BULGARIAN ACADEMY OF SCIENCES

CYBERNETICS AND INFORMATION TECHNOLOGIES • Volume **16**, No 4
Sofia • 2016 Print ISSN: 1311-9702; Online ISSN: 1314-4081
DOI: 10.1515/cait-2016-0070

Spectrum Allocation of Cognitive Radio Based on Autonomy Evolutionary Algorithm

Yongcheng Li[1], *Hai Shen*[2,3], *Manxi Wang*[1]

[1]*State Key Laboratory of Complex Electromagnetic Environment Effects on Electronics and Information System, Luoyang, China*
[2]*College of Physics Science and Technology, Shenyang Normal University, Shenyang, China*
[3]*Control Theory and Control Engineering Postdoctoral Research Station, Shenyang Institute of Automation, Shenyang, China*
Email: shenhai@sia.cn

Abstract: *Reasonable and effective allocation of cognitive radio spectrum resource according to user's requirements is the key task of cognitive radio network. Cognitive radio spectrum allocation problem can be viewed as an optimization problem. This paper analyzes the application of bio-inspired intelligent algorithm in cognitive radio network spectrum allocation, and based on graph theory model of spectrum allocation, proposes a spectrum allocation algorithm based on autonomously evolutionary scheme. Three objective functions: Max-Min-Reward, Max-Sum-Reward and Max-Proportional-Fair are employed to evaluate the proposed algorithm capacity. The simulation result reveals that the proposed method can make the system user to obtain better network benefits and better embody the fairness between cognitive users. In the process of allocation, the proposed method was not restricted by user scale and the number of spectrums.*

Keywords: *Cognitive radio, spectrum allocation, graph theory, bio-inspired computing, autonomously evolutionary algorithm.*

1. Introduction

With the development of wireless communication technology, an increasingly serious problem in front of us is increasingly lack of spectrum resources. On the other hand, there are many idle wireless spectrum resources varying in space and time, therefore, Cognitive Radio (CR) technology was put forward to solve the spectrum resource utilization problem [1]. CR User can sense the wireless communication environment; if there is spectrum hole, CR User can access spectrum resource, thus improving the spectrum utilization and realizing the flexible distribution of spectrum [2, 3].

Spectrum allocation, as one of the core technologies of CR, means allocate idle spectrum to cognitive user. In cognitive radio networks, the Secondary Users (also known as an unauthorized user, SU) should sense real-time spectrum allocation status. Under the permission of the Primary User (also known as authorized users, PU), SU should dynamic access idle spectrum, and at the same time not to interfere with the communication of other user [4]. Fig. 1 shows a simple cognitive radio communication scenario with distributed PU and SU.

Spectrum allocation is a complex and difficult problem [5, 6]. Spectrum allocation strategy should not only avoid the interference between cognitive users and authorized users, or the self-interference between cognitive users, but also meet the demands of different user on spectrum resources. Thus, CR network can't adopt the traditional static spectrum allocation methods, instead of adopting dynamic spectrum allocation strategy. The current spectrum allocation models mainly include interference temperature model, graph coloring model, game theory model and auction bidding model. The above four kinds of spectrum allocation models are suitable for different working conditions, and have different characteristics. Comparing the current spectrum allocation strategies, graph coloring theory method is more suitable for this problem.

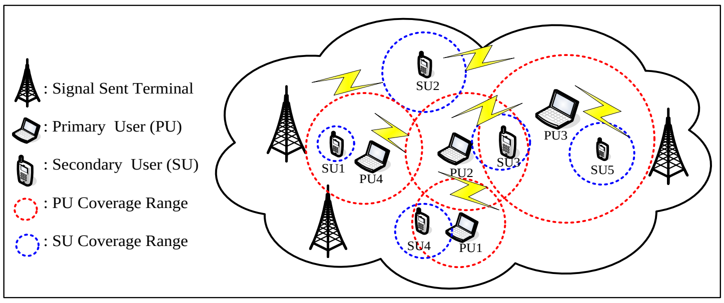


Fig. 1. A sample cognitive radio communication scenario

Graph coloring model used for spectrum allocation is a typical NP-hard problem, which is difficult to be solved by traditional optimization methods. Bio-inspired computing methods are random search technology, which doesn't rely on precise mathematical model of the optimization problem. Therefore these algorithms are more suitable for solving complex optimization problems [7-10]. In this paper, Autonomously Evolutionary Algorithm (AEA) inspired by biological behavior is proposed and employed to solve the spectrum allocation problem. According to the experimental results, the AEA algorithm enables the system users to obtain greater network benefits under the different evaluation rules, including maximum average system benefit and the maximum proportion fairness; the AEA algorithm can better ensure the fairness feature of spectrum allocation, even without restriction by number of PU, SU and the spectrums.

The rest of this paper is organized as follows. In Section 2 the graph coloring mathematical model of spectrum allocation is described and then compared to the existing allocation algorithm based on the graph colouring model. Autonomously evolutionary algorithm inspired by biology life-cycle is given in Section 3. Cognitive radio spectrum allocation algorithms based on autonomously evolutionary algorithm is also presented in Section 3. Simulation results and discussions are provided in Section 4 and Section 5. Finally, Section 6 concludes the paper.

2. The spectrum allocation algorithm based on Graph theory model

2.1. Graph colouring model

Spectrum allocation problem based on graph coloring was mapped into an undirected graph G. Each node of an undirected graph represents a radio user; each side represents the interference and conflicts between users. When two nodes in the graph are connected by a side, these nodes cannot use the same spectrum. In addition, each node has a set of optional color. Different colors correspond to different spectrum. Different nodes correspond to the different sets of available spectrum. This optional spectrum set is decided by the status of use spectrum, geographic location, coverage range of authorized users, and has the dynamic characteristics. Generally, graph coloring mathematical model includes available spectrum matrix, benefit matrix, interference matrix and allocation matrix. The specific definition of each matrix is as follows:

(1) Available spectrum matrix

Available spectrum matrix, also called idle spectrum matrix, refers to the set of unused spectrum by PU within a certain period of time and certain space. $L=\left\{l_{n,m} \mid l_{n,m}\in\{0,1\}\right\}_{N\times M}$ is used to represent idle spectrum matrix, where N is user label; M is spectrum label; $l_{n,m}$=1 indicates that spectrum band m is available for user n; on the contrary, $l_{n,m}$=0 indicates that spectrum band m is not available for user n.

(2) Reward matrix

$B=\left\{b_{n,m}\right\}_{N\times M}$ is used to represent the reward matrix, where $b_{n,m}$ indicates the rewards when user n uses spectrum m. After combing the available spectrum matrix L and reward matrix B, available reward matrix $L_B=\left\{l_{n,m}\bullet b_{n,m}\right\}_{N\times M}$ can be obtained. The users would face different environments and adopt different modulation techniques or transmitting powers, so the rewards may be different when they use the same channel.

(3) Interference constraint matrix

$C=\left\{c_{n,k,m} \mid c_{n,k,m}\in\{0,1\}\right\}_{N\times N\times M}$ is used to represent interference matrix. $c_{n,k,m}$=1 indicates that interference emerges when users n and k use spectrum m at the same time; when $n = k$, $c_{n,k,m}=l_{n,m}$. Interference constraint matrix C is decided only by available spectrum matrix L.

(4) Non-interference allocation matrix

$A=\left\{a_{n,m} \mid a_{n,m}\in\{0,1\}\right\}_{N\times M}$ is used to denote non-interference allocation matrix. $A=\left\{a_{n,m} \mid a_{n,m}\in\{0,1\}\right\}_{N\times M}=1$ shows that channel m is allocated to user n. Obviously, non-interference allocation matrix must satisfy the following constraint:

$$a_{n,m}\bullet a_{k,m}=0,\quad fc_{n,k,m}=1,\quad n,k<N,\; m<M.$$

Spectrum allocation problem is abstracted to the graph coloring model $G(U, E_c, L_B)$. U is the node set of graph G and denotes the SU in radio network; L_B denotes the set and weight of node optional spectrum; E_c is the side set and is determined by interference constraint matrix; and only if $c_{n,k,m}$=1, there is a side with the color m (band m) between two different nodes (SU). Allocation conditions without interference can be described as follows: when there is m color side between two different nodes, they cannot have the color m at the same time.

In this paper, the objective of spectrum allocation is to maximize network benefit $U(R)$, in order to balance many requirements of cognitive user. The next three formulas to definition $U(R)$ is used generally.

1. Max-Min-Reward (MMR)

MMR function maximizes spectrum utilization of limited users. This optimization problem is expressed as follows:

$$U_{\min} = \min_{1\le n\le N} r_n = \min_{1\le n\le N}\left(\sum_{m=1}^{M} a_{n,m}\times b_{n,m}\right). \tag{1}$$

2. Max-Sum-Reward (MSR)

MSR function maximizes the total spectrum utilization of the system. This optimization problem is expressed as follows:

$$U_{\text{sum}} = \sum_{n=1}^{N} r_n = \sum_{n=1}^{N}\sum_{m=1}^{M} a_{n,m}\times b_{n,m}. \tag{2}$$

3. Max-Proportional-Fair (MPF)

The goal of MPF is to consider the fairness of each user when using spectrum resources. This optimization problem is expressed as follows:

$$U_{\text{fair}} = \left(\prod_{n=1}^{N} r_n\right)^{\frac{1}{N}} = \left(\prod_{n=1}^{N}\sum_{m=1}^{M} a_{n,m}\times b_{n,m} + 10^{-4}\right)^{\frac{1}{N}}. \tag{3}$$

2.2. Spectrum allocation algorithm based on graph coloring model

Current spectrum allocation algorithms based on graph theory model mainly include list-coloring algorithm, color sensitive graph coloring and so on. List-coloring algorithm adopts a distributed network structure, which purpose is to obtain the optimal number of channel allocation even under the communication constraints [11]. But list-coloring algorithm doesn't consider the spectrum difference problem. Zheng and Peng [12] propose the Color Sensitive Graph Coloring (CSGC) algorithm. CSGC considers the spectrum differences problem adopting reward matrix, but its drawback is a larger number of computational cost. With the increase of the number of spectrums, the computational cost shows also nonlinear increase. The actual cognitive radio environment is usually a very complex and fast time-varying communication environment. However, in the existing solving scheme, the defecting made them not suitable for spectrum allocation.

Bio-inspired optimization algorithms, such as GA, PSO, BFO, ACO, ABC, etc., adopt fitness function to evaluate individuals. They obtain the optimal value through simulation in a certain social behavior and natural phenomena, so their optimization process does not depend on strict mathematical properties of the optimization problem, such as continuity, conductivity, and the precise mathematical description on objective function and constraint conditions, etc. Those characteristics make bio-inspired optimization algorithms suitable for solving the complex decision problem of spectrum allocation. GA is the first one employed to solve a spectrum allocation problem; designing the map matrix relationship between chromosome and channel assignment GA proves its feasibility. Then FA, ABC, QGA were used to solve the spectrum allocation problem [13-17].

3. Autonomously searching algorithm

All living organisms have lifecycle, although different organisms have different lifecycle lengths, but they all undergo the process from birth to death. When an original life ends, a new life will be generated. The biology evolution of nature follows the "cycle relay" pattern, which is a cycle process of "life and death alternation". This process is repeated continuously making the life on earth endless, and biologic evolution becomes more and more perfecting. In this paper, the four stages of a life-cycle are borrowed (foraging, reproduction, death and mutation), and an autonomously evolutionary algorithm is proposed.

3.1. Foraging

In foraging stage each individual has its foraging characteristic in autonomously evolutionary algorithm, which is inspired by animal searching behaviour and the producer-scrounger model. There are two equations:

(4) $$x_i^{k+1} = x_i^k + r_1(x_p^k - x_i^k),$$

(5) $$x_i^{k+1} = r_2(\mathrm{ub} - \mathrm{lb}) + \mathrm{lb},$$

where, x_p is producer, r_1 and r_2 are uniform random sequences in the range (0, 1); and there are three kinds of individuals in the population:

(1) One producer searches for food. At each iteration, the individual located in the most promising resource is producer; the resource remains the current better location in the next iteration.

(2) Scrounger performs area copying behaviour. Scrounger uses Equation (4) to keep searching opportunities found by the producer. At each iteration, a number of individuals except producer in the population are randomly selected as scroungers.

(3) Ranger employs random walk searching strategies for randomly distributed resources. Ranger performs random walk motion using Equation (5). At each iteration, the remaining individuals are rangers.

3.2. Death

According to "the survival of the fittest" theory and for ensuring a fixed population size, AEA takes a certain method which can make some individuals retained and others eliminated. In this algorithm, the selection operator performs roulette selection strategy. A number of individuals with the best fitness values are chosen to pass to the next generation.

3.3. Reproduction

In AEA, the reproduction operator selects single-point crossover method. One crossover point is selected, information from the beginning to the crossover point is copied from one of the parents, and the rest is copied from the second parent.

3.4. Mutation

In AEA algorithm, the mutation operator performs dimension-mutation strategy. For each individual $X_i \in R^n$, $X_i = (x_{i1}, x_{i1}, ..., x_{in})$, one dimension of an individual selected according to the probability will get re-location in search space,

$$x_{ij} = \mathrm{rand}(1)(\mathrm{ub} - \mathrm{lb}) + \mathrm{lb}, \tag{6}$$

where, ub and lb are the upper boundary and lower boundary of search space. In the *N*-dimension search space, the x_{ij} is the position of the *j*-th dimension of the *i*-th individual; the value *j* is in the interval [1, *N*].

3.5. Spectrum allocation steps based on AEA algorithm

Spectrum allocation steps based on **AEA algorithm** are as follows:

Step 1. Setting parameters

Setting values of all parameters: the number of PU, SU and the spectrum, the coverage radius of PU, the maximum and minimum coverage of SU, population size, algorithm iteration number, crossover probability, mutation probability and so on.

Step 2. Initialization of spectrum environment and population

Available spectrum matrix *L*, reward matrix *B* and interference constraint matrix *C* are randomly generated, in order to simulate spectrum allocation environment. Additionally, the dimension of each individual in the initial population is determined according to the matrix *L*, and population is initialized randomly.

Step 3. Calculation of the fitness

Each individual in the population represents a possible spectrum scheme, but it is also limited by the interference allocation matrix, and needs to be limited through non-interference allocation matrix. Specific implementation process is as follows: finding all *n* and *k* when $c_{n,k,m} = 1$, and checking whether the value of the element which corresponds to *m*-th column *n*-th row and *m*-th column *k*-th row in matrix *A* is 1; if it is so, one of them should be randomly set to be 0. After restricting spectrum matrix, the fitness value is calculated for each individual in the population using Equations (1)-(3).

Step 4. Population evolution

For each member *i* in the population, if *i*-th member is producer, it remains on the current position; if else, some members perform scrounging strategy using Equation (4); the rest of the members perform ranging strategy using Equation (5). Then the selection, crossover and mutation operation are carried out, respectively, for all individuals.

Step 5. Steps 3 and 4 are repeated, until the termination conditions are achieved, then the optimal spectrum allocation scheme is output.

4. Experiment setting

The simulation experiments are conducted in order to test and verify the effectiveness of the spectrum allocation scheme based on AEA. Assuming communication environment is in the area [–10, 10], network topology is randomly generated with a certain number of PU, SU and the available spectrums. M, N and K represent the number of PU, SU and the available spectrums, respectively. The radius of PU power coverage range R_{PU} is set to 3, the maximum coverage of SU R_{sumax} is 4, and the minimum coverage R_{sumin} is 1. The CR network topology structure shown in Fig. 2 has 5 PU and 10 SU, which places are chosen randomly.

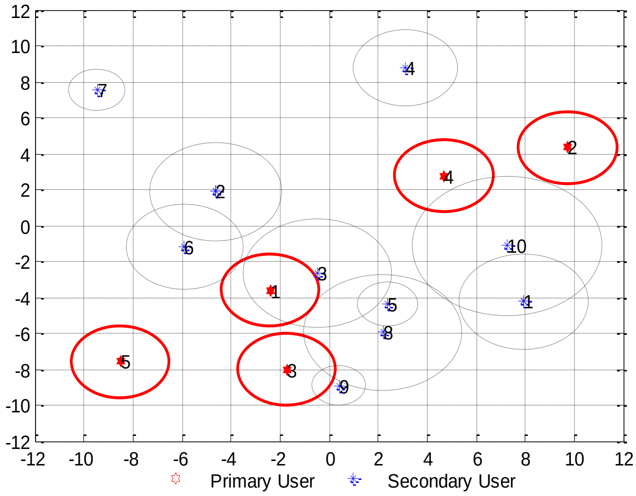


Fig. 2. CR network topology structure with randomly 5 PU and 10 SU

For comprehensive analysis of the proposed algorithm performance, the experimental results are compared with spectrum allocation schemes based on GA and PSO. Furthermore, for three parameters, M, N, K, the performance changes of those algorithms are tested under the parameters environment by changing a parameter value while keeping the other two parameters. These tests are divided into three types. For achieving a fair comparison, channel availability matrix L is determined by the position of the user and is randomly distributed; effective channel matrix B is generated randomly; interference matrix C is calculated by L and interference is limited; the comparative tests of those algorithms use the same L, B, C and initial population.

The following parameters are considered: 30 individuals are employed; the simulation results are obtained over 30 times and use the average value; selected operation adopts the roulette method; single point crossover probability is 0.8 and mutation probability is 0.1; inertia weight is linearly decreased from 0.9 to 0.4; both the acceleration constants are set to 2.

5. Results and discussion

This paper includes three types of experiments. The first type is fixing the number of PU and spectrums, changing the number of SU. The second type is fixing the number of SU and spectrums, changing the number of PU. The third type is fixing the number of PU and SU, changing the number of spectrums. The different types of experiment represent different communication topology structure. In the first study, the number of SU adopts two different values: 5 and 30, and the number of PU and spectrums are set to 10. In the second study, two different values of the number of primary users are considered, 5 and 30; the number of SU and spectrums is 10. In the third study, the numbers of spectrums are set to two different values: 5 and 20, and the number of PU and SU are set to 20.

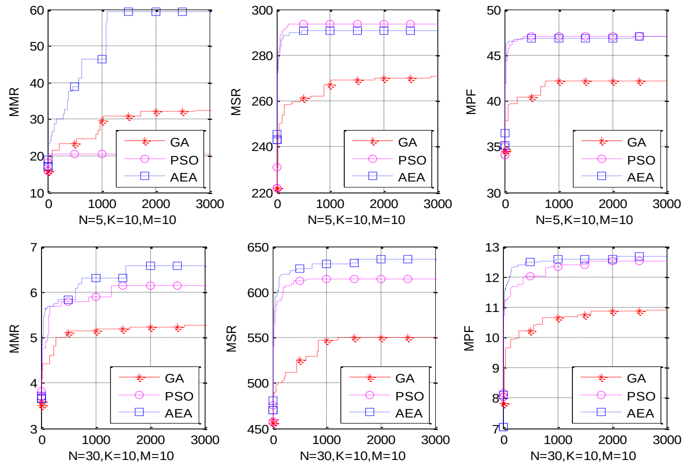
Table 1 and Fig. 3 show the network rewards value and its convergence curve. Experimental results obtained by AEA algorithm on MMR, MSR and MPF are better than that of GA and PSO on most communication topology structures, which proved the superiority of the AEA algorithm. These results are also shown, compared with GA and PSO, no matter in what kind of cognitive environment; the maximizing limited user spectrum, utilization and fairness of cognitive users accessing idle spectrum are all improved by AEA. Also, it can be seen that AEA algorithm shows faster convergence speed than others with the increase of the number of iterations.

In the first type experiments, network rewards are reduced accordingly with the increase in the number of SU, but AEA algorithm also yields higher value than other algorithms. In the second type experiment, with the increase in the number of PU, experimental results realized by AEA algorithm are superior to GA and PSO on most topology structure. In the third type experiment, it can be seen with the spectrums number increases; the user's system reward on three indicators is also increased. But obtained results by AEA are always higher than others. It proves that users can get better spectrum allocation scheme using AEA in more numbers of spectrum allocation problem.

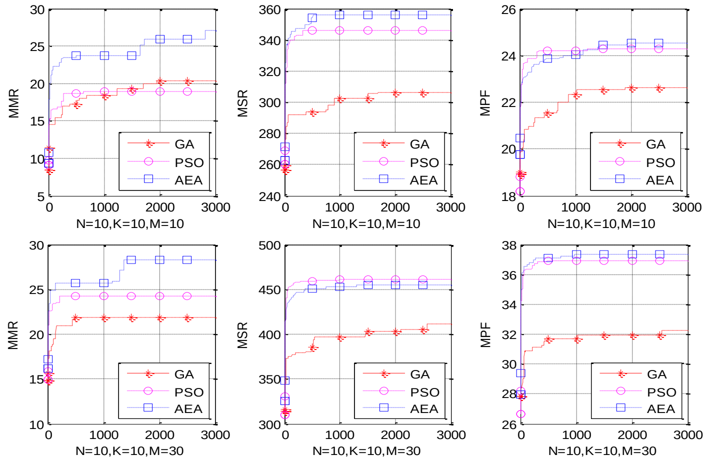
From above discussion, AEA algorithm can get better spectrum allocation effect and has faster convergence speed compared with the GA and PSO. Based on three evaluation functions, the proposed algorithm ensures that the system users gain much more network rewards, and effectively reflects the spectrum allocation fairness. The AEA algorithm is not restricted by number of users and spectrums.

Table 1. Experimental results of three types

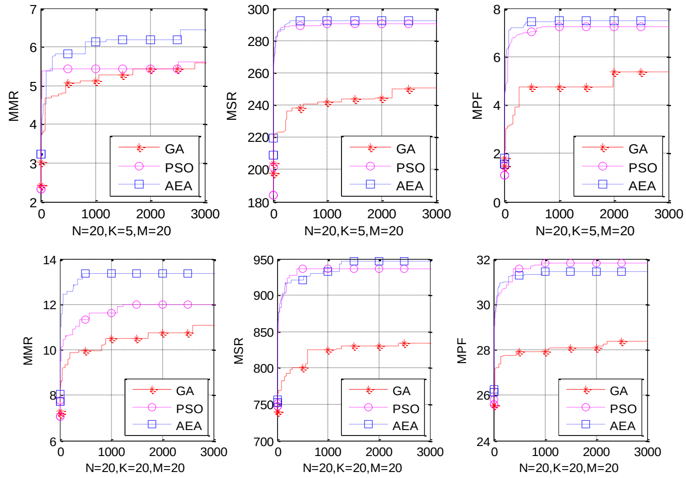
	Algorithm	GA	PSO	AEA			GA	PSO	AEA
	MMR	32.4	20.5	59.5(1)		MMR	5.26	6.15	6.58(1)
N=5	MSR	271	294	291(2)	*N*=30	MSR	550	614	636(1)
	MPF	42.1	47.1	47.1(1)		MPF	10.9	12.5	12.7(1)
M=10	MMR	20.3	19	27.1(1)	*M*=30	MMR	21.8	24.3	28.3(1)
	MSR	307	346	356(1)		MSR	411	461	455(2)
	MPF	22.6	24.3	24.5(1)		MPF	32.3	36.9	37.3(1)
K=5	MMR	5.59	5.62	6.46(1)	*K*=20	MMR	11.1	12	13.3(1)
	MSR	251	291	292(1)		MSR	834	937	947(1)
	MPF	5.36	7.25	7.49(1)		MPF	28.4	31.8	31.4(2)



(a) The first type experiment: Change the number of secondary users



(b)The second type experiment: Change the number of primary users



(c)The third type experiment: Change the number of spectrums

Fig. 3. Converge results under different topology structures

6. Conclusions

Reasonable and effective allocation of spectrum according to cognitive user requirements is quite significant for CR network. Spectrum allocation strategy should effectively select and use idle spectrum, and avoid conflicts between authorized users and unauthorized users. The strategy should even enable all users to fairly share spectrum resources and meet the needs of different business users. Inspired by the biological life-cycle theory, this paper proposed autonomously searching algorithm. The proposed algorithm simulates life-cycle in four stages and four evolution operators are designed: foraging, selecting, reproduction and mutation. Based on graph theory model, this paper introduces spectrum allocation scheme which is base of the AEA algorithm. Firstly, populations are encoded and the best spectrum allocation scheme is quickly determined through the foraging, selection, crossover and mutation operations. The experimental results show that the proposed algorithm is effective and rapid convergence.

In practical application, CR communications environment is dynamic, and the communication state of PU is changing in real time, so the spectrum allocation algorithm should have real-time characteristics. So far, research work under static environment has been completed. In the further work, we should consider the dynamic spectrum allocation scheme and ensure the flexibility and real-time features of spectrum allocation.

Acknowledgements**:** This research was supported by The Open Project Foundation of CEMEE State Key Laboratory (CEMEE2016K0204B), National Natural Science Foundation of China (Grant No 61502318) and the Program for Liaoning Excellent Talents in University (LJQ2015014).

References

1. M i t o l a, J. I., G. Q. M a g u i r e. Cognitive Radio: Making Software Radios More Personal. – IEEE Personal Communications, Vol. **6**, 1999, No 4, pp. 13-18.
2. Q a d i r, J. Artificial Intelligence Based Cognitive Routing for Cognitive Radio Networks. – Artificial Intelligence Review, Vol. **45**, 2016, No 1, pp. 25-96.
3. A b b a s, N., Y. N a s s e r, K. E. A h m a d. Recent Advances on Artificial Intelligence and Learning Techniques in Cognitive Radio Networks. – Eurasip Journal on Wireless Communications & Networking, Vol. **2015**, 2015, No 174, pp. 1-20.
4. T r a g o s, E. Z., S. Z e a d a l l y, A. G. F r a g k i a d a k i s, V. A. S i r i s. Spectrum Assignment in Cognitive Radio Networks: A Comprehensive Survey. – IEEE Communications Surveys & Tutorials, Vol. **15**, 2013, No 3, pp. 1108-1135.
5. J o s h i, G. P., N. S. Y e o b, K. S. W o n. Cognitive Radio Wireless Sensor Networks: Applications, Challenges and Research Trends. – Sensors, Vol. **13**, 2013, No 9, pp. 11196-11228.
6. X u, T., Z. L i, J. G e, H. Y. D i n g. A Survey on Spectrum Sharing in Cognitive Radio Networks. – Ksii Transactions on Internet & Information Systems, Vol. **8**, 2014, No 11, pp. 3751-3774.
7. Z h u, Y. L., H. N. C h e n, H. S h e n. Bio-Inspired Computing: Individual, Population, Colony Evolution Model and Method. – Tsinghua University Press, Beijing, 2013.
8. K a r, A. K. Bio-Inspired Computing – A Review of Algorithms and Scope of Applications. – Expert Systems with Applications, Vol. **59**, 2016, pp. 20-32.
9. L v, J, X. Y o u, S. L i u. α-Nearness Ant Colony System with Adaptive Strategies and Performance Analysis. – Cybernetics & Information Technologies, Vol. **15**, 2015, No 1, pp. 3-13.

10. T h e j a, P. R., S. K. K. B a b u. Evolutionary Computing Based on QoS Oriented Energy Efficient VM Consolidation Scheme for Large Scale Cloud Data Centers. – Cybernetics & Information Technologies, Vol. **16**, 2016, No 2, pp. 97-112.
11. W a n g, W., X. L i u. List-Coloring Based Channel Allocation for Open-Spectrum Wireless Networks. – In: Proc. of IEEE Vehicular Technology Conference, Vol. **1**, 2005, pp. 690-694.
12. Z h e n g, H., C. P e n g. Collaboration and Fairness in Opportunistic Spectrum Access. – In: Proc. of IEEE International Conference on Communications, Vol. **5**, 2005, pp. 3132-3136.
13. A n u m a n d l a, K. K., S. K u d i k a l a, B. A. V e n k a t a, S. L. S a b a t. Spectrum Allocation in Cognitive Radio Networks Using Firefly Algorithm. – Swarm, Evolutionary, and Memetic Computing, Vol. **8297**, 2013, pp. 366-376.
14. L i, X. B., L. L u i, A. W. S h i, M. A. K a i, X. P. G u a n. Cognitive Radio Spectrum Allocation Based on an Improved Population Adaptive Artificial Bee Colony Algorithm. – Journal of Applied Sciences, Vol. **31**, 2013, No 5, pp. 448-453.
15. E l h a c h m i, J., Z. G u e n n o u n. Cognitive Radio Spectrum Allocation Using Genetic Algorithm. – Eurasip Journal on Wireless Communications & Networking, Vol. **2016**, 2016, No 133, pp. 1-11.
16. M a r t í n e z-V a r g a s, A., G. Á. A n d r a d e, R. S e p ú l v e d a. An Admission Control and Channel Allocation Algorithm Based on Particle Swarm Optimization for Cognitive Cellular Networks. – Recent Advances on Hybrid Approaches for Designing Intelligent Systems, 2014, pp. 151-162.
17. L e z a m a, F., G. C a s t a ñ ó n, A. M. S a r m i e n t o. Differential Evolution Optimization Applied to the Routing and Spectrum Allocation Problem in Flexgrid Optical Networks. – In: Proc. of International Conference on Transparent Optical Networks, 2016, pp. 129-146.