A Fast Anti-jamming Decision Method Based on the Rule-Reduced Genetic Algorithm

Jin Hui[1,2], Song Xiaoqin[1,2], Wang Miao[1,2], Niu Yingtao[3], Li Ke[4]
[1]Jiangsu Key Laboratory of Internet of Things and Control Technologies,
Nanjing University of Aeronautics and Astronautics, Nanjing, China
[2]College of Electronic and Information Engineering,
Nanjing University of Aeronautics and Astronautics, Nanjing, China
[e-mail: jinhuinuaa@126.com, xiaoqin.song@163.com, wm891230@126.com]
[3]Nanjing Telecommunications institute, Nanjing, China
[e-mail:niuyingtao78@hotmail.com]
[4]College of Information Technology, Beijing Union University, Beijing, China
[e-mail:ke.li@139.com]
[*]Corresponding Author: Song Xiaoqin

Received December 10, 2015; revised March 19, 2016; revised April 11, 2016; accepted May 18, 2016; published September 30, 2016

Abstract

To cope with the complex electromagnetic environment of wireless communication systems, anti-jamming decision methods are necessary to keep the reliability of communication. Basing on the rule-reduced genetic algorithm (RRGA), an anti-jamming decision method is proposed in this paper to adapt to the fast channel variations. Firstly, the reduced decision rules are obtained according to the rough set (RS) theory. Secondly, the randomly generated initial population of the genetic algorithm (GA) is screened and the individuals are preserved in accordance with the reduced decision rules. Finally, the initial population after screening is utilized in the genetic algorithm to optimize the communication parameters. In order to remove the dependency on the weights, this paper deploys an anti-jamming decision objective function, which aims at maximizing the normalized transmission rate under the constraints of minimizing the normalized transmitting power with the pre-defined bit error rate (BER). Simulations are carried out to verify the performance of both the traditional genetic algorithm and the adaptive genetic algorithm. Simulation results show that the convergence rates of the two algorithms increase significantly thanks to the initial population determined by the reduced-rules, without losing the accuracy of the decision-making. Meanwhile, the weight-independent objective function makes the algorithm more practical than the traditional methods.

Key Words**:** anti-jamming, rough set theory, genetic algorithm, objective function

This work is supported by National Natural Science Foundation of China under grant No.61301103.

http://dx.doi.org/10.3837/tiis.2016.09.028 **ISSN : 1976-7277**

1. Introduction

In the last two decades, the wireless communication technology has developed sharply with its wide applications related to government agencies, commercial areas and daily life of all aspects. Yet wireless communication systems are confronted with various artificial jamming due to their open characteristic. For a long time, spread-spectrum communication is one of the major technical methods for anti-jamming in the frequency domain. With the increasingly scarce of spectrum resources, it becomes too expensive to occupy more spectrums for a larger jamming tolerance.

The cognitive radio (CR) [1-3] offers a new approach to solve this problem. The capability of learning, reasoning and reconfiguring communication parameters is the core of CR research. In this case, the concepts of cognition and decision-making are introduced into communication anti-jamming field. This new method enables the system to choose proper communication parameters according to environmental changes so as to adapt to the jamming situation [4]. In [5], the bit error rate (BER) performance function and the normalized objective function are introduced to evaluate the quality of communication in detail. It proposes a weight-based method by combining different objective functions into a multi-objective function.

Many decision-making methods based on evolutionary algorithms have been proposed. Those methods are typically based on the genetic algorithm (GA), which searches the optimized configuration in parameters' configurable fields. However, an initial population needs to be generated randomly in the GA-based decision-making, which results in a very large search space in some cases. Traversing the entire space always requires quite long time, which then adversely affects the timely decision. Many scholars have improved the algorithm to compensate for this disadvantage [6-11].

Tim Newman et. al. [6] proposes a new method to initialize the population. As a CR environment changes smoothly, the decision engine adds previous cognitive results to the next initial population. This algorithm reduces the decision-making time required and improves the real-time performance. Some further achievements have been reported to cope with other disadvantages of the traditional GA. For example, adaptive genetic algorithm（AGA）which employs adaptive crossover probability and mutation probability has been proposed in [7]. According to population evolutionary situation, the evolutionary strategy could adjust at any time to avoid the "premature" problem. In [8], the authors propose a simulated annealing genetic algorithm (SAGA), which employs simulated annealing to decide whether to accept the chromosome after crossover and mutation or not. By admitting some bad chromosomes into the next generation, this algorithm enlarges the range of parameter optimization, improves the climbing ability and the optimal range. Furthermore, [10] proposes a quantum genetic algorithm (QGA), which employs a quantum bit to encode chromosomes. It also introduces a quantum revolving door to update the population and to make the algorithm more nonlinear and non-deterministic, in conformity with the evolutionary model of the social intelligent community. This method works without–a priori and historical experience. However, it requires the parameters affecting the performance of the system to be expressed as a more accurate formula. In addition, it always takes several iterations to converge to the optimal target value. Therefore, the convergence rate is slow and the computational cost is quite large.

Considering the shortcomings of the existing genetic algorithms, this paper proposes an algorithm named Rule-Reduced Genetic Algorithm (RRGA) by combining decision rules with GA [12-13]. The idea of reduced-rules is introduced into the algorithm to improve the convergence rate of GA, as well as to decrease the complexity of the algorithm and ensure timely decisions. The innovation of the proposed algorithm is as follows. Firstly, by condensing the decision space according to a certain criterion without influencing the decision results, the order of the decision space can be reduced from 10^4 to 10^2. This change reduces the time overhead for searching the decision space. Secondly, the RS theory that can be done offline without any a priori is employed to extract decision rules from the condensed space. Thirdly, by introducing these rules into the initialization of GA, the convergence rate can be improved remarkably. Finally, the anti-jamming decision objective function which maximizing the normalized transmission rate at the expense of minimizing the normalized transmitting power is applied so as to reduce the dependency on the weights.

Compared with the existing algorithms, pre-processing is necessary for the RS theory employed in the decision-making space reduction, which requires additional calculations. Fortunately, the pre-processing can be completed in advance and stored, and then the impact on the overall system complexity is negligible.

The remainder of the paper is organized as follows. The anti-jamming decision-making model is introduced in Section 2. The reduction of the decision space based on the RS theory and the extraction of decision rules are presented in Section 3. The objective function and RRGA algorithm are proposed in Section 4, where two genetic algorithms named traditional genetic algorithm and the adaptive genetic algorithm are utilized respectively. In Section 5, the simulations and analysis are provided. Finally, the paper is concluded in Section 6.

