Journal of Southeast University (English Edition) Vol. 31, No. 4, pp. 431 - 436 Dec. 2015 ISSN 1003—7985

Throughput scheduling in cognitive radio networks based on immune optimization

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Abstract: To study the throughput scheduling problem under interference temperature in cognitive radio networks, an immune algorithm-based suboptimal method was proposed based on its NP-hard feature. The problem is modeled as a constrained optimization problem to maximize the total throughput of the secondary users (SUs). The mapping between the throughput scheduling problems and the immune algorithm is given. Suitable immune operators are designed such as binary antibody encoding, antibody initialization based on pre-knowledge, a proportional clone to its affinity and an adaptive mutation operator associated with the evolutionary generation. The simulation results show that the proposed algorithm can obtain about 95% of the optimal throughput and operate with much lower liner computational complexity.

Key words: cognitive radio networks; throughput scheduling; immune algorithm; interference temperature

doi: 10.3969/j.issn.1003-7985.2015.04.001

The increasing growth in wireless communication demands has intensified the shortage crisis for the radio spectrum, while a significant amount of the licensed spectrum is not currently being utilized[1]. The spectrum is far more underutilized rather than naturally scarce. A cognitive radio network (CRN) is a kind of intelligent communication system, which enables the devices to opportunistically access the licensed spectrum, and thereby enhance the utilization of the existing spectrum resources[2-3]. The nodes in a cognitive radio network can be classified into primary users (PUs) and secondary users (SUs). A PU is a licensed user that has exclusive rights to the access spectrum. A SU is an unlicensed user that can utilize the spectrum opportunistically with primary users under interference restriction.

Throughput optimal scheduling for cognitive radio networks under interference temperature constraints is an open research issue[4]. The throughput scheduling determines how many packets and with which frequency each SU will transmit in each time slot[5]. The aim of it is to maximize the total throughput of the SUs in the cell. The throughput scheduler issue in conventional networks has been widely studied[6]. Nonetheless, the cognitive radio paradigm brings new challenges into the issue because of the coexistence of the PUs and the SUs. The throughput scheduling problem considered in this paper can be distinguished from these works by its cognitive radio specific nature. That is, not only the availability of different frequencies but also the maximum allowable transmission rate of the frequency bands are time-varying[5].

Researchers have done some work with different scenarios. In Ref. [6], a throughput scheduling algorithm was proposed which does not enable the true coexistence of the PUs and the SUs. The authors in Ref. [7] formulated a distributed heuristic to determine the channels and time slots for the cognitive nodes. However, they do not consider the interference for the PUs either in their optimization formulation or in their suboptimal heuristic. The interference temperature model provides the true coexistence data of its licensed and unlicensed users. The throughput optimization is a binary integer programming problem, so the formulated scheduling algorithms have a high computational complexity[3-7]. In Ref. [3], its optimal solution was obtained by the branch-and-bound algorithm with very high computational complexity. In Ref. [4], the authors focused on throughput scheduling under interference temperature constraints and formulated the throughput maximization problems. Then, the authors proposed suboptimal schedulers, referred to as maximum frequency selection (MFS) and probabilistic frequency selection (PFS), with low complexity at the expense of poor throughput performance. Hence, the design of better performing suboptimal scheduling with reasonable complexity is very meaningful.

It is known that bio-inspired methods are ideal for such nonlinear optimization problems[8]. Some bio-inspired methods have been employed in conventional (non-cognitive) schedulers, such as the genetic algorithm[9] and particle swarm optimization[10]. In this paper, an improved

Received 2015-04-20.

Biography: Chai Zhengyi (1976—), male, doctor, associate professor, super_chai@126.com.

Foundation items: The National Natural Science Foundation of China (No. U1504613, 61202099, 61201175, U1204618), China Postdoctoral Science Foundation (No. 2013M541586).

Citation: Chai Zhengyi, Zheng Baolin, Shen Lianfeng, et al. Throughput scheduling in cognitive radio networks based on immune optimization[J]. Journal of Southeast University (English Edition), 2015, 31(4): 431 - 436. [doi: 10.3969/j.issn.1003-7985.2015.04.001]

immune algorithm is introduced to solve the throughput scheduling problem. The inspiration comes from the fact that the immune algorithm is ideal for nonlinear optimization problems with a large feasible solution space where a quick sub-optimal solution will suffice. Also, to the best of our knowledge, the use of the immune algorithm for scheduling in cognitive radio networks has not previously been explored.

1 System Model

Consider a time-slotted IEEE 802.22 system in which the SUs are controlled and guided by the cognitive base station (CBS)[4-5]. The scheduler is at the CBS. Assume that the interference temperature perceived by the PUs is within the interference temperature limits; reliable communication between the CBS and the SUs is achieved; and collisions among the SUs are avoided[4]. Each SU n calculates every frequency f, and the value is denoted as U_{nf}, which is the maximum number of packets that it can transmit for frequency f in a time slot. The calculation procedure for U_{nf} values guarantees that the interference temperature perceived by the PUs is within the predetermined limits. The CBS then constitutes a matrix called $\boldsymbol{U} = [U_{nf}]$.

The throughput optimal schedule can be formatted as

$$Q = \max \sum_{n=1}^{N} \sum_{f=1}^{F} \sum_{t=1}^{T} \frac{U_{nf} X_{nft}}{T} \tag{1}$$

$$\text{s.t.} \quad \sum_{f=1}^{F} \sum_{t=1}^{T} X_{nft} \geqslant 1 \qquad \forall n \in 1, 2, \ldots, N \tag{1a}$$

$$X_{nft} + X_{n'ft} \leqslant 1 \qquad \forall n, n' \in 1, 2, \ldots, N;\ n \neq n';\ \forall f,\ \forall t \tag{1b}$$

where N, F, T are the total number of SUs, frequencies, time slots, respectively; X_{nft} is a binary variable such that $X_{nft} = 1$ if user n transmits with frequency f in time slot t and 0 otherwise. Constraint (1a) guarantees that at least one time slot is assigned to each SU, whereas constraint (1b) makes certain that at most one user can transmit at a particular time slot and frequency combination, and consequently preventing collisions among the cognitive nodes. Moreover, the schedule length T is the time period in which the spectral and networking environment changes slowly enough so that the X_{nft} values are not affected. For example, the TV bands used by an IEEE 802.22 network constitute a slowly altering spectral environment, and hence enable T to be large enough[4].

2 Proposed Algorithm

2.1 Overview of immune optimization algorithm

The artificial immune system (AIS) is inspired by the human immune system. The AIS-based algorithms typically extract ideas from the human immune system's characteristics of learning and adaptability to solve some complicated problems[10]. Most immune system inspired optimization algorithms are based on the clone selection principle. Clone selection is a dynamic simulation process of the immune system that is self-adaptive against antigens. The clone selection algorithm for optimization has been widely used in engineering-oriented fields, such as spectrum allocation[11], job scheduling[12], and image segmentation[13] and so on. These algorithms essentially evolve solutions to problems via the repetition of a clone, affinity maturation (via mutation) and a selection cycle for a candidate solutions population, and remaining good solutions in the population[10-12].

Some related terms are described briefly as follows:

1) Antigen. An antigen represents one sample in the solution space of the problem. In this paper, antigen refers to the throughput schedule problem to be solved and the total constraints.

2) Antibody. An antibody represents a candidate solution to the problem in this paper.

3) Antibody population. The complete antibodies consist of antibody population.

4) Affinity. Affinity is the fitness measurement for an antibody, which indicates the extent that the antigen satisfies the problem requirements.

5) Clone. In immunology, cloning means asexual propagation so that a group of identical cells can be descended from a single common ancestor. It is used to enlarge the search region.

6) Mutation. In immunology, mutation means the immune system recognizes external patterns from antibody gene mutation in order to obtain a higher affinity. Mutations take the search procedure out of a locally optimal region, and enable it to possibly enter a better region of the search space.

7) Selection. An immune algorithm takes a group of antigens from a population using an operation called selection. The selection operation serves the purpose of eliminating the relatively bad solution candidates and focusing the search operation on a relatively good portion of the solution space.

