcomes of the PS method are affected by the selection of initial points obviously. We further give the numerical results as shown in Fig. 6, where the initial point is randomly set to be $[40, 40, 40, 40, 40]$ mW. The powers obtained increase remarkably and converge to a local optimum configuration, which is not ideal and could not be the optimal solution. This is the reason why we introduce the GA method to ascertain the initial point first.

We also investigate the performance of another traditional power allocation method named balancing algorithm to testify the effects of our proposed solution for power control. As shown in Fig. 7, we give the power and SINR effects of the balancing algorithm which is a well-known iterative power control algorithm [34]. The iterative power control algorithm can be performed as the following steps.

Iterative Power Balancing algorithm (IPB): Step 1: Initialization: initialize original transmit power $p_i^{(0)} = 0$; **Step 2: begin iteration,** (i) the secondary user updates its power by $p_i^{(k+1)} = \min\{\gamma_i^{tar}(\frac{p_i^{(k)}}{\gamma_i^{(k)}}), p_i^{max}\}$, and updates SINR by $\gamma_i^{(k+1)} = \frac{g_{ii}f_{ii}p_i^{(k)}}{\sum_{j \neq i} g_{ij}f_{ij}p_j^{(k)} + \sigma^2}$. **Repeat (i) and (ii) over again until the algorithm converges. END**

We give the performance of the IPB algorithm in Fig. 7. In Fig. 7(a), the five curves represent the power values of five cognitive users. In Fig. 7(b), five curves which are overlapping totally mean the SINR levels obtained by the corresponding cognitive users when the transmit powers above can be attained. In this paper, our technical solution is to search for an optimal power allocation strategy in order to obtain the lowest outage probability denoted in Eq.(15). It can be concluded that the outcomes of the balancing algorithm and our method is close.

On the other hand, we can obtain from Fig. 7 and IPB procedure that the traditional method has less complexity compared with our proposal. IPB algorithm generally converges with no more than ten iterations. As shown in Fig. 7(a), the power curves begin to converge and become steady after several iterations no matter what the initial powers of cognitive users are. The balancing algorithm aims to find minimal power allocation values when the SINR thresholds are just met. Whereas, the algorithm is subject to the preconditions of uniform SINR threshold and fixed optimization objective. We can obtain a rational power allocation for different terminals by balanc-

Fig. 4 Iterative convergency of GA.

Fig. 5 Iterative convergency of PS method.

Fig. 6 Numerical results returned by the PS method with changed initial point. SU means the secondary user.

ing algorithm when an uniform SINR threshold is settled. However, it cannot be applied when the objective function is very complicated or different user demands are required.

In addition, we further give the outage probability effects of our proposed solution with various SINR thresholds to define the transmission outage as shown in Fig 8. It is apparent that the outage probabilities increase linearly and slowly when the SINR thresholds arise due to different QoS requirements. The comparison of the effects of our proposal and that of the uniformed power allocation is also presented in Fig. 9. Furthermore, We give the numerical results by the PS method in Fig. 10 in condition that there are ten cognitive terminals distributing randomly in the networks. In this case, the initial point is still obtained through the GA. With the increase of system loading, the transmitted power of every cognitive user decreases distinctly so as to avoid severe interference to the primary user whose power remains relatively low. At the same time, the outage probabilities increase slightly due to the increased secondary users. As a whole, the PS optimization can reap a steady and rational results in this circumstance with an appropriate initial point.

5 Conclusions

The contribution of this paper mainly lies in the introduction of hybrid intelligent algorithms combining PS method and GA to solve the problem of optimal power allocation in CR networks, when it is uneasy to solve the objective function by using complicated mathematical deduction or traditional linear optimization approaches. In the underlay mode, floating interference temperature is the primary characteristic for cognitive networks, which adds

Fig. 7 Power and SINR effects by the balancing algorithm.

a special constraint to the fitness function and influences the result notably. Through a number of tests, we utilize the PS method to obtain a set of ideal and steady power allocation after using the GA to ascertain the initial point carefully. In addition, how to accelerate the convergence speed in the use of PS method, especially when system loading increases expensively, remains practically important and may indeed be the guiding force of our following research.

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Fig. 8 Outage probabilities with various SINR thresholds.

Fig. 9 Outage comparison of our proposal and the uniform power allocation.

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Fig. 10 Power allocation and outage probabilities in the presences of ten secondary users.

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