2. Anti-jamming Decision-making Model

The anti-jamming decision-making based on the RRGA approach condenses the decision space of the system at first, and then applies the RS theory to obtain decision rules. On one hand, the decision engine improves the initial population according to these rules. On the other hand, it identifies the objective function according to the parameters of the electromagnetic environment (such as the signal-to-jamming ratio (SJNR) of each channel), user's requirements (such as the BER threshold), and the decision criterion. The GA searches throughout the decision space until it acquires the proper parameters. The anti-jamming decision-making model based on jamming cognitive is shown in **Fig. 1**.

According to the anti-jamming decision-making model shown in **Fig. 1**, we have the following assumptions:

(1) The number of modulation modes is M_1, all these modes constitute a modulation subspace which is defined as $\mathbf{Mod} \triangleq \{Mod_1, Mod_2, ..., Mod_{M_1}\}$.

(2) The number of encoding rate is M_2, all these rates constitute an encoding subspace that is defined as $\mathbf{Cod} \triangleq \{Cod_1, Cod_2, ..., Cod_{M_2}\}$.

(3) The minimum transmitting power is $P_{s\min}$, while the maximum transmitting power is $P_{s\max}$. The number of power grade is N_P. All these grades constitute a power subspace that is defined as $\mathbf{Pow} \triangleq \{P_{s1}, P_{s2}, ..., P_{sN_p}\}$.

(4) The system has K non-overlapping channels, where each communication occupies one channel. All these channels constitute a channel subspace that is defined as $\mathbf{CH} \triangleq \{CH_1, CH_2, ..., CH_K\}$.

(5) Use SJNR to represent the jamming state of the Kth channel. Each channel's SJNR is decided by the jamming environment, which is out of control. All the jamming states constitute state space of decision-making defined as $\gamma = \{\gamma(1), \gamma(2), ..., \gamma(K)\}$. All the states are to be provided by the cognitive model, which is known a priori.

(6) The system's constraints are obtained from the user requirement U_{req}, which defines the objective function together with the decision criterion. In this paper, user requirement is to keep the BER below a pre-defined threshold. The decision criterion is to maximize the normalized transmission rate at the expense of minimizing the normalized transmitting power.

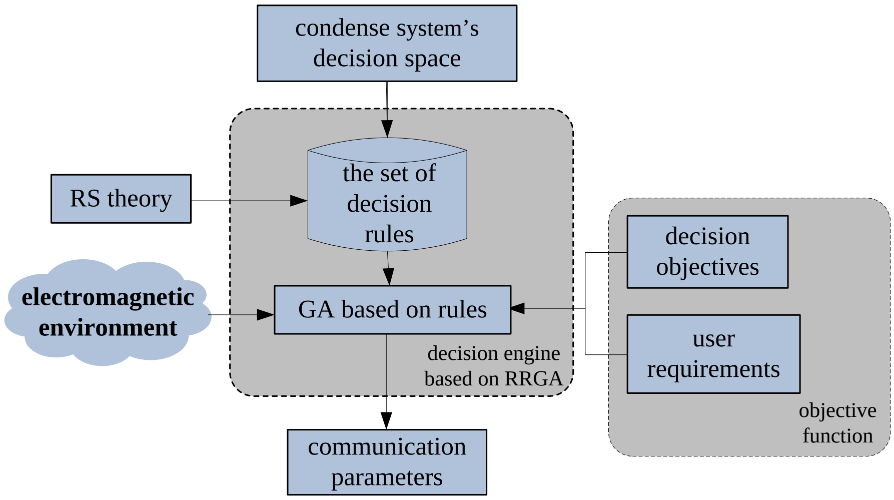

Fig. 1. Anti-jamming decision-making model

Therefore, the decision space can be defined as $\Psi \triangleq \mathbf{Mod} \times \mathbf{Cod} \times \mathbf{Pow} \times \mathbf{CH}$, which is the Cartesian product of all the parameters. The number of the space states is $(M_1 M_2 N_p K)$. For example, if there are 4 modulation schemes, 3 encoding schemes, 80 channels and 20 power grades, theoretically the total number of decision space states is $4 \times 3 \times 20 \times 80 = 19200$. Each decision-making is to choose the most suitable combination of the parameters $\Psi_{opt} = < Mod, Cod, P_s, CH >_{opt}$, which decides the behavior of the decision engine in one communication under some certain criteria in the decision space Ψ.

3. Anti-Jamming Decision Rules with Condensed Decision Space

In view of the advantage that the RS theory needs no any a priori knowledge, it can be applied to wireless communication systems to solve the decision-making problems where no a priori information is available. And the RS theory is capable of dealing with uncertainty and inaccuracy issues.

3.1 Condensed decision space

3.1.1 Reduction of modulation and coding combinations

Since there are M_1 kinds of modulation and M_2 encoding schemes, the number of valid transmission rates would be $K_1 = M_1 M_2$. Because the differences between the practical transmission rate of some modulation-coding combinations lead to poor BER performance or inappropriate SJNR interval, we can abandon certain combinations. We select $K_2 (K_2 < K_1)$ combinations which have proper SJNR interval, the scale of the decision space condensed from $K_1 \times N_p \times K$ to $K_2 \times N_p \times K$.

3.1.2 Reduction of alternative channels

Generally speaking, the large number of alternative channels also leads to the large decision space [12]. Therefore, we can further condense the space by aggregating individual channel states; this aggregation allows the system to make decisions according to several channel states instead of every channel state. After acquiring the best channel state, we select the ideal channel from channel set that corresponds to the channel state. The details are as follows:

As we supposed that the channel interference state $\gamma(k)$ is arbitrary, and it goes against the state aggregation. Therefore, we employ the discrete channel state instead of the original randomly generated channel state, according to Eq. (1) and (2).

$$R_{\min}(k) = \max(\mathbf{R})\Big|_{\gamma_{\min}(k)} \tag{1}$$

$$R_{\max}(k) = \max(\mathbf{R})\Big|_{\gamma_{\max}(k)} \tag{2}$$

where $R_{\min}(k)$ is the maximum transmission rate that can be achieved under the constraints of $\gamma_{\min}(k)$ and user's BER (e.g. $\leq 10^{-4}$). $R_{\max}(k)$ is the maximum transmission rate that can be achieved under the constraints of $\gamma_{\max}(k)$ and user's BER. So the channel state of the system in k can be expressed as $\mathbf{R}_c(k) = [\gamma_{\min}(k), \gamma_{\max}(k)]$.

