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A bio-inspired approach for cognitive radio networks

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The recent increasing interest in cognitive radio networks has motivated the study and development of new approaches capable of coping with the intrinsic challenges of this kind of network, such as dynamic spectrum availability, distributed and heterogeneous network architectures, and soaring complexity. The bio-inspired approaches, with appealing characteristics such as autonomy, adaptation and collective intelligence of collaborative individuals, have been extensively studied. This paper presents a comprehensive survey of bio-inspired approaches for cognitive radio networks, emphasizing their domains of application. Specifically, ant colony optimization and particle warm optimization are further investigated with examples and numerical simulation.

cognitive radio networks, bio-inspired networking, ant colony optimization, particle swarm optimization

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In the past decade, the cognitive radio technology, which was a term first coined by Mitola et al. [1], has attracted tremendous attention in the wireless communications to improve the spectrum-scarcity problem in static spectrum-assignment policy. It facilitates the coexistence and efficiently exploits available spectrum in heterogeneous networks. However, the cognitive radio networks (CRN) faces many intractable challenges, such as sensing dynamic spectrum availability and complexity of distributed and heterogeneous network architectures, and hardware. These challenges are mainly caused by the discriminatory of the co-existence of secondary network within the primary network and the decentralized physical and access networking mechanisms of secondary network.

For the sake of highly capable of autonomy and adaptation, bio-inspired approaches seem to be the promising methods to cope with the challenges in CRN, although they can be rather slow to adapt to environmental changes. Of course, the application of bio-inspired approaches in information technologies is not a new issue. A survey of the bio-inspired networking and its communication protocols and algorithms devised by looking at biology as a source of inspiration, and by mimicking the laws and dynamics governing these systems, is given by [2]. But most of the related works have been focused on optimization problems in network management, especially for the field of swarm intelligence such as ant colony optimization (ACO), particle swarm optimization (PSO) and so on. In order to excavate the scalability, adaptability, robustness and self-organization properties of biological systems, a detailed model description of bio-inspired approaches in every aspects of CRN, e.g. spectrum sensing and spectrum sharing, should be given.

In general, this paper intends to introduce a general concept in bio-inspired approaches and show their possible application in the field of CRN. The main objective is to provide better understanding of the current state-of-the-art and the research issues in the broad field of bio-inspired approaches and help the research community to find appealing hints for future explorative activities on bio-inspired approaches in CRN.

1 Bio-inspired cognitive radio network

Clearly, there are many exiting challenges due to the intro-

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duction of new networking functions into CRN. In this section, we concentrate on the application domains of bio-inspired approaches to problems related to communications and networking in CRN. Firstly, we review the most challenging fundamental issues for CRN and analyze the potential of using bio-inspired approaches to solve the challenges in CRN. Then, the most representative bio-inspired approaches, ACO and PSO, and their applications for CRN have been investigated.

1.1 Bio-inspired approaches for CRN

(1) Bio-inspired networking. Due to the nature evolution for millions of years, biological systems and processes have presented many intrinsic appealing characteristics, which can be modeled and applied to cope with many challenges in wireless networking. Currently, the emerging approaches and bio-inspired networking that imitated by the nature biological systems, are applied in miscellaneous aspects, for examples, ACO for radio resource allocation, artificial immune system for network security and so on. The most favorable characteristics include the following:

(i) Autonomous operation. Biological system can autonomously organize the coordinated individuals to perform specific functions, even there are capability differences between different biological individuals. With the autonomy characteristic, the biological system is capable of protecting its operations from any unplanned external influences or threats and performing management tasks in the most efficient manner.

(ii) Adaptation to varying environment. The biological system can efficiently detect variations in the dynamic environment or deviations from the expected system patterns. Then it makes proper decisions to adapt to the variations, although it may spend a very long time. So designing bio-inspired approaches with good convergence is very important.

(iii) Collective intelligence. Collective intelligence is a powerful tool to solve large scale optimization problems in a distributed way. It is inspired by the collective behaviors of social insects. An insect is a simple creature, but a colony of insects can present a highly structured social organization. As a result of this organization, ant colonies can accomplish complex tasks that in some cases far exceed the individual capabilities of a single insect.

Among those bio-inspired approaches, ACO and PSO are well-known for their wide applications as efficient evolutionary optimization algorithms. However, as depicted in the next sections at length, intelligence of swarm cooperation and social interaction mode of biological behaviors are the essentials exploited and modeled respectively by PSO and ACO.

Firefly synchronization mechanism for robust and fully distributed clock synchronization is another typical imitation to nature behavior of insects. Identical pulse-coupled integrate-and-fire oscillator with local variable x_i integrated from zero to one, are assumed equipped by each node. When $x_i = 1$, the oscillator fires then the x_i is reset to zero. For interaction among multiple oscillators, simple pulse coupling is adopted: when a given oscillator fires, it pulls the others up by a fixed amount, or brings them to the firing threshold, whichever is less. As a result, the population evolves to a synchronous state of firing for almost any initial conditions. For application details we refer to [2].

With progressive understanding of life science, many nature efficient self-organized mechanisms from immunology and cytology have been modeled and introduced in wireless engineering, for examples, artificial immune system (AIS) and cellular signaling networks (CSN). Inspired by the principles and processes of the mammalian immune system, AIS can be used to efficiently detect changes in the environment or deviations from the normal system behavior in complex problems domains [2,3]. AIS exploits the characteristics of self-learning and memorization basically consists of three parts: system representations, affinity measures, and adaptation procedures. CSN is typically applied to coordinate and control in massively distributed systems, and programming of network-centric operating sensor and actor networks.

Besides above, researchers have developed approaches inspired by many other biological processes, like activator-inhibitor systems. Reaction-diffusion mechanisms are the essential element to be exploited with the characteristics of activator-inhibitor systems [2,3], which have been successfully described in the form of differential equations in a ring of cells. Activator-inhibitor systems are usually employed in the organization of autonomous systems, distributed coordination, and continuous adaptation of system parameters in highly dynamic environments.

Although there are many successful applications of bio-inspired approaches, we also need to emphasize that the main challenge is neither the inspiration nor the application, but the understanding of biological system and its behavior, the modeling of the system, and the conceptual derivation of technical solutions, e.g. the convergence of bio-inspired approaches.

(2) Challenges in CRN and its bio-inspired solutions. The work of designing and implementing an efficient cognitive radio network is full of challenges. First of all, dynamic spectrum availability for cognitive nodes is an immediate one. In CRN scenarios, the spectrum availability depends on the state of primary nodes. Hence, if the specific portion of the spectrum used is required by a primary node, the communication must be continued in another vacant portion of the spectrum or with lower transmission power to maintain the interference to primary node below the threshold. Thus, spectrum availability detection techniques with cooperation of nodes and communication techniques that are inherently adaptive to the highly dynamic network conditions should be developed. Network heterogeneity and

distributivity are also the key challenges. Cognitive radio network is generally envisioned as a vast class of communicating nodes with different transmission, processing and storage capabilities, which could result in extremely complex global behavior. Furthermore, the cognitive devices can establish networks in a dynamic ad hoc way, without necessarily using a centralized infrastructure, so the networks must be capable of self-organized and self-healed to adapt to the heterogeneity and distributivity of CRN.

Another major challenge is the soaring complexity cognitive nodes introduced in the conventional wireless networks. The degrees of freedom of network management could increase as the spectrum efficiency being improved. On the other hand, the associated optimization problems become much more complicated and the global complexity increases exponentially with the number of cognitive nodes. Hence, low complexity approaches with the features of cooperation and distribution are to be adopted to realize those advanced functions in CRN.

In this paper, we focus on the most representative and widely applied bio-inspired approaches, ACO and PSO. The detail description, recent researches and future discussions of these two approaches, especially for application to CRN, have been given in the following two subsections.

1.2 Design and optimize cognitive radio network with ACO

ACO is one of the best analyzed and most frequently applied branches in the field of swarm intelligence. In this section, we first give the detailed description of ACO, followed by a discussion of ACO's application in CRN.

(1) Approach description. ACO takes inspiration from the foraging behavior of some ant species. These ants deposit pheromone on the ground in order to mark some favorable path that should be followed by other members of the colony. ACO exploits a similar mechanism for solving optimization problems.

A general-purpose algorithmic framework is first proposed by Dorigo et al. [4,5]. The ACO includes three main elements: pheromone, heuristic information, and decision function. Pheromone is something that deposited on the ground when ants walking to or from the food source, can be used to help other ants to make the path selection. Other ants perceive the presence of pheromone and tend to follow paths where pheromone concentration is higher. Heuristic information, which is usually proportional to the profits or cost when ants select some path, is another important parameter for ants to make decision. If heuristic information is higher, the ants will prone to select the path with higher probability. Once the two parameters, pheromone and heuristic information, are determined, the decision function can be setup with respect to the two parameters, which can be represented as:

$$p_{ij}^{k}=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{c_{il}\in\Omega}[\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}} & \text{if } c_{ij}\in\Omega,\\ 0 & \text{otherwise,}\end{cases} \tag{1}$$

where Ω is the set of feasible components, that is, edges (i, l) where l is a node not yet visited by the ant k, $\tau_{ij}(t)$ and η_{ij} represent the quantity of pheromone and the heuristic information associated with edge (i, j). It is worth noting that pheromone is related to time t and heuristic information is related to specific research problems. The parameters α and β are used to control the relative importance of the pheromone versus the heuristic information.

In addition to determine the decision function, there is another important process, pheromone update, associated with the ACO approach.

Pheromone update, which describes the pheromone evaporation process, plays an important role in implementing ACO approach. For different ACO algorithms, the pheromone update process is different. We take the original Ant System for example. The pheromone update process can be represented as:

$$\tau_{ij}(t+1)\leftarrow(1-\rho)\cdot\tau_{ij}(t)+\sum_{k=1}^{K}\Delta\tau_{ij}^{k}(t), \tag{2}$$

where ρ is the evaporation rate, $\Delta\tau_{ij}^{k}(t)$ is the quantity of pheromone laid on edge (i, j) by ant k:

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}Q/L_k & \text{if } (i,j) \text{ belongs to ant } k,\\ 0 & \text{otherwise,}\end{cases} \tag{3}$$

where Q is a constant, and L_k is the cost of the solution constructed by ant k.

Pheromone update process of the two most successful variants of the Ant System, MAX-MIN Ant System and Ant Colony System, can be seen as an improvement over the original Ant System. The characterizing elements of MAX-MIN Ant System are that only the best ant updates the pheromone of the edge passed by and that the value of the pheromone is bounded, which can be represented as:

$$\tau_{ij}(t+1)\leftarrow\Big[(1-\rho)\cdot\tau_{ij}(t)+\Delta\tau_{ij}^{\text{best}}(t)\Big]_{\tau_{\min}}^{\tau_{\max}}, \tag{4}$$

where $\tau_{\min}$ and $\tau_{\max}$ are respectively the upper and lower bounds imposed on the pheromone, we can obtain the lower and upper bounds on the pheromone values empirically and tuned on the specific problem considered. And $\Delta\tau_{ij}^{\text{best}}(t)$ can be represented as:

$$\Delta\tau_{ij}^{\text{best}}=\begin{cases}1/L_{\text{best}} & \text{if} (i,j) \text{ belongs to the best solution,}\\ 0 & \text{otherwise,}\end{cases} \tag{5}$$

where L_{best} is the cost of the solution of the best ant.

For Ant Colony System, the pheromone update process is divided into two steps: local pheromone update and offline pheromone update. The main contribution of Ant Colony System is the introduction of a local pheromone update to diversify the search performed by subsequent ants and make it less likely that several ants produce identical solution during an iteration, which can be defined as:

$$\tau_{ij}(t) = (1-\varphi)\cdot\tau_{ij}(t) + \varphi\cdot\tau_0, \tag{6}$$

where $\varphi \in (0,1]$ is the pheromone decay coefficient, and τ_0 is the initial value of the pheromone. The offline pheromone update is similar to the process in MAX-MIN Ant System, which is depicted in eq. (4).

(2) Recent researches of ACO'S applications to CRN. The majority of ACO's applications are to NP-hard problems, that is, to problems for which the best known algorithms that guarantee to identify an optimal solution have exponential time worst case complexity. The use of such algorithms is often infeasible in practice, and ACO algorithms can be useful for quickly finding high-quality solutions. The main NP-hard problems exist in traditional wireless networks, including routing, resource allocation and scheduling, which are also applied to CRN with increased complexity. Because CRN is implemented based on spectrum sensing results of cognitive radios, the application of ACO to spectrum sensing in CRN become a new research direction. We intend to give a summary of ACO modeling of different aspects of CRN, including routing, spectrum sharing, and spectrum sensing.

The application of ACO to find a shortest tour in traveling salesman problem can be seen as an inspiration for routing problem in wireless networks. In traveling salesman problem, a routing construction graph must be obtained by defining the vertex and edge, where vertex represents a city and the edge means pairs of cities to be visited one after the other. The goal is to find a Hamiltonian tour of minimal length on the constructed graph, so heuristic information can be defined as the reciprocal of distance between two cities.

Based on the application of ACO to traveling salesman problem, an improved ant-based routing scheme for CRN is proposed in [6], whose cost function takes into account many kinds of delay simultaneously. The delay includes transmission delay, switching delay due to the neighbor nodes transmit data on different channel and backoff delay due to secondary nodes' contend of spectrum resource. The main purpose is to minimize total delay, instead of minimize the length of tour, which also can be realized by designing heuristic information as the reciprocal of cost function. Furthermore, the proposed scheme does not need a common control channel which is necessary for traditional cooperation routing strategy [7].

ACO is also a good approach to solve the spectrum sharing problem. Because different cognitive nodes have different cognition capability, there exist many spectrum sharing methods in CRN, e.g. overlay, underlay, joint overlay and underlay.

An ACO-based algorithm to solve opportunistic spectrum access problem in CRN is proposed [8], which can be mapped to NP-hard Graph Coloring Problem. The vertex and edge of the proposed graph represent the secondary nodes and available channels, respectively. The interference between secondary nodes due to using same channel is taken into consideration when designing the cost function, which is used to make assignment decision. In addition, the rewards of assigning a channel to secondary nodes are also taken into consideration in pheromone update process for the purpose of maximizing the total reward of CRN. The pheromone update scheme of Ant Colony System is adopted in this paper.

Different from the algorithm proposed in [8], an ACO-based algorithm is proposed for underlay spectrum sharing in OFDMA CRN [9]. The MAX-MIN Ant System is adopted to solve the optimization problem. In order to quantify the trade-off between data rate and link reliability, goodput, which is defined as the number of data bits delivered in error-free packets per unit of time, is selected for measure achievable rate of secondary users.

(3) Future discussions. Besides using ACO to solve the routing and spectrum sharing problem in CRN, we also need to apply ACO to further study spectrum sensing in CRN, which is an advanced technique for solving spectrum underutilized problem. Although the application of ACO to perform spectrum sensing has not been studied, we can use the bio-inspired consensus-based algorithm to deal with the cooperative sensing in CRN [10]. On the one hand, there is no need for centralized node to perform data fusion and make final decision. The secondary nodes need only to set up local interactions. On the other hand, the proposed scheme eases the problem of security in CRN, e.g. incumbent emulation and spectrum sensing data falsification.

As we have discussed above, nowadays some researchers have applied ACO to classic NP-hard optimization problems in CRN, while the research community is quite young and there still remain significantly challenging issues to be addressed. On the one hand, a better understanding of the theoretical properties of ACO algorithm is certainly one research direction that will be pursued in the future. For example, the main concerned question is "Will the given ACO algorithm ever find an optimal solution?" On the other hand, in order to apply the ACO to more complicated and practical CRN, the study of how best to apply ACO to such CRN will certainly be another major research direction. It is similar to previous work that we apply the ACO to the resource allocation problem in multi-cell OFDMA system [11], we can extend the research to the large scale CRN.

1.3 Swarm intelligence-empowered CRN

(1) PSO approach description. PSO is a swarm intelli-

gence-based evolutionary algorithm inspired by the behavior of birds looking for food, which is originated by Kennedy et al. [12]. They take the space of solution as the bird's flying space, and the birds are simulated as small particles that denote the solutions. The PSO was proven to be very efficient to optimize real life problems of dynamic and distributed tasks allocation in the industry [13]. The general algorithm of PSO [14] is shown in Table 1.

Particle swarm intelligence provides an efficient approach to solve time-variable, multi-objective and large-scale problems, both continuous nonlinear and discrete binary optimization. So all kinds of complicated problems in CRN, including dynamic spectrum management [15–19] (i.e. spectrum sensing and sharing) and network resource allocation [20,21] are proposed to enforce autonomy and adaptation using PSO.

(2) Recent researches of PSO's applications to CRN. It is a key enabling functionality in CRN of spectrum sensing to detect weak primary signals from licensed users/networks. An intuitional method for the single node detection of spectrum occupancy is energy detection by judging the strength of the detected signal within a predefined bandwidth, while more signal processing schemes like feature detection, cyclostationary-based detection and wavelet detection can be adopted for better accuracy with additional costs. However cooperative spectrum sensing among multiple nodes is proven to be much more reliable and effective on the account of well-designed cooperation protocols [22].

The cooperative spectrum sensing is reformulated into a constrained optimization problem, and solved by using PSO in [16]. Within the cooperative sensing framework, local sensed statistics of multiple nodes are linearly fused with a weight vector. It is formulated to find the optimal weight vector that maximizes the probability of detection for all CRs, which corresponds to the global best particle at the iterations. The simulations show that the PSO-based method outperforms the modified deflection coefficient (MDC)-based method in all the proposed scenarios. Meanwhile, a clusters-based spectrum sensing framework imitating the swarm system for multi-node CRN is proposed [15], where a number of cognitive radios in a network cluster to a swarm that is then sub-divided into several cognitive sub-networks each employing cooperative spectrum sensing in it.

Table 1 PSO pseudo code

Algorithm processing
1. For i = 1 to M (M = population size)
Initialize $P[i]$ randomly (P is the population of particles)
Initialize $V[i] = 0$ (V = speed of each particle)
Evaluate $P[i]$
G_{BEST} = best particle found in $P[i]$
2. End for
3. For i = 1 to M
$P_{\mathrm{BESTS}}[i] = P[i]$ (Initialize the "memory" of each particle)
4. End for
5. Repeat
For i = 1 to M
$V[i] = w \times V[i] + C_1 \times R_1 \times (P_{\mathrm{BESTS}}[i] - P[i])$
$+C_2 \times R_2 \times (P_{\mathrm{BESTS}}[G_{\mathrm{BEST}}] - P[i])$
(Calculate speed of each particle)
(w = inertia weight, C_1, C_2 are positive constants)
(R_1, R_2 are random numbers in the range [0,1])
$\mathrm{POP}[i] = P[i] + V[i]$
If a particle gets outside the pre-defined hypercube
then it is reintegrated to its boundaries
Evaluate $P[i]$
If new position is better, then $P_{\mathrm{BESTS}}[i] = P[i]$
G_{BEST} = best particle found in $P[i]$
End for
6. Until stopping condition is reached

As available spectrum bands have been identified through spectrum sensing, cognitive radios should be scheduled and allocated the best spectrum band to meet the quality of service (QoS) requirements and overall network utility, while limiting destructive interference to primary users. Such spectrum sharing problem involves several aspects of dynamics, available spectrum determined by activities of primary users, interference constraints between the heterogeneous networks, temporal channel statue of the CR links, and different QoS requirements for each CR. Therefore, the community has addressed a lot to it, where PSO is proven an effective method to mitigate such sophisticated problems.

The problem of spectrum sharing between primary and secondary networks is discussed in [17], where the centralized spectrum allocation aiming to maximize system sum unity and fairness of secondary access is modeled as a graph-coloring problem. Such NP-hard problem is proposed to solve using PSO algorithm. Simulation results show that the PSO method performs with a good tradeoff between the system's sum bandwidth reward and the secondary users' access fairness. In [18], three methods based on different kinds of evolutionary algorithms including PSO are presented to conduct the spectrum allocation. The channel assignment matrix is mapped to the position of the particle of PSO to decrease the search space, taking the characteristics of the channel availability matrix and the interference constraints into account. The simulations also show that the proposed methods greatly outperform the commonly used color sensitive graph coloring algorithm.

Inspired by the adaptive task allocation model in insect colonies, a BIOlogically-inspired Spectrum Sharing (BIOSS) algorithm to enable self-determination of appropriate channels without coordination is introduced in [19], which is proven that it could achieve high spectrum utilization without any spectrum handoff latency. Within such task allocation model, channel selection probability measures the fitness between the available channels and cognitive radios, which is optimized to attain effective spectrum sharing. The mapping relationship between colony system and CRN is shown in Table 2.

Besides dynamic spectrum management discussed above, the PSO is also well employed for network resource allocation scenarios in CRN, e.g. power allocation and multi-

Table 2 Relationship between colony system and CRNs

Colony system	CRN
An insect	A cognitive radio
Tasks	Available channels
The task associated stimuli	Permissible power P_j to channel j
Response threshold	Required transmission power P_{ij} for CR i to channel j

antenna beamforming.

For cognitive radio transceivers equipped with multiple antennas, the objective considered in [20] is expected to maximize the transmission capacity of the secondary users subject to minimum interference and maximum quality of service of the primary users with minimum transmission power for secondary users by beamforming approach. According to the well formulated optimization model, PSO is adopted to iteratively adjust the pre and pro beamforming vectors to achieve the goal above. It is seen that PSO presents good performance of convergence (no more than ten iterations before the convergence) and global efficiency.

The adaptive power and bit allocation problems in multiuser OFDMA cognitive radio system are formulated in [21]. And the proposed PSO solution exerts satisfactory performance for it, where mutual interference between primary and secondary networks is considered. A nonlinear method of updating the inertia weight is adopted there, that is

$$\omega = \begin{cases} \omega_{\min} + \dfrac{(\omega_{\max} - \omega_{\min})(F - F_{\min})}{F_{\text{avg}} - F_{\min}}, F \leqslant F_{\text{avg}}, \\ \omega_{\max}, \qquad\qquad\qquad\qquad\quad F > F_{\text{avg}}, \end{cases} \tag{7}$$

where $\omega_{\max}, \omega_{\min}$ denote the extremum, and $F_{\text{avg}}, F_{\min}$ denote the average and minimum of the fitness values.

(3) Approach review for future work. From the application view of point, PSO also can be used for cluster head selection, which plays a very important role for cooperative spectrum sensing in cognitive ad hoc network. By applying the PSO to perform cluster head selection, we can further minimize the energy consumed and maximize the total data gathered. From the implementation point of view, fitness evaluation of swarm intelligence plays a key role of conducting the adaptation of such social actions to approximately global optima. Moreover, the mechanisms of probability-based search imitating particle swarm behaviors should be carefully designed to capture the characteristics of the specific problems, then autonomy can be efficiently imposed to the iterative optimization process.

In summary, the greatest advantages of PSO are its simplicity both conceptually and at the implementation level, ease of use and high convergence rate. However, as most of the bio-inspired algorithms, PSO cannot guarantee the global optimum. At the same time, there still lacks general theoretical analysis of the solution efficiency and convergence properties of the evolutionary algorithms in the literatures, since numerical simulation is mostly adopted.

2 Numerical simulation

In order to demonstrate the effectiveness of the bio-inspired approaches, numerical simulation results are provided for the multi-user OFDMA-based CRN downlink power allocation.

2.1 Simulation settings

We assume the primary network and secondary network are cellular network and the secondary BS is co-located with the primary BS. All users, including primary users (PUs) and secondary users (SUs), are uniformly distributed within a circle where the radius of circle for SUs is smaller than PUs. The details of the system simulation settings are shown in Table 3.

For bio-inspired approaches, there are many parameters needed to be carefully designed because they will affect the convergence of the approaches. In this paper, the parameters associated with the simulation for ACO and PSO are given by Tables 4 and 5.

Table 3 System parameters

Parameter	Value
The total power of secondary BS	28 dBm
Subcarriers for SUs	16
SUs	16
PUs	3
Cell radius	500 m
User distribution	Uniform
The interference from PUs to SUs	10^{-13} W
Interference threshold for PUs	6×10^{-14} W
Noise power	10^{-14} W
Deviation of shadowing	10 dB
Large scale fade factor	4

Table 4 ACO simulation parameters

Parameter	Value
Number of ants	16
α	1
β	1
Iterations	200
Q	1
ρ	0.1
Power step size	$P_{\text{total}}/100$

Table 5 PSO Simulation parameters

Parameter	Value
Number of particles	20
Particle dimensions	16
Inertia weight	0.9–0.4
Iterations	200
Cognition weight	2
Social part weight	2
Rate limit per dimension	$0.02P_{\text{total}}/M$

2.2 Performance evaluation

In this section, we compare ACO and PSO, with the non-cooperative game (NCG) scheme to evaluate the performance. We focus mainly on the performance metrics such as the system frequency efficiency and the convergence rate of three schemes.

We first investigated the system frequency efficiencies of the three different schemes which are shown in Figure 1. We assume that the secondary users in NCG each has an upper power constraint and is constrained by the total power for ACO and PSO, which indicates the power allocation in ACO and PSO achieve more degree of freedom than NCG. Furthermore, we can see that the PSO outperforms ACO since PSO is more suitable to solve continuous variables optimization.

Since the convergence of bio-inspired approaches plays a very important role during the application to CRN. We give the convergence analysis through simulation which is shown in Figure 2. All three schemes converge within 50 iterations. For NCG, it converges more quickly than ACO and PSO. The spectrum efficiency of three schemes is very close to each other with the difference less than 3%. There is a hop before convergence in NCG as the power is preset there then deviated gradually to satisfy those constraints within iterations.

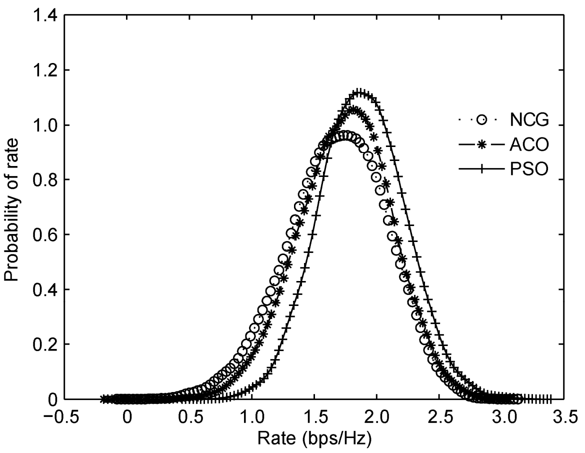

Figure 1 Probability density distribution comparison.

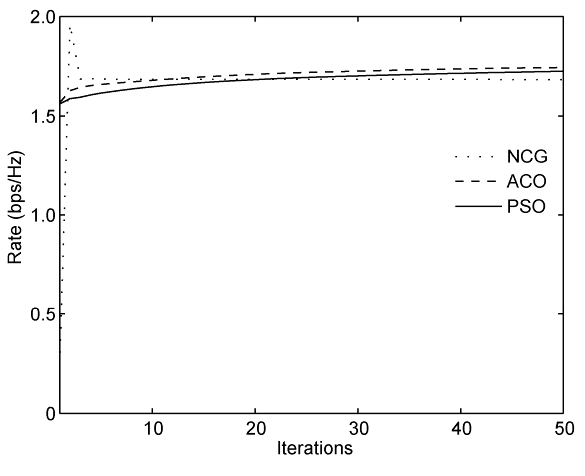

Figure 2 Algorithm convergence comparison.

3 Conclusions

In this paper, we have investigated the critical challenges in designing and optimizing CRN and proposed the bio-inspired approach exploiting evolutionary and collective intelligence. A general summarization on applications in CRN is given, followed by further analysis of two specific bio-inspired methods, ACO and PSO. As shown above, these methods are widely applied on many problems in CRN, like spectrum sensing and sharing, resource allocation and path routing. A numerical simulation of multi-user OFDMA-based CRN downlink power allocation problem is carried out for intuitional illustration of those bio-inspired approaches. It can be concluded that, adaptation and autonomy would be enforced efficiently in such bio-inspired way for CRN to handle dynamic spectrum availability, distributed and heterogeneous network architectures, and soaring complexity.

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