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A Simple Quantum-inspired Particle Swarm Optimization and its Application

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Abstract: In order to solve discrete optimization problem, present study proposes a novel Quantum-inspired Particle Swarm Optimization (QPSO) based on particle swarm optimization and quantum evolutionary theory and we evaluate the performance of the QPSO through some classical benchmark functions. The proposed QPSO algorithm applies the quantum computing theory to particle swarm optimization and thus has the advantages of both quantum computing theory and particle swarm optimization. We also use it to solve cognitive radio spectrum allocation problem. The new spectrum allocation method has the ability to search global optimal solution under different network utility functions. Simulation results for cognitive radio system are provided to show that the designed spectrum allocation algorithm is superior to some previous spectrum allocation algorithms.

Key words: Quantum-inspired particle swarm optimization, benchmark function, spectrum allocation, network utility function, cognitive radio

INTRODUCTION

The natural system that has developed for so long is one of the rich sources of inspiration for inventing new intelligent algorithms. Inspiring intelligence algorithms are important scientific fields that are closely related to physical and biological phenomenon existing in nature and some algorithms are widely studied for application, such as Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1997; Yuan and Chen, 2010) and ant colony optimization (Hijazi and Natarajan, 2004). Particle swarm optimization (Zhao and Zheng, 2004) and ant colony optimization (Zhu *et al*., 2007) were successfully applied to solve engineering problem of discrete optimization.

Quantum information science is a result of merging physical science with information science. The quantum idea is introduced the quantum idea into classical algorithm and improved the conventional algorithm to get a better performance (Jiao *et al*., 2008). Quantum-inspired Genetic Algorithm (QGA), a new and promising genetic algorithm developed in recent years, is the product of quantum computing theory and genetic algorithm. QGA is based on the concepts of quantum computing (quantum bit, quantum superposition and quantum entanglement) and quantum theory, such as quantum logic gate. In QGA, quantum bit encoding is used to represent the chromosome and evolutionary process is implemented by using quantum logic gate operation on the chromosomes. Now, much attention is paid to QGA because it has the characteristics of strong searching capability, rapid convergence, short computing time and small population size (Han and Kim, 2000; Han *et al*., 2001; Li and Zhuang, 2002; Yang *et al*., 2003). Quantum Particle Swarm Optimization (QPSO) (Gao and Diao, 2009) is an effective swarm intelligence method for multi-user detection. Simulation comparisons prove that the performance of the QPSO algorithm is competitive to other intelligence computing algorithms with an advantage of employing fewer control parameters for multi-user detection. But it is complexity algorithm which using quantum individuals. All quantum evolutionary use quantum bit and quantum gate in quantum domain. In order to design the simple quantum-inspired particle swarm optimization to solve optimization problem, quantum particle swarm optimization is improved by good evolutional equations and simple updating equations. A simple evolutionary algorithm with high performance is vital for function optimization and engineering application.

Cognitive Radio (CR) provides a feasible solution for dynamic spectrum access. It solves the contradiction between the scarcity of spectrum resources and increasing radio access demands through letting the secondary users use the available spectrum while avoiding interference with the primary users and their neighbors. This new wireless technology can sense the wireless environment, search for available spectrum

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resources and allocate spectrum dynamically, so that the efficiency of spectrum usage is improved and the capacity of wireless communication system is increased. Cognitive radio has the ability to sense, to learn and to adapt to the outside world (Haykin, 2005). Based on centralized or distributed architecture, cooperative or non-cooperative spectrum allocation behavior, overlay or underlay spectrum access technique, lots of models have been proposed for dynamic spectrum access, including game theory (Nie and Comaniciu, 2005), pricing and auction mechanisms (Huang *et al*., 2006), local bargaining (Cao and Zheng, 2005) and graph coloring (Zheng and Peng, 2005). Assuming that the environmental conditions are static during the time it takes to perform spectrum assignment, an allocation model is proposed in (Peng *et al*., 2006) and Color Sensitive Graph Coloring (CSGC), genetic algorithm, PSO algorithm (Zhao *et al*., 2009a) and Quantum Genetic Algorithm (QGA) (Zhao *et al*., 2009b) are used to solve the spectrum allocation problem. Our method, simple Quantum-inspired Particle Swarm Optimization (QPSO) which is based on PSO and simulating of quantum computing theory, has the advantages of both PSO and quantum computing.

SIMPLE QUANTUM-INSPIRED PARTICLE SWARM OPTIMIZATION

Quantum-inspired particle swarm optimization is based on the consideration of that modifying the conventional algorithm to get a better performance. Since there is no published work to deal with discrete optimization problem by using a single quantum rotation gate simulation, we propose a simple quantum-inspired particle swarm optimization for discrete optimization problem.

In quantum particle swarm optimization, a number of different representations can be used to encode the solutions onto particles. The QPSO uses quantum coding, called a quantum bit or Q-bit, for the probabilistic representation that is based on the concept of quantum bit and a quantum velocity is defined as a string of quantum bits. One quantum bit is defined as the smallest unit of information in the QPSO which is defined as a pair of composite numbers (α, β), where $|\alpha|^2+|\beta| = 1$. $|\alpha|^2$ gives the probability that the quantum bit will be found in the '0' state and $|\beta|^2$ gives the probability that the quantum bit will be found in the '1' state. The quantum velocity of the *i*th quantum particle is defined as:

$$v_i = \begin{bmatrix} \alpha_{i1} & \alpha_{i2} & \cdots & \alpha_{il} \\ \beta_{i1} & \beta_{i2} & \cdots & \beta_{il} \end{bmatrix} \tag{1}$$

where, $|\alpha_{ij}|^2+|\beta_{ij}|^2 = 1$, (j = 1, 2,..., l), the quantum velocity can represent 2^l states simultaneously. For simplicity and efficient design of the QPSO algorithm, we define α_{ij} and β_{ij} as real numbers and $0 \le \alpha_{ij} \le 1$, $0 \le \beta_{ij} \le 1$. Therefore, $\alpha_{ij} = \sqrt{1-\beta_{ij}^2}$ and quantum velocity of equation (1) can be simplified as:

$$v_i = [\alpha_{i1}\ \alpha_{i2} \ldots \alpha_{il}] = [v_{i1}\ v_{i2} \ldots v_{il}] \tag{2}$$

The evolutionary process of quantum velocity is mainly completed through quantum rotation gate (Gao and Diao, 2009). In our algorithm, for simplicity, the jth quantum bit v_{ij} is updated as:

$$v_{ij}^{t+1} = | v_{ij}^t \cos\theta_{ij}^{t+1} - \sqrt{1-(v_{ij}^t)^2} \sin\theta_{ij}^{t+1} | \tag{3}$$

where, abs () is an absolute function which makes quantum bit in the real domain [0, 1].

If $\theta_{ij} = 0$, a quantum bit velocity v_{ij} is updated in a certain small probability by the operator which is described below:

$$v_{ij}^{t+1} = \sqrt{1-(v_{ij}^t)^2} \tag{4}$$

Quantum-inspired particle swarm optimization is a novel multi-agent optimization system inspired by social behavior metaphor of agents. Each agent, called quantum particle, flies in an l-dimensional space according to the historical experiences of its own and its colleagues'. There are h quantum particles that are in a space of l dimensions in a quantum swarm, the ith quantum particle's position in the space is $x_i = [x_{i1}, x_{i2},\ldots, x_{il}]$, (i = 1, 2,..., h) which is a latent solution. The *i*th particle's quantum velocity is $v_i = [v_{i1}, v_{i2},\ldots, v_{il}]$ and until now the best position (the local optimal position) of the ith quantum particle is $p_i = [p_{i1}, p_{i2},\ldots, p_{il}]$, (i = 1, 2,..., h). $p_g = [p_{g1}, p_{g2},\ldots, p_{gl}]$ is the global optimal position discovered by the whole quantum particle population until now. At each generation, the ith quantum particle is updated by the following quantum moving equations:

$$\theta_{id}^{t+1} = e_1 (p_{id}^t - x_{id}^t) + e_2 (p_{gd}^t - x_{id}^t) \tag{5}$$

$$v_{id}^{t+1} = \begin{cases} \sqrt{1-(v_{id}^t)^2}, & \text{if } (p_{id}^t = x_{id}^t = p_{gd}^t \text{ and } r < c_1); \\ | v_{id}^t \cos\theta_{id}^{t+1} - \sqrt{1-(v_{id}^t)^2} \sin\theta_{id}^{t+1} |, & \text{else.} \end{cases} \tag{6}$$

$$x_{id}^{t+1} = \begin{cases} 1, & \text{if } \gamma_{id}^{t+1} > (v_{id}^{t+1})^2; \\ 0, & \text{if } \gamma_{id}^{t+1} \le (v_{id}^{t+1})^2. \end{cases} \tag{7}$$

where, (i = 1, 2,..., h), (d = 1, 2,..., l), r is uniform random number between 0 and 1, c_1 is mutation probability which is a constant among [0, 1/l], $\gamma_{id}^{t+1} \in [0, 1]$ is uniform random number, superscript t+1 and t represent number of iterations (generations), $(v_{id}^{t+1})^2$ represents the selection probability of bit position state in the (t+1) h generation. The value of e_1 and e_2 expresses the relative important degree of p^i and p^g in the moving process.

THE PERFORMANCE OF THE SIMPLE QUANTUM-INSPIRED PARTICLE SWARM OPTIMIZATION

We use two benchmark functions to evaluate the performance of the simple quantum-inspired particle swarm optimization. We set initial population and maximum generation of the four evolutionary algorithms identical. For GA, QGA, PSO and QPSO, the population size is set to 20. For GA, the crossover probability and the mutation probability are set to 0.8 and 0.02, respectively and the GA is configured to replace 85% of its population each generation, 17 of every 20 population members (Zhao *et al*., 2009a). As for QGA, the rotation angle of quantum gates decreases linearly from 0.1π at the first generation to 0.005π at the last generation [19]. In PSO, the two acceleration coefficients are equal to 2 and $V_{max} = 4$ (Zhao *et al*., 2009a). For QPSO, we set $e_1 = 0.06$, $e_2 = 0.03$, $c_1 = 1/300$. Two benchmark functions are as follows:

$$F_1(x) = \frac{1}{4000}\left(\sum_{i=1}^{n}(x_i - 100)^2\right) - \left(\prod_{i=1}^{n}\cos\left(\frac{x_i - 100}{\sqrt{i}}\right)\right) + 1, (-600 \le x_i \le 600,$$

$$i = 1, 2, \cdots n); F_2(x) = \sum_{i=1}^{n}(x_i^2 - 10\cos(2px_i) + 10),$$

$$(-5.12 \le x_i \le 5.12, i = 1, 2, \cdots, n)$$

In the following simulations, we use binary-encoding and the encoding-length of every variable is 15 bits. We also set n = 2 for all benchmark functions, i.e., i = 1, 2. Each experiment was run 200 times during simulation.

The first function we use is Griewank function. x_i is in the interval of [-600, 600]. The global minimum value for this function is 0 and the corresponding global optimum solution is $x_{opt} = (x_1, x_2,..., x_n) = (100, 100,..., 100)$. From Fig. 1, we can see that although classic algorithms have fast convergence rate but they all trap into local convergence. Our algorithm, however, overcomes the disadvantage of local convergence and has a more accurate convergence value.

The second function is Rastrigin function whose value is 0 at its global minimum solution $x_{opt} = (x_1, x_2,..., x_n) = (0, 0,..., 0)$. x_i is in the interval of [-5.12, 5.12]. The difficult part about finding optimal solutions to this function is that an optimization algorithm can easily be trapped in a local optimum on its way towards the global optimum. From Fig. 2, we can see that GA and QGA have the similar performance while PSO outperforms GA and QGA. It also presents that our algorithm, i.e. QPSO, has a very accurate convergence value compared to the other three algorithms.

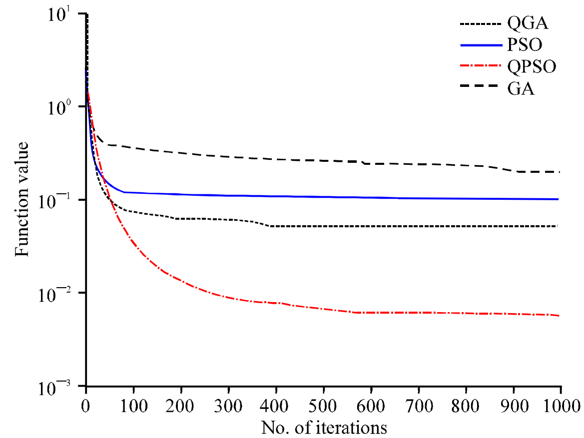

Fig. 1: The performance of four algorithms using Griewank function using Rastrigin function

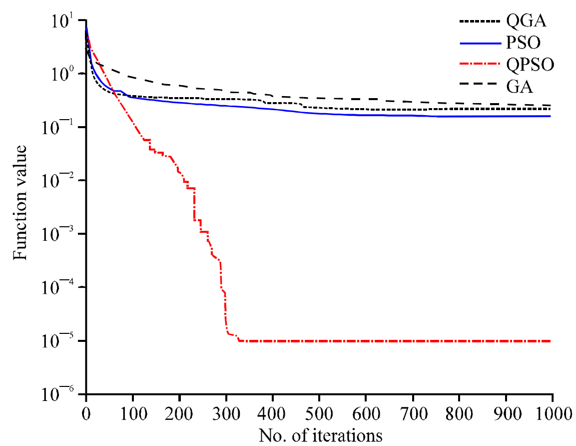

Fig. 2: The performance of four algorithms

SPECTRUM ALLOCATION BASED ON QUANTUM-INSPIRED PARTICLE SWARM OPTIMIZATION AND EXPERIMENTAL RESULTS

Description of cognitive spectrum allocation model: The general spectrum allocation model consists of channel availability matrix, channel reward matrix, interference constraint matrix and conflict free channel assignment matrix. Assume a network of secondary users indexed from 1 to N competing for spectrum channels indexed from 1 to M which are non-overlapping orthogonal. Each secondary user can be a transmission link or a broadcast access point. The channel availability matrix $L = \{l_{n,m} | l_{n,m} \in \{0, 1\}\}_{N\times M}$ is an N by M binary matrix representing the channel availability. Secondary user n determines whether channel m is available by detecting the signal of primary users and if it is not occupied by primary users which means channel m is available to user n, then $l_{n,m} = 1$ and $l_{n,m} = 0$ otherwise. The channel reward matrix $B = \{b_{n,m}\}_{N\times M}$ is an N by M matrix representing the channel reward, where $b_{n,m}$ represents the reward that can be obtained by user n using channel m. As two or more secondary users may use the same channel at the same time, they may interfere with each other. The interference constraint matrix $C = \{c_{n,k,m} | c_{n,k,m} \in \{0, 1\}\}$ is an N by N by M matrix representing the interference constraint among secondary users, where $c_{n,k,m} = 1$ if users n and k would interfere with each other if they use channel m simultaneously and $c_{n,k,m} = 0$ otherwise. In particular, $c_{n,k,m} = 1-l_{n,m}$ if $n = k$, which is only decided by the channel availability matrix.

In real applications, the spectrum environment varies slowly while users quickly perform network-wide spectrum allocation. We assume that the location, available spectrum, etc. are static during the spectrum allocation, thus L, B and C are constants in an allocation period.

The conflict free channel assignment matrix $A = \{a_{n,m} | a_{n,m} \in \{0, 1\}\}_{N\times M}$ represents the channel assignment, where $a_{n,m} = 1$ if channel m is allocated to secondary user n and $a_{n,m} = 0$ otherwise. A must satisfy the interference constraints defined by C: $a_{n,m} \cdot a_{k,m} = 0$, if $c_{n,k,m} = 1, \forall 1 \le n,k \le N, 1 \le m \le M$. Given a conflict free channel assignment, the reward user n gets is defined as:

$$r_n = \sum_{m=1}^{M} a_{n,m} \cdot b_{n,m}.$$

We use:

$$R = \{r_n = \sum_{m=1}^{M} a_{n,m} \cdot b_{n,m}\}_{N\times 1}$$

to represent the reward vector that each user gets for a given channel assignment. Let $\Lambda\ (L, C)_{N\times M}$ be the set of conflict free channel assignment for a given L and C. The spectrum allocation is to maximize network utilization U (R). Given the model above, the spectrum allocation problem can be defined as the following optimization problem:

$$A^* = \underset{A\in\Lambda(L,C)}{\arg\max}\, U(R) \tag{8}$$

where, A* is the optimal conflict free channel assignment matrix. We use the first utility function of Max-sum-Reward (MSR) as follows:

$$U_{MSR}(R) = \frac{1}{N}\sum_{n=1}^{N} r_n = \frac{1}{N}\sum_{n=1}^{N}\sum_{m=1}^{M} a_{n,m} \cdot b_{n,m} \tag{9}$$

which means that we use the average reward instead of sum reward in the following simulations.

In addition, we use fairness based utility function of Max-Proportional-Fair (MPF) as follows:

$$U_{MPF}(R) = \left(\prod_{n=1}^{N}(r_n + 1e-6)\right)^{\frac{1}{N}} = \left(\prod_{n=1}^{N}\left(\sum_{m=1}^{M} a_{n,m} \cdot b_{n,m} + 1e-6\right)\right)^{\frac{1}{N}} \tag{10}$$

which means every secondary user has a baseline reward of le-6.

Spectrum allocation using simple quantum-inspired particle swarm optimization: The initial position population of quantum-inspired particle swarm is randomly chosen from the solution space. All initial quantum bits of quantum velocity may be defined as $1/\sqrt{2}$. The goal of the objective function is to evaluate the status of each quantum particle. In the spectrum allocation, the target of position optimization is the maximization of network utilization function.

The proposed Quantum-inspired Particle Swarm Optimization (QPSO) applies the quantum computing theory to the particle swarm optimization. In this algorithm, every quantum velocity is updated by quantum particle swarm theory. The particle swarm optimization is able to locate the appropriate regions for a solution in the search space but fairly slow to find the near-optimal solution using the moving equations that are random in nature. It has the disadvantage of local convergence. However, the proposed QPSO has the advantages of quantum computing theory and the particle swarm optimization and can find the near-optimal solution compared to other algorithms. Summarizing, the proposed new algorithm can overcome the disadvantages of the PSO.

According to the above analysis, the work processes of quantum-inspired particle swarm algorithm for spectrum allocation are shown below:

Step 1: Given $L = \{l_{n,m} | l_{n,m} \in \{0, 1\}\}_{N\times M}$, $C = \{c_{n,k,m} | c_{n,k,m} \in \{0, 1\}\}_{N\times N\times M}$ and $B = \{b_{n,m}\}_{N\times M}$, set the length of the position and quantum velocity as:

$$l = \sum_{n=1}^{N}\sum_{m=1}^{M} l_{n,m}$$

and set $L_1 = \{(n, m)|l_{n,m} = 1\}$ such that elements in L_1 are arranged increasingly in n and m. Therefore, the number of elements in L_1 is equal to the value of l

Step 2: Randomly generate an initial quantum particle swarm based on binary coding and quantum coding mechanism

Step 3: For all quantum particle positions, map the *j*th bit of the position to $a_{n,m}$, where (n, m) is the jth element in L_1 and $1 \le j \le l$. For all m, search all (n, k) that satisfies $c_{n,k,m} = 1$ and $n \neq k$ and check whether both of the two bits corresponding to the element in the nth line and mth column of A and the element in the kth line and mth column of A are equal to 1; if so, randomly set one of them to 0

Step 4: Compute the fitness of each quantum particle

Step 5: Renew each quantum particle's local optimal position. Update the global optimal position as evolutionary objective of the whole particle population

Step 6: Update quantum velocities and positions of quantum particles

Step 7: If it reaches the predefined maximum generation, stop and output outcome; if not, go to step 3

Evaluation and experimental results: In present study, we set initial population and maximum generation (iteration) of the four evolutionary algorithms identical. For GA, QGA and PSO, the parameters settings are identical with simple QPSO. For QPSO, we set $e1 = 0.06$, $e_2 = 0.03$, $c_1 = 0$. This is because in step 3 we change some bits of the quantum particles, so we set the mutation possibility to 0. All intelligence algorithms will be terminated at the same iterations (maximum iteration number is set as 1000). Each experiment was run 200 times during simulation.

The commonly used algorithm to solve the spectrum allocation problem presented in Description of Cognitive Spectrum allocation Model is Color Sensitive Graph Coloring Algorithm (CSGC). For more information of CSGC, please refer to study (Peng *et al*., 2006). In order to evaluate the performance of the proposed QPSO-based spectrum allocation method, we compare it with CSGC and other evolutionary algorithms in our simulations. During the simulation, B, L, C are generated by the pseudo code for modeling network conflict graph in the study (Peng *et al*., 2006). CSGC using the noncollabarative labeling rule.

First, we set the number of secondary users to 10, the number of channels available to 30, the number of primary users to 20 and see the performance of the four algorithms. Figure 3-4 illustrate the performance gain offered by the QPSO approaches using Max-Sum-Reward utility function and Max-Proportional-Fair utility function respectively. When all simulation conditions are identical and CSGC, QGA and GA are also included, they show the target gap of performance.

We can see that the average reward obtained by GA, QGA and QPSO after 300 iterations are better than CSGC which validates the effectiveness of the proposed evolutionary algorithms-based spectrum allocation methods. QPSO performs the best under objectives MSR and MPF in terms of convergence value while QGA and GA has similar performance under objectives MSR and MPF. Even though GA and QGA perform better than CSGC, the convergence values after 400 iterations by

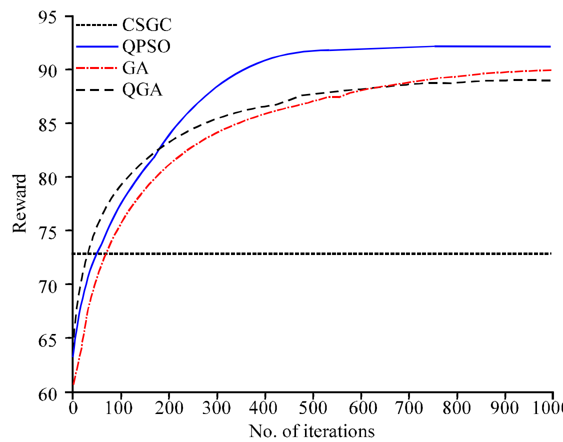

Fig. 3: The convergence curve for the four algorithms

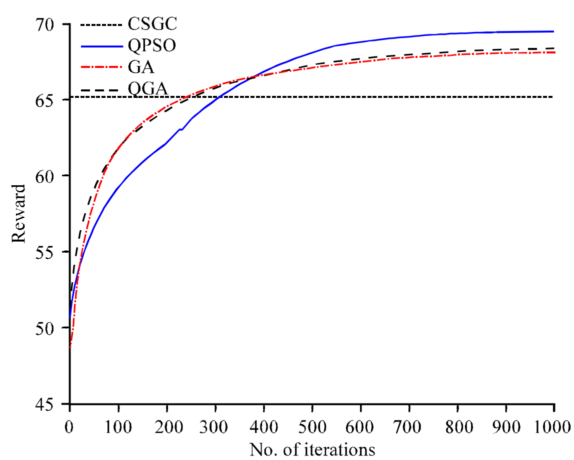

Fig. 4: The comparison of convergence curve for the four algorithms using MPF utility function

Table 1: Reward values of five spectrum allocation methods using MSR utility function as the number of secondary users increases

	The number of secondary users					
Algorithm	5	10	15	20	25	30
CSGC	33.617	20.280	15.914	12.192	10.606	9.1354
GA	35.559	23.239	18.485	14.267	12.621	10.923
QGA	35.554	23.205	18.364	14.139	12.555	10.782
PSO	35.561	23.263	18.506	14.312	12.726	11.027
QPSO	35.561	23.275	18.528	14.359	12.740	11.051

Table 2: Reward values of five spectrum allocation methods using MPF utility function as the number of secondary users increases

	The number of secondary users					
Algorithm	5	10	15	20	25	30
CSGC	24.366	8.8559	2.1298	0.54978	0.17299	0.071994
GA	27.216	15.749	9.1972	5.6505	2.4122	0.98789
QGA	27.293	16.012	9.3451	5.5749	2.1378	0.89429
PSO	27.349	16.031	9.5655	5.7752	2.7884	1.15910
QPSO	27.451	16.387	9.7540	6.3373	3.1676	1.51450

Table 3: Reward values of five spectrum allocation methods using MSR utility function as the number of channels available increases

	The number of channels available					
Algorithm	5	10	15	20	25	30
CSGC	7.1335	20.280	34.131	48.130	59.529	72.706
GA	7.4059	23.239	40.251	58.612	72.870	89.790
QGA	7.4097	23.205	40.152	57.915	72.551	88.958
PSO	7.4097	23.263	40.365	58.737	73.683	91.512
QPSO	7.4097	23.275	40.410	59.000	73.840	92.036

Table 4: Reward values of five spectrum allocation methods using MPF utility function as the number of channels available increases

	The number of channels available					
Algorithm	5	10	15	20	25	30
CSGC	0.10473	8.8559	27.224	39.625	53.999	65.109
GA	0.58484	15.749	29.522	42.349	57.078	68.113
QGA	0.61269	16.012	29.591	42.594	57.229	68.296
PSO	0.65894	16.031	29.716	42.850	57.796	69.166
QPSO	0.66443	16.387	29.96	43.112	57.929	69.397

QPSO are still higher than those obtained by GA and QGA. For both two simulations, QPSO performs better than GA and QGA in terms of convergence value.

We set the number of secondary users increases while the number of primary users and the number of channels available remain constant (20 and 10, respectively). Increasing the number of secondary users in one area, thus increases the user density and then creates additional interference constraints. So from Table 1 and 2, we can see that the average reward degrades as the number of secondary users increases. Also, we can see that our method is better than other methods. Table 1 and 2 show the QPSO is superior to GA, QGA, PSO and CSGC.

We set the number of channels available increases while the number of secondary users and the number of primary users remain constant (10 and 20, respectively). Increasing the number of channels available in one area makes secondary users get more reward from the increasing channels, so the reward upgrades as the number of channels available increases. Table 3 and 4 clearly show that the QPSO achieves near-optimal performance from 5 to 30 channels. Although the GA, the QGA and the PSO have good performance, in some cases they are unable to reach the optimal solution in limited iterations. As is observed above, the QPSO shows good performance. So from Table 3 and 4, we can see that the average reward upgrades as the number of channels increases. Also, we can see our method is better than other methods. Table 3 and 4 show the QPSO is superior to GA, QGA, PSO and CSGC.

CONCLUSION AND FUTURE WORK

Present study has proposed a QPSO algorithm which is a novel algorithm for discrete optimization problems. Though testing classical Benchmark functions, we can see that our algorithm outperforms other classical evolutionary algorithms. Based on QPSO, we have proposed a spectrum allocation method. Experimental results show that our method not only improves the reward gotten by the secondary users but also has better convergence rate.

In present study, we consider only one objective during one simulation. But sometimes we should consider two objectives, i.e., max reward and fairness and then the optimization problem becomes multi-objective optimization and thus becomes more complex. In the simulation, we also assume that available spectra are static during the time it takes to perform spectrum assignment. But if we consider a dynamic network, spectrum allocation becomes a more complex problem and all of the algorithms need to compute spectrum allocations again. So, an adaptive approach should be developed to adapt the environment change and the change of spectrum availability.

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