2.2 Realization of throughput scheduling based on the immune algorithm

Our motivations for utilizing the immune algorithm for the throughput optimal scheduling problems are manifold. First, the immune algorithm is suitable for problems with large search spaces. It is equipped with many tools to reduce the computational complexity and produce a diverse set of solutions. The fact that the immune algorithm operates on a population of solutions rather than a single solution implies that the algorithm makes parallel searches in the search space. Considering that the solution space in the throughput scheduling problems is enormous (even for

5 nodes, 3 frequencies, and 3 time slots, the size of the solution space is 2^{45}), the immune algorithm appears to be a suitable tool. Secondly, the immune algorithm can be conveniently implemented. The binary decision variables X_{nft} can be easily encoded to a binary string.

Some key techniques are as follows:

1) Antigen representation (encoding). We use the binary encoded antigen which contains X_{nft} values. Thus, the antigen $[X_{111}, X_{211}, X_{311}, X_{112}, X_{212}, \ldots, X_{123}, X_{223}, X_{323}]$, whereas the other antigen structure is $[X_{111}, X_{112}, X_{113}, X_{121}, X_{122}, \ldots, X_{322}, X_{323}]$. X_{nft} is a gene bit of antibody.

2) Affinity evaluation. In this paper, the optimization model is described in Eq. (1). The affinity is a mapping of the value of Eq. (1) for a given antibody. Since Q is to be maximized, it can be stated that if an antibody has higher affinity, it is the better one.

The proposed algorithm for throughput optimal scheduling schemes is implemented as follows:

Step 1 Initialization. Set the maximum iterative generation $t_{\max}$. Set $t=0$, where t is termed as the current iterative generation. Create an initial antibody population $\boldsymbol{A}(t)$ with size k in accordance with antibody encoding in section 3.2. That is

$$\boldsymbol{A}(t) = \{\boldsymbol{p}_1(t), \boldsymbol{p}_2(t), \ldots, \boldsymbol{p}_k(t)\} \tag{2}$$

where $\boldsymbol{p}_i(1 \leqslant i \leqslant k)$ is a candidate throughput scheduling scheme; $\boldsymbol{A}(t)$ is a set of candidate throughput scheduling schemes.

Here, some pre-knowledge is used to initialize the antibody $\boldsymbol{p}_i$ in order to accelerate algorithm convergence, which is proved by the latter simulation experiments. From constraint (1a), it is known that at least one time slot is assigned to each SU. Constraint (1b) makes certain that at most, one user can transmit at a particular time slot and frequency combination. Each antibody $\boldsymbol{p}_i(1 \leqslant i \leqslant k)$ that satisfies the constraints (1a) and (1b) will be a candidate.

Step 2 Affinity evaluation. The affinities of all antibodies in $\boldsymbol{A}(t)$ are calculated according to Eq. (1) and it is denoted as

$$f(\boldsymbol{A}(t)) = \{f(\boldsymbol{p}_1(t)), f(\boldsymbol{p}_2(t)), \ldots, f(\boldsymbol{p}_k(t))\} \tag{3}$$

If an antibody $\boldsymbol{p}_i(t)$ $(1 < i < k)$ has a higher affinity, the throughput scheduling scheme is the better one.

Step 3 Proportional clone T_c. In this paper, $\boldsymbol{B}(t)$ is obtained by applying clone proliferation T_c to $\boldsymbol{A}(t)$, and it is defined as

$$\boldsymbol{B}(t) = T_c(\boldsymbol{A}(t)) = \{T_c(\boldsymbol{p}_1(t)), T_c(\boldsymbol{p}_2(t)), \ldots, T_c(\boldsymbol{p}_k(t))\} \tag{4}$$

Here, the clone scale q_i for each antibody $\boldsymbol{p}_i(1 \leqslant i \leqslant k)$ is proportional to its affinity $f(\boldsymbol{p}_i(t))$. That is

$$q_i(t) = \mathrm{Int}\left(n_c \frac{f(\boldsymbol{p}_i(t))}{\sum_{i=1}^{k} f(\boldsymbol{p}_i(t))}\right) \tag{5}$$

where Int( ) denotes the integer function, and n_c is a given value ($n_c > k$). The antibody with a large affinity value (objective function value of Eq. (1)) has a large q_i.

Let $z = \sum_{i=1}^{k} q_i$, then $\boldsymbol{B}(t)$ can be expressed as

$$\boldsymbol{B}(t) = \{\boldsymbol{p}'_1(t), \boldsymbol{p}'_2(t), \ldots, \boldsymbol{p}'_z(t)\} \tag{6}$$

Actually, clone proliferation on antibody $\boldsymbol{p}_i(t)$ is to make multiple identical copies of it.

Step 4 Mutation T_m. In this paper, it is defined as $\boldsymbol{C}(t) = T_m(\boldsymbol{B}(t))$. An adaptive mutation which associates the mutation probability m_p with the evolutionary generation is designed. That is

$$m_p = m_p \times \left(1 - \frac{t}{t_{\max}}\right) \tag{7}$$

where t is the current evolutionary generation; $t_{\max}$ is the maximum evolutionary generation.

The advantages of the mutation lie in its searching ability within a large scope in the early evolution process while it searches in a local scope in the latter evolution process, which can accelerate the convergence. After mutation, the population becomes

$$\boldsymbol{C}(t) = \{\boldsymbol{p}''_1(t), \boldsymbol{p}''_2(t), \ldots, \boldsymbol{p}''_z(t)\} \tag{8}$$

In this paper, the mutation is done by exchanging the element one and element zero with each other with probability m_p. The proposed mutation is easily realized and it does not violate the constraints.

Step 5 Affinity evaluation. The affinities of all antibodies in $\boldsymbol{C}(t)$ are calculated according to Eq. (1) and it is defined as

$$f(\boldsymbol{C}(t)) = \{f(\boldsymbol{p}''_1(t)), f(\boldsymbol{p}''_2(t)), \ldots, f(\boldsymbol{p}''_z(t))\} \tag{9}$$

Step 6 Clone selection T_s is defined as

$$\boldsymbol{A}(t+1) = T_s(\boldsymbol{C}(t) \cup \boldsymbol{A}(t)) = (\boldsymbol{p}_1(t+1), \boldsymbol{p}_2(t+1), \ldots, \boldsymbol{p}_k(t+1)) \tag{10}$$

That is, k antibodies with a high affinity are selected from $\boldsymbol{C}(t)$ and $\boldsymbol{A}(t)$ to form the next population $\boldsymbol{A}(t+1)$.

Step 7 Termination test. If $t_{\max}$ is reached, stop the algorithm. Output the antibody with the maximum affinity in $\boldsymbol{A}(t+1)$ as the result of the throughout scheme. Otherwise, $t = t+1$, and go to Step 3.

2.3 Computational complexity

Recall that N denotes the number of SU, and F denotes the number of available frequencies. For the immune-based scheme, the total computational complexity is mainly composed of that for initialization, affinity evalua-

tion, cloning, mutation, and selection. Given the population size k, the clone scale $n_c(n_c > k)$ and the maximum generation t_{max}, the procedure of population initialization, the affinity evaluation and proportional clone (Step 1 to Step 3) has the same computational complexity of $O(kFN)$ in each generation, while the procedure of mutation, affinity evaluation, selection (Step 4 to Step 6) has the computational complexity of $O(kn_cFN)$ in each generation. Hence, for each generation, the total computational complexity is $O(3kFN + 3kn_cFN)$. Since $n_c > k$, according to the properties of symbolic O[10, 13-14], it can be denoted as $O(n_cFN)$. When the throughout scheduling is finished, it has the total computational complexity of $O(t_{max}n_cFN)$.

The computer simulations show that t_{max} implicitly depends on F and N. The more complex the search space is, the larger the number of generations should be. Thus, for given n_c and t_{max}, the gradual computational complexity of the proposed algorithm is $O(NF)$ in accordance with the properties of symbolic O.

A brief summary of the complexities of previous typical algorithms and our proposed algorithm is as follows. The complexity of algorithm in Ref. [3] is $O(FN^2)$, while the complexity of our proposed algorithm is the same as the algorithm in Ref. [4], which is $O(FN)$.

3 Simulation Results and Discussion

3.1 Experimental environments and parameter settings

We simulated the suboptimal schedulers and acquired the U_{nf} values in OPNET Modeler, and we solved the optimization problems in CPLEX [15]. Additive white Gaussian noise (AWGN) channels are considered. In all the simulations, each SU has three primary neighbors in its interference range. The simulation results are the average of 100 independent tests. The parameter settings are as the same as that in Refs. [4-5]. There are three frequencies with interference temperature thresholds of 1 000, 2 000, and 3 000 K.

3.2 Sensitivity in relation to the immune algorithm parameters

Four parameters are to be set at the initialization phase: the antibody population size k, the clone population size n_c, the mutation probability m_p, and the maximum number of generations t_{max}. The sequential experimental design method of employing a series of small experiments each with a specific objective is a common method in experimental design[16], because the experimenter can quickly learn crucial information from a small group of runs that can be used to plan the next experiment. k and n_c directly affect the computational complexity of the algorithm[10-13]. If the given k and n_c are large enough, the diversity of the population can be enhanced and the prematurity can be avoided in some extent, but the computational complexity will also be very large. t_{max} clearly depends on F and N. The more complex the search space is, the larger the number of generations should be. m_p is very important for local search in the algorithm. A large m_p has the ability to produce more new antibodies, but it also has the probability to destroy some good antibodies. When m_p is too small, the convergence speed is not quick enough to find the best solution in appointed generations.

Since the optimal choice is difficult to determine by theoretical analysis, it is important to analyze the performance affected by experiments in different cases. After trial and error, the parameters employed in the proposed immune algorithm are as follows: the number of generations t_{max} is 100; the population size k is 50; the clone scale n_c is 10; and the mutation probability m_p is 0.3.

3.3 The performances of the proposed algorithm

In order to evaluate the performances of the proposed algorithm, the effect of number of iterations (evolutionary generation) on throughout scheduling is studied, and the number of SUs is set to be 5. As it is evident from Fig. 1, the throughout initially increases with the number of evolutionary generations and then gradually converges to the high value, close to an optimal point. It is also can be seen that the proposed method provides significant gain in throughout and fast convergence rate. The simulation results prove the effectiveness of the proposed immune operators. It also can be seen from Fig. 2 that the evolutionary generation increases with the numbers of SUs. It is effective.

The results of different numbers of SUs are shown in Tab. 1. It can be seen that the proposed algorithm gives consistent good results. First of all, the proposed solution yields better results than the MFS and PFS schedulers proposed in Ref. [4], at the same time being very close to the throughput optimal scheduler performance in Ref. [3].

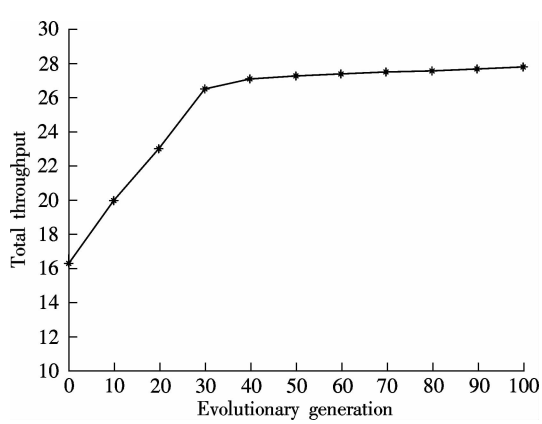

Fig. 1 Throughout vs. evolutionary generation

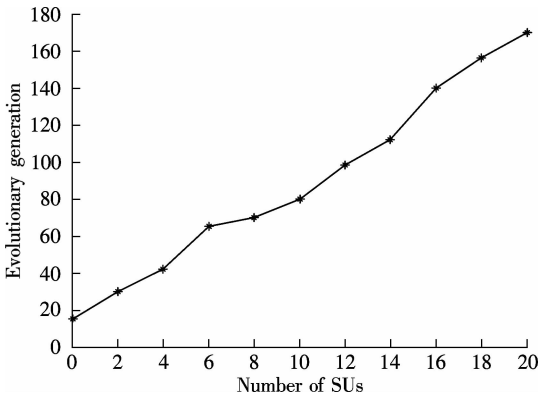

Fig. 2 Evolutionary generation vs. different numbers of SUs

Tab. 1 The results of relative algorithms for different numbers of SUs

Algorithm	Number of SUs			
	5	10	15	20
Proposed throughout	27.85	27.97	2 841	2 872
Optimal throughout[3]	27.91	28.79	29.46	29.89
MFS[4]	14.33	15.16	16.06	16.81
PFS[4]	13.74	14.50	15.97	16.01

Fig. 3 presents the optimal throughput[3], MFS, and PFS[4] scheduling schemes compared with the proposed scheduling scheme. The algorithm in Ref. [3] can be regarded as the upper-bound of the proposed heuristic algorithm.

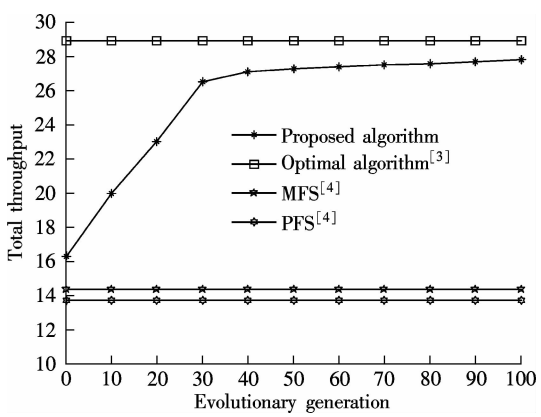

Fig. 3 Comparison of different algorithms

Fig. 4 shows the performances comparisons of relative algorithms with the increase in the numbers of SUs. It can be seen that the proposed algorithm performs excellently. It is very close to the optimal performances in Ref. [3] and is better than the algorithm in Ref. [4].

All in all, the proposed scheduling scheme achieves performances close to the optimal scheduling operating with much lower complexity. However, the iterations in the simulation results reveal that the proposed algorithm is computationally more costly than the MFS and the PFS schedulers in Ref. [4]. Nevertheless, when they are compared with the throughput performance, we can see that the proposed algorithm is approximately twice as good as

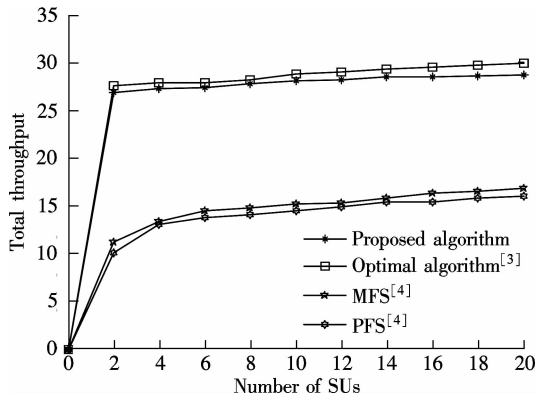

Fig. 4 Throughout vs. numbers of SUs

the MFS and the PFS schedulers. Moreover, the proposed algorithm is computationally more efficient than the classical branch and bound algorithms that are used to solve binary integer programming problems. Therefore, ther proposed algorithm presents a very reasonable tradeoff between computational complexity and performance.

4 Conclusion

The immune algorithm-based suboptimal scheduling for the throughput problem in cognitive radio networks is proposed. The simulation results show that the proposed algorithm is very close to optimal performance with a relatively lower complexity. Hence, it can be concluded that the proposed scheduling is more suitable for slowly varying spectral environments. Considering that IEEE 802.22 networks that operate on the TV broadcast bands that are slowly changing, it can be confidently concluded that the proposed algorithm can operate in realistic network settings, and provide useful solutions for the open research problem.

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认知无线电网络中基于免疫优化的吞吐量调度

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摘要:针对认知无线电网络中干扰温度下的吞吐量调度问题,基于问题的 NP-hard 特性,提出一种基于智能免疫优化的次优吞吐量调度算法. 将吞吐量调度问题建模为一个最大化所有认知用户吞吐量的约束优化问题,给出了吞吐量调度问题和免疫算法的映射关系,设计了适合问题求解的二进制抗体编码方式、基于先验知识的抗体初始化方法、基于抗体亲和度的比例克隆方式及基于进化代数的变异算子. 实验结果表明,所提算法可以得到大约 95% 的最优吞吐量,并且具有较低的线性复杂度.

关键词:认知无线电网络;吞吐量调度;免疫算法;干扰温度

中图分类号:TN311