After the discretization of channel states, the channels with the same state are aggregated into one channel subspace. Eventually, all the k channels can be aggregated into G ($G \leq K_1 + 1$) channel subspaces $\mathbf{CH}_{\mathbf{A1}}$, $\mathbf{CH}_{\mathbf{A2}}$, ... , $\mathbf{CH}_{\mathbf{AG}}$. Each channel state contains K_3 ($0 \leq K_3 \leq K$) channels. In addition, channel subspace $\mathbf{CH}_{\mathbf{Ai}}$ can be expressed as:

$$\mathbf{CH}_{\mathbf{A}i} \cap \mathbf{CH}_{\mathbf{A}j} = \phi, \ \forall i \neq j \tag{3}$$

$$\mathbf{CH}_{\mathbf{A1}} \cup \mathbf{CH}_{\mathbf{A2}} \cup \cdots \cup \mathbf{CH}_{\mathbf{A}G} = \mathbf{CH} \tag{4}$$

It should be noted that, all the channels with very low SJNR are aggregated into one channel subspace, whose state is recorded as 0.

Thanks to the channel state aggregation, the selection of anti-jamming decision-making changes into the selection of channel subspace. And then the decision space is further reduced to $K_2 N_p (K_2 + 1) + K_3$, in which K_3 stands for the number of channels in the selected channel state ($K_3 \leq K$). For example, suppose $K = 80$, $N_p = 20$ and $K_2 = 6$, all these channels aggregate into $K_2 + 1 = 7$ channel states. If choosing a channel state, which contains 23 channels, the decision space reduced from $4 \times 3 \times 20 \times 80 = 19200$ to $6 \times 20 \times 7 + 23 = 863$. That is, its order decreases from 10^4 to 10^2, condensed more than 95%.

So far, the scale of the decision space has been condensed dramatically. Suppose the space contains N decision schemes. If for each scheme we define the modulation mode, the encoding rate, and the channel state as conditional attributes, while the transmitting power is the decision attribute, then we get an initial decision table. This table has two problems: 1) The probable existence of some relevance between different conditional attributes will cause attribute confusion during the decision-making, and then decrease the distinctiveness of the derived rules. 2) The scale of the decision table is still too large, as the rules derived directly are not universal. Therefore, it is necessary to reduce the conditional attributes and their values.

3.2 Reduction rule attributes

This work applies the RS theory [13] to reduce the decision space to obtain the minimized decision rules. We use a tetrad $\mathrm{DT}=(U,A,V,f)$ to represent the decision system, where $U=\{x_1,x_2,...x_N\}$ stands for the decision space, that is, the set of all attributes. $A=C\bigcup D$ is a set of the whole attributes. $C=\{C_1,C_2,C_3\}$ represents conditional attributes, while $D=\{d\}$ stands for the decision attribute. Here, we define the transmitting power as a decision attribute; $V=\bigcup_{a\in A}V_a$ is a set of values for all the attributes, in which V_a is the value domain of attribute a; f is the mapping function from $U\times A$ to V, which sets the value for every attribute of each scheme.

3.2.1 Definitions

For convenience, some definitions related to the RS theory are presented .

Definition 1: Division and Equivalence Class

Assuming that $P\subseteq A$ is a random attribute subset of the decision system, if the whole system is traversed and all the schemes which have an equal attribute value to any attribute in the subset P are put in a set, all those sets form a set cluster, namely a division of U under P, This can be expressed algebraically as:

Given $x\in U$, $y\in U$, $P\subseteq A$ for $\forall a\in P$, if x , y satisfies with

$$f(x,a)=f(y,a) \tag{5}$$

Then, sets of y , y in (5) constitute the division of U under P , denoted as U/P , y is the equivalence class of x , denoted as $[x]_P$.

Definition 2: Positive Domain

Assuming that $P\subseteq C$ is a random conditional attribute subset of decision system, and D is the decision attribute, if Y_i is a subset in the set cluster U/D , at the same time, it is a set in the set cluster U/P , then, all these Y_i are termed the P positive domain of D ,denoted as $POS_P(D)$. This can be expressed like:

$$\mathrm{POS}_P(D)=\bigcup\{Y_i\in U/P\,|\,Y_i\subseteq U/D\} \tag{6}$$

Definition 3: Core

Based on definition 2, for any individual $p_i\in P$, if p_i satisfies $\mathrm{POS}_{P-p_i}(D)\neq\mathrm{POS}_P(D)$, p_i is necessary for D within the range of P , all these p_i constitute a set called the relative- D -core of P , denoted as $\mathrm{CORE}_D(P)$.

Definition 4: Significance

Assuming that C is the set of the whole conditional attributes, $\forall B\subseteq C$ and $\forall\alpha\in C-B$, define

$$\mathrm{sig}(\alpha,B;C)=\frac{\mathrm{card}(U/(B\bigcup\{\alpha\})-\mathrm{card}(U/B))}{\mathrm{card}(U)} \tag{7}$$

as the significance of the attribute α to subset B, in which $\mathrm{card}(X)$ is the number of the individuals in set X.

3.2.2 Attributing reduction algorithm based on RS theory

The procedure of the algorithm is as follows:

Input: Elements of the decision system: U, A, V, f.

Output: The reduction of C with regard to the decision attribute D, denoted as $\mathrm{RED}_D(C)$.

Step 1: Calculate the division of U under the set of condition attribute C with definition 1, which means classifying all the schemes according to C, suppose the total number of the resulting class is H_1, i.e. $U/C = \{X_1, X_2, ..., X_{H_1}\}$.

Step 2: Calculate the division of U under decision attribute D, suppose the total number of the resulting class is H_2, i.e. $U/D = \{X_1, X_2, ..., X_{H_2}\}$.

Step 3: Remove one condition attribute $C_i \in C$ at a time, in succession. Recalculate the division of U under the other conditions, suppose the corresponding number of the class is L_i, i.e. $U/(C - C_i) = \{X_1, X_2, ..., X_{L_i}\}$.

Step 4: Calculate the D positive domain of the set of condition attributes C and $\forall(C - C_i)$ with definition 2, and compare every $\mathrm{POS}_{C-C_i}(D)$ to $\mathrm{POS}_C(D)$ according to definition 3, if the two are not equal, condition attribute C_i is necessary to D, all these necessary condition attributes constitute the relative- D -core of C .Suppose the number of the attribute in the core is l, i.e. $\mathrm{CORE}_D(C) = \{C_1, ..., C_l\}$.

Step 5: If the number of the individuals in the set $\mathrm{CORE}_D(C)$ equals to the number of individuals in set C, let $\mathrm{RED}_D(\mathrm{C}) = \mathrm{CORE}_D(C)$ and go to Step 6. Otherwise, calculate the significance of the individuals that appear in the difference set between C, $\mathrm{CORE}_D(C)$ and D. C_m is the one that has the largest significance value. Let $\mathrm{RED}_D(\mathrm{C}) = C_m \cup \mathrm{CORE}_D(C)$.

Step 6: Output $\mathrm{RED}_D(\mathrm{C})$.

3.3 Attributing value reduction algorithm based on RS theory

Now the decision system becomes $\mathrm{DT}' = (U, A', V, f)$, $A' = RED_D(C) \cup D$. Set each ordered pair of conditional attribute and its value to be a category. Several categories compose a category cluster.

For the *i-th* scheme, all the conditional attribute and its value constitute a category cluster $F_i = \{(C_1', v_{i1}), ..., (C_S', v_{iS})\}, i = 1, 2...., N, S = \mathrm{card}(\mathrm{RED}_D(C))$. In which, C_j' is the *j-th* condition attribute in $\mathrm{RED}_D(C)$, v_{ij} is its value of the *i-th* scheme. Adding decision attribute and its value to each category cluster, we define every scheme as one decision rule. The algorithm proceeds as follows:

Input: Elements of the current decision system: U, A, V, f.

Output: A set of simplified decision rules R^*.

Step1: Change each category cluster into corresponding decision rule r_i, i.e. $r_i : (C_1', v_{i1}) \wedge ... \wedge (C_S', v_{iS}) \to (d, \overline{d}_i)$, in which, "$\wedge$"represents "and", "$\to$"represents "derive", $\overline{d}_i$ is the value of decision attribute of *i-th* decision scheme.

Step2: For each r_i, obtain a new rule r_i' after removing (C_j', v_{ij}), some of the schemes also need to remove the attribute value that C_j' corresponds to. If there are no rules which have the same conditional attributes but a different decision value with r_i, the value v_{ij} corresponding to attribute C_j' is not necessary for the decision attribute D, and then we can remove it. Apply to all the condition attribute values in r_i to obtain a reduction of r_i as r_i^*. Apply this method while traversing all the decision rules.

Step3: Output R^*.

At this time, we have the simplified decision rules, which minimize the transmitting power under the BER constraint.

It shall be noted that the decision rules can be extracted offline, thus brings no additional computational burden during the system operation.

4. Objective Function Design and RRGA Algorithm

For the anti-jamming communication system shown in **Fig. 1**, the most common decision objectives are minimal transmitting power, maximal transmission rate, and minimal BER. All the objectives interfere with each other and cannot reach optimum for all of them at the same time. Currently, the GA-based methods always transform the above three decision objectives into objective functions respectively, and then weight them. However, without having a scientific foundation to determine the weights, the choice of weights depends on a certain subjectivity. Furthermore, this differs greatly from the actual situation of a communication system. For these reasons, we design a new objective function according to the following considerations. Try to meet the user's BER requirement, minimize the transmitting power first, and on that base maximize the transmission rate. In this case, the resulting objective function is closer to the requirements of a practical application. After designing the objective function, combine the decision rules in Section 3 with the traditional genetic algorithm [6, 12] or adaptive genetic algorithm [7], and adaptively select the transmitting power, the channel state, the modulation mode and the coding rate.

4.1 Objective function

In this paper, modulation schemes of PSK, QAM and LDPC with different orders are employed. However, when the BER is under certain threshold (i.e. waterfall region), the index value of the BER of each combination has an approximately linear relationship with the corresponding SJNR. Thus, a straight-line approximation is used to match this curve to get a simple BER formula. The normalized transmitting power $f_{norm-power}$ and the normalized transmission rate $f_{norm-put}$ are defined as follows respectively:

$$f_{norm-power} = \frac{p_i}{p_{\max}} \tag{8}$$

$$f_{norm-put} = \frac{C_i \times \log_2 M_i}{C_{\max} \times \log_2 M_{\max}} \tag{9}$$

where p_i represents the transmitting power of the *i-th* scheme and $p_{\max}$ represents the maximum transmitting power. C_i represents the coding rate of the *i-th* scheme and M_i

represents the modulation mode of the $i\text{-}th$ scheme, $C_{\max}$ represents the maximum coding rate, while $M_{\max}$ represents the maximum modulation mode. Then the objective function f can be defined as:

$$f = \frac{f_{\max-put}}{f_{\min-power}} \tag{10}$$

where $f_{\min-power}$ represents the minimum of $f_{norm-power}$ the algorithm can find under the requirement of a pre-defined target BER, while $f_{\max-put}$ represents the maximum of $f_{norm-put}$ the algorithm can find under the condition of $f_{\min-power}$. The target of anti-jamming decision-making procedure is to adapt the communication parameters to maximize f as defined in Eq.(10).

4.2 Adaptive genetic algorithm

The procedure of the traditional GA (Tra GA) contains coding, fitness calculation, selection, crossover and mutation [12]. But adaptive genetic algorithm [7] (AGA) has proportional selection. It is the abbreviation of genetic algorithm with adaptive crossover and mutation operation. The convergence of the genetic algorithms primarily depends on their core operations of crossover and mutation operator because crossover operator offers the global search capability and mutation operator offers the local search capability. AGA adjusts the crossover and mutation rate to improve the traditional genetic algorithm.

$$p_c = \begin{cases} p_{c\_\max} - (\dfrac{p_{c\_\max} - p_{c\_\min}}{it\max}) * iter, & f^{'} > f_{avg} \\ p_{c\_\max} & , f^{'} \le f_{avg} \end{cases} \tag{11}$$

$$p_m = \begin{cases} p_{m\_\min} - (\dfrac{p_{m\_\max} - p_{m\_\min}}{it\max}) * iter, & f^{'} > f_{avg} \\ p_{m\_\min} & , f^{'} \le f_{avg} \end{cases} \tag{12}$$

where p_c represents crossover probability, $p_{c\_\max}$ and $p_{c\_\min}$ are the maximum and minimum crossover probability respectively, p_m represents mutation probability, $p_{m\_\max}$ and $p_{m\_\min}$ are the maximum and minimum mutation probability respectively, $it\max$ represents the maximum generation, $iter$ represents current generation, f_{avg} represents the average fitness of population, f' represents the bigger fitness in two individuals to crossover, f represents the fitness in individual to mutation.

Eq. (11) and (12) show that if the individual is poor (that is, fitness value is less than the average fitness), it would give larger crossover probability and smaller mutation probability; if the individual is good (fitness value is greater than the average fitness value), the crossover probability and the mutation probability will be adjusted. This measure contributes to protect the individual an effective model of good, easy to find the global optimum and prevent "premature" phenomenon.

In addition, comparison of individual fitness values is increased or decreased after crossover and mutation. Compared with the traditional algorithm, this measure ensures that the new individual generated by genetic manipulation is excellent and accelerates the speed of the evolution of the genetic algorithm so that it can avoid the evolution of individual self-degradation.

4.3 RRGA Algorithm

In this paper, we encode working parameters in the form of binary, and then connect them to form a chromosome. After generating the initial population randomly, we screen it according to the decision rules, by utilizing the objective function as the criterion to choose superior ones. Then the superior ones are crossed over, recombined, and mutated. The process is iterated over the whole population. In this paper, we apply the form of roulette to choose the superior chromosomes, and then use the single-point crossover and basic-point mutation method. The population evolves during iteration, and generates chromosomes, which are close to the optimum gradually. The algorithm flow chart is shown in **Fig. 2**.

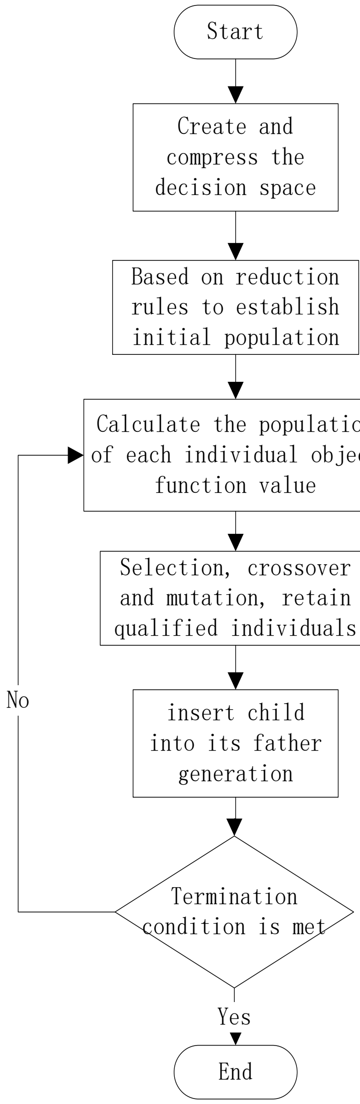

Fig. 2. Flow chart of RRGA algorithm

The procedure of RRGA is as follows:

Step 1: Set up the decision space, condense it under the condition of not influencing the decision result.

Step 2: Reduce the decision space and then obtain the simplified decision rules.

Step 3: Initialize the population according to the value range of each parameter; initialize the iteration counter.

Step 4: Screen the population according to the rules obtained in Step 2, acquiring a new population with all feasible schemes.

Step 5: Calculate the objective value of every chromosome according to Eq. (8), (9), and (10).

Step 6: Choose several chromosomes, which have superior objective value, then crossover, recombine, mutate them, and get child generation. Calculate BER (bit error ratio) of each chromosome according to its SJNR (signal to jamming and noise ratio) and the BER formula, and then reserve those chromosomes, which conform to user's BER requirement. Return to Step 5, get the objective value of every chromosome in child generation, insert superior child chromosome into its father generation, and get the complete population.

Step 7: Complete one iteration, increment the iteration counter. If the number of iterations is smaller than a pre-defined threshold, return to Step 5 or Step 6, or stop the iteration.

5. Simulations and analysis

As shown in **Table 1**, six modulation-encoding combinations that have proper SJNR intervals are selected.

Table 1. Proper modulation-encoding combinations

	NO.1	NO.2	NO.3	NO.4	NO.5	NO.6
Modulation Mode	BPSK	QPSK	QPSK	QPSK	8QAM	32QAM
LDPC Encoding Rate	1/4	1/4	1/2	4/5	4/5	4/5
Normalized Rate	0.0625	0.125	0.25	0.4	0.6	1.0

The BER performance of the 6 types of modulation and coding combinations in the case of Rician channel is presented in **Fig. 3**.

Each SJNR interval of modulation and coding scheme can be achieved from **Fig. 3**, and is shown in **Table 2**.

In order to obtain the minimum decision rules, firstly a decision table shall be set up, in which the decision schemes are the permutations and combinations of the 6 combinations as shown in **Fig. 3** and the 7 channel states as shown in **Table 2**. The target BER is 10^{-4}. We can obtain the channel state of each combination according to the BER target, and calculate the minimum value range of transmitting power. The minimum transmitting power is taken as the decision criterion. The value domain of each attribute in the decision table is expressed as follows: 1) Modulation mode (C_1): BPSK, QPSK, 8QAM, 32QAM. 2) Encoding rate (C_2): $1/4$, $1/2$, $4/5$. 3) Channel state (C_3): the channel states under the condition of minimum transmitting power, as shown in **Table 2**. 4) Transmitting power (d): $0 \sim 20\text{dBm}$, with intervals of 0.1dBm. Thus the size of decision space is $6\times 7\times 200 = 8400$. Part of the decision table is given in **Table 3**. Different from the approach in **Table 1**, the BER target can be reached by increasing the transmitting power in case the channel state is 0.

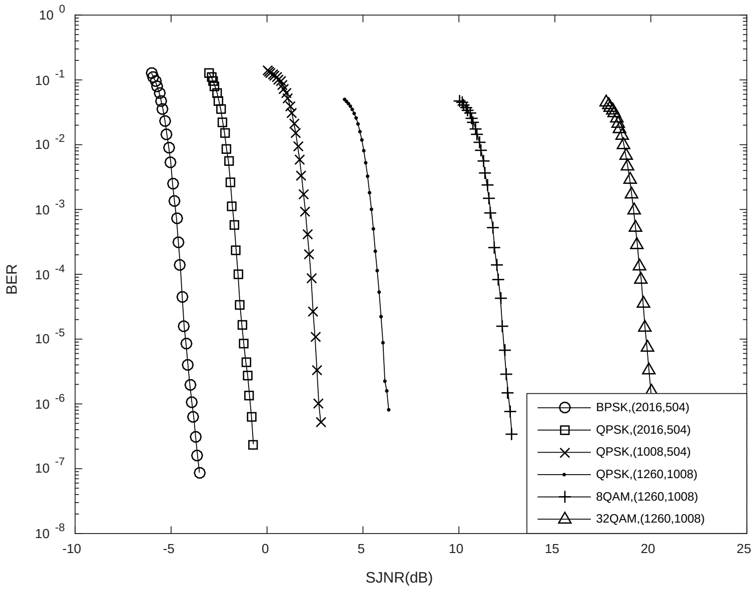

Fig. 3. BER performance of different combinations of LDPC coding and modulation

Table 2. SJNR interval of each modulation-encoding combination

BER	State 0	State 1	State 2	State 3	State 4	State 5	State 6
10^{-4}	(-6,-4.4)	[-4.4,-1.5)	[-1.5,2.3)	[2.3,5.8)	[5.8,12.0)	[12.0,19.5)	≥19.5
10^{-5}	(-6,-4.2)	[-4.2,-1.2)	[-1.2,2.7)	[2.7,6.0)	[6.0,12.3)	[12.3,19.8)	≥19.8
10^{-6}	(-6,-3.8)	[-3.8,-0.8)	[-0.8,2.7)	[2.7,6.3)	[6.3,12.7)	[12.7,20.1)	≥20.1

Table 3. Anti-jamming decision table

Schemes U	Condition Attribute C			Decision Attribute D
	Modulation C1	Encoding C2	Channel C3	Power（dBm）
1	BPSK	1/4	0	(0,20)
2,3,4,5,6,7	BPSK	1/4	1,2,3,4,5,6	0
8	QPSK	1/4	0	(2.9,20)
9	QPSK	1/4	1	(0,2.9]
10,11,12,13,14	QPSK	1/4	2,3,4,5,6	0
15	QPSK	1/2	0	(6.7,20)
16	QPSK	1/2	1	(3.8,6.7]
17	QPSK	1/2	2	(0,3.8]
18,19,20,21	QPSK	1/2	3,4,5,6	0
22	QPSK	4/5	0	(10.2,20)
23	QPSK	4/5	1	(7.3,10.2]
24	QPSK	4/5	2	(3.5,7.3]
25	QPSK	4/5	3	(0,3.5]
26,27,28	QPSK	4/5	4,5,6	0
29	8QAM	4/5	0	(16.4,20)
30	8QAM	4/5	1	(13.5,16.4]

Schemes U	Condition Attribute C			Decision Attribute D
	Modulation C1	Encoding C2	Channel C3	Power（dBm）
31	8QAM	4/5	2	(9.7,13.5]
32	8QAM	4/5	3	(6.2,9.7]
33	8QAM	4/5	4	(0,6.2]
34,35	8QAM	4/5	5,6	0
36	32QAM	4/5	2	(17.2,20]
37	32QAM	4/5	3	(13.7,17.2]
38	32QAM	4/5	4	(7.5,13.7]
39	32QAM	4/5	5	(0,7.5]
40	32QAM	4/5	6	0

By utilizing the method of Sec. 4, one can achieve the minimal decision table as shown in **Table 4**.

Table 4. The minimal decision table

Channel State C_3	Modulation Mode C_1	Encoding Rate C_2	Transmitting Power D
0	BPSK	—	(0,20)
	QPSK	1/4	(2.9,20)
	—	1/2	(6.7,20)
	QPSK	4/5	(10.2,20)
	8PSK	4/5	(16.4,20)
1	BPSK	—	0
	QPSK	1/4	(0,2.9]
	—	1/2	(3.8,6.7]
	QPSK	4/5	(7.3,10.2]
	8QAM	—	(13.5,16.4]
2	—	1/4	0
	—	1/2	(0,3.8]
	QPSK	4/5	(3.5,7.3]
	8QAM	—	(9.7,13.5]
	32QAM	—	(17.2,20]
3	—	1/2	0
	QPSK	4/5	(0,3.5]
	8QAM	—	(6.2,9.7]
	32QAM	—	(13.7,17.2]
4	QPSK	—	0
	8QAM	—	(0,6.2]
	32QAM	—	(7.5,13.7]
5	8QAM	—	0
	32QAM	—	(0,7.5]
6	32QAM	—	0

The universal decision rules can then be achieved based on the core value table after the rules reduction, as given in **Table 5**.

In practice, the interference information is reflected in the channel states. As can be seen from the decision rule set, if the channel state is determined, one can still minimize the transmitting power without making a choice of all the condition attributes. To some extent, it reduces the complexity of the decision-making process. For example, $(c_1, BPSK) \wedge (c_3 \neq 0) \to p = 0$ (coverage rules 2-7). It means that as long as the selected channel is not 0 and when the modulation is $BPSK$, it can be determined without considering coding rate and that the minimum transmitting power is 0.

For the convenience of binary-coded GA, it is supposed that the transmitting power is in the range $0 \sim 25.5\text{dBm}$ with a 0.1dBm interval, and encoded in 8-bit binary. The SJNR is $-4 \sim 21.5\text{dBm}$ with a 0.1dBm interval, and encoded with 8-bit binary as well. In addition to the 6 modulation-encoding combinations shown in **Fig. 2**, and encoded with 3-bit binary. After generating the initial population, we screen it with the rules shown in **Table 4**, and integrated the chromosomes that meet the rules into the new population, then evolved it to reach the optimum. The parameter settings in the GA are as follows: the selection probability is 0.8, the crossover probability is 0.8, the mutation probability is 0.01, the amount of population is 150, and the maximum evolutionary generation is 300.

Table 5. Decision Rules

Decision Rules	Object Covered
$(C_1, BPSK)\Lambda(C_3,0) \to p \in (0,5.6)$	{1}
$(C_1, BPSK)\Lambda(C_3 \neq 0) \to p = 0$	{2,3,4,5,6,7}
$(C_1, QPSK)\Lambda(C_2,1/4)\Lambda(C_3,1) \to p \in (2.9,8.5)$	{8}
$(C_1, QPSK)\Lambda(C_2,1/4)\Lambda(C_3,1) \to p \in (0,2.9]$	{9}
$(C_2,1/4)\Lambda(C_3,2) \to p = 0$	{10}
$(C_2,1/4)\Lambda(C_3,3) \to p = 0$	{11}
$(C_1, QPSK)\Lambda(C_3,4) \to p = 0$	{12,19,26}
$(C_1, QPSK)\Lambda(C_3,5) \to p = 0$	{13,20,27}
$(C_3,6) \to p = 0$	{14,21,28,35,40}
$(C_2,1/2)\Lambda(C_3,0) \to p \in (6.7,12.3)$	{15}
$(C_2,1/2)\Lambda(C_3,1) \to p \in (3.8,6.7]$	{16}
$(C_2,1/2)\Lambda(C_3,2) \to p \in (0,3.8]$	{17}
$(C_2,1/2)\Lambda(C_3,3) \to p = 0$	{18}
$(C_1, QPSK)\Lambda(C_2,4/5)\Lambda(C_3,0) \to p \in (10.2,15.8)$	{22}
$(C_1, QPSK)\Lambda(C_2,4/5)\Lambda(C_3,1) \to p \in (7.3,10.2]$	{23}
$(C_1, QPSK)\Lambda(C_2,4/5)\Lambda(C_3,2) \to p \in (3.5,7.3]$	{24}
$(C_1, QPSK)\Lambda(C_2,4/5)\Lambda(C_3,3) \to p \in (0,3.5]$	{25}
$(C_1, 8PSK)\Lambda(C_3,0) \to p \in (16.4,22.0)$	{29}
$(C_1, 8PSK)\Lambda(C_3,1) \to p \in (13.5,16.4]$	{30}
$(C_1, 8PSK)\Lambda(C_3,2) \to p \in (9.7,13.5]$	{31}
$(C_1, 8PSK)\Lambda(C_3,3) \to p \in (6.2,9.7]$	{32}
$(C_1, 8PSK)\Lambda(C_3,4) \to p \in (0,6.2]$	{33}

$(C_1, 8PSK)\Lambda(C_3, 5) \to p = 0$	{34}
$(C_1, 32QAM)\Lambda(C_3, 2) \to p \in (17.2, 21]$	{36}
$(C_1, 32QAM)\Lambda(C_3, 3) \to p \in (13.7, 17.2]$	{37}
$(C_1, 32QAM)\Lambda(C_3, 4) \to p \in (7.5, 13.7]$	{38}
$(C_1, 32QAM)\Lambda(C_3, 5) \to p \in (0, 7.5]$	{39}

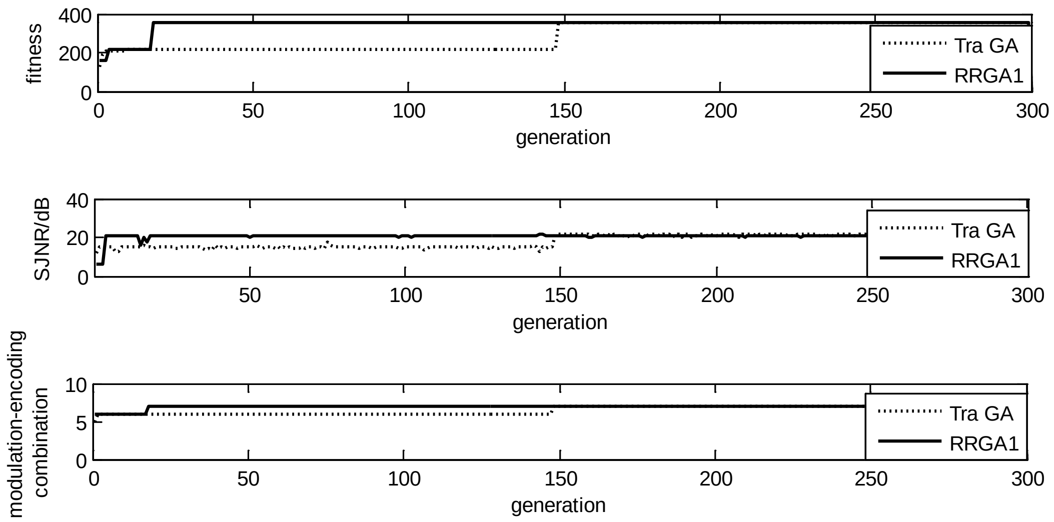

Fig. 4. Comparison of Tra GA with RRGA1

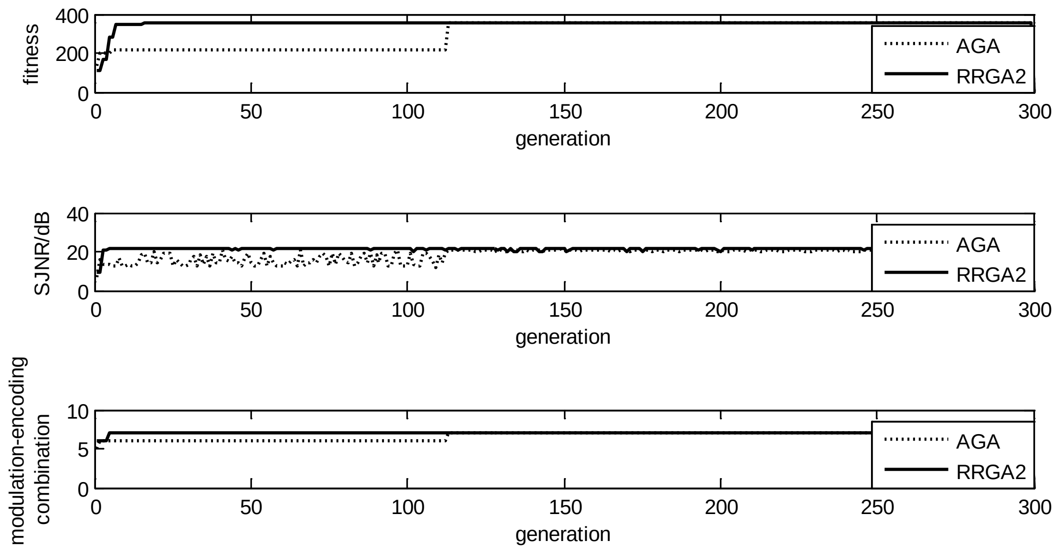

Fig. 5. Comparison of AGA with RRGA2

Fig. 4 and **Fig. 5** illustrate the design of objective function according to 4.1 and three operational parameters selection results that the anti-jamming decision-making system uses before and after the reduction in GA. In the implementation of RRGA, the use of the Tra GA is named RRGA1; the use of the AGA is named RRGA2.

The overlapping part of the two curves in **Fig. 4** and **Fig. 5** means the same results are obtained using these two different methods. In the later stage of evolution, all curves tended to be stable, which means parameters-adaptation had reached the optimum. During the evolution, the value of a parameter changed within its domain and stayed on a fixed value eventually. The parameter-adaptation results are SJNR=21.4dBm; modulation-encoding combination is (32QAM, 4/5).

The smaller number of evolutionary generation is needed to reach the same objective value, the higher the convergence rate of an algorithm. RRGA has a much higher convergence rate than the traditional GA, which results from screening the initial population by decision rules, and by decreasing the scale of the population on the condition of not losing feasible schemes. The computational complexity of GA is mainly in the calculation of objective function. AGA algorithm is mainly concentrated in the calculation of the objective function out of local optimal to overcome "premature". By designing a simplified objective function than those weight-based, the convergence rate can be improved significantly.

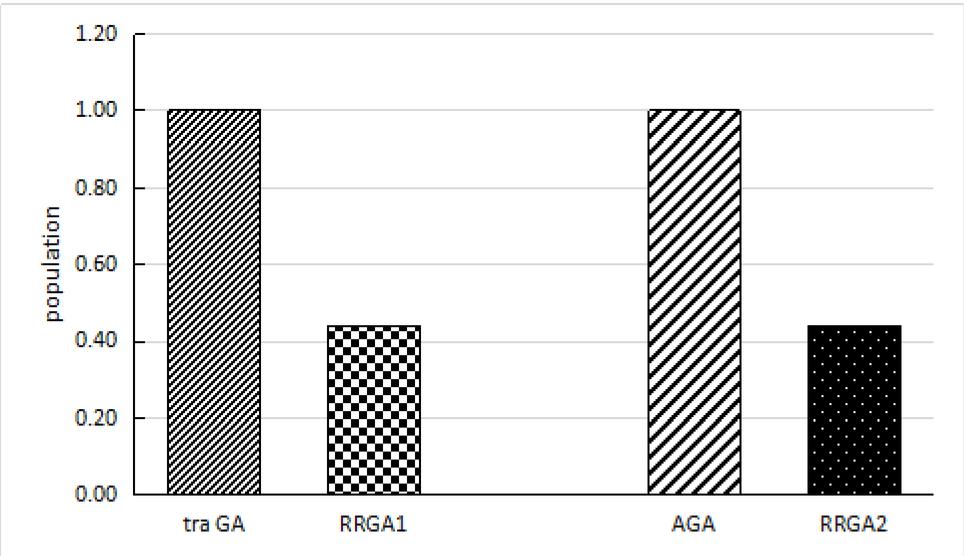

Fig. 6. Normalized anti-jamming decision's initial population in different algorithms

The experiment is repeated for 100 times independently, and the objective function is optimized by using the Tra GA, AGA and two types of proposed RRGA (named RRGA1 and RRGA2). Tra GA parameters are normalized as the benchmark and the other algorithms (AGA, RRGA1 and RRGA2) are compared with it.

Fig. 6 shows the comparison of population before and after the reduction. It can be seen from **Fig. 6**, the initial population of two genetic algorithms (Tra GA and AGA) is the same. That means the initial population of RRGA1 and RRGA2 are the same after using reduced-rules. The population after reduction is only the 43.754% of the original one.

Fig. 7 and **Fig. 8** are the comparison of generation and the average SJNR of each algorithm to Tra GA before convergence.

As can be seen from the results of the **Fig. 7** and **Fig. 8**, when the objective function optimized, the results of RRGA1 and RRGA2 are much better than the Tra GA and AGA. The results demonstrated that compared with Tra GA and AGA, RRGA1 and RRGA2 have strongly improved in search efficiency and convergence speed.

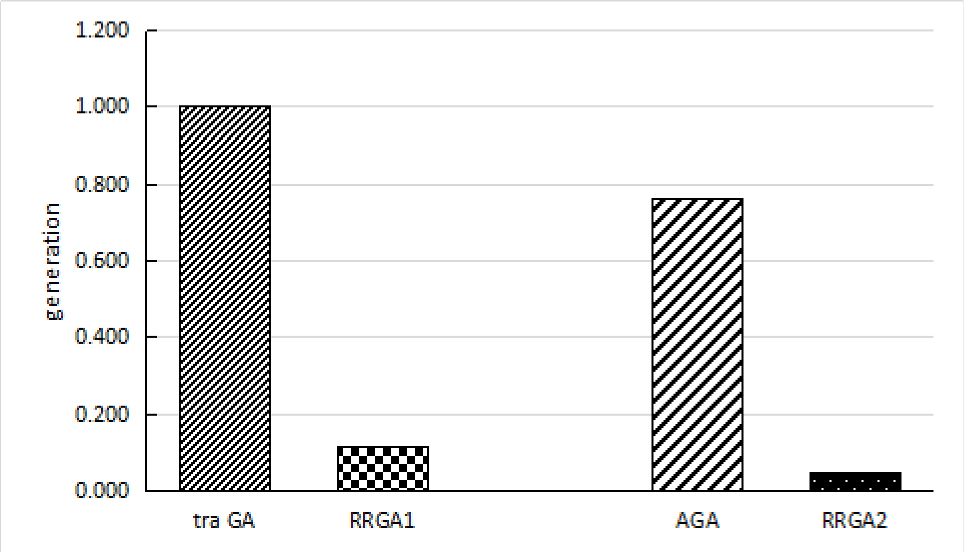

Fig. 7. Normalized evolution generation comparison chart

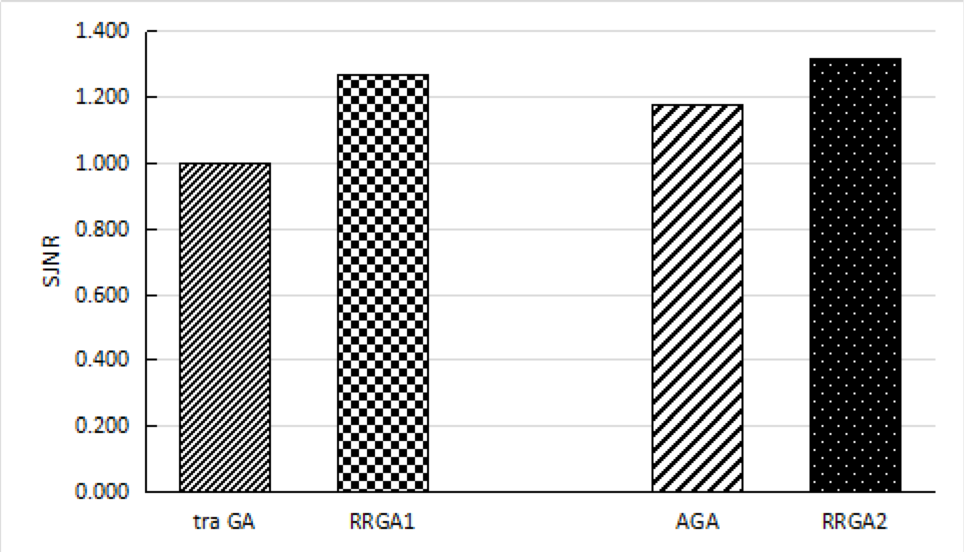

Fig. 8. Normalized average SJNR comparison chart

6. Conclusions

In this paper, an anti-jamming decision-making method named RRGA is proposed, which combines the reduced decision rules and GA, and utilizes the adaptation of communication parameters. Without loss of generality, two typical genetic algorithms (Tra GA and AGA) are simulated separately. Simulation results prove that RRGA1 and RRGA2 are superior to Tra

GA and AGA in terms of search efficiency, convergence rate and algorithm stability. The proposed method condenses the decision space at first, then evolves the resulting population under the condition of not losing feasible schemes, which finally reduces the decision time under the condition of not influencing the decision accuracy. As in practice, each decision objective weight value cannot be given accurately, we also proposes the criteria of minimizing the normalized transmitting power and maximizing the normalized transmission rate, in the presence of the BER constraint. Therefore, it is also more applicable than traditional methods. In the future, other evolutionary algorithms can also be considered.

References

[1] He A., Kyung Kyoon Bae, Newman, T.R., et al., "A Survey of Artificial Intelligence for Cognitive Radios[J]," *IEEE Transactions on Vehicular Technology*, vol.59, no.4, pp.1578-1592, 2010. Article (CrossRef Link)

[2] Lei Xu, Tong-ming Lv, Qian-mu Li, et al., "Proportional Fair Resource Allocation Based on Chance-Constrained Programming for Cognitive OFDM Network[J]," *Wireless Personal Communications*, vol.79, no.2, pp.1591-1607, 2014. Article (CrossRef Link)

[3] Lei Xu, Jun Wang, Yaping Li, et al., "Resource Allocation Algorithm based on Hybrid Particle Swarm Optimization for Multiuser Cognitive OFDM Network," *Expert Syst*. Appl. vol. 42, no. 20, pp.7186-7196, 2015. Article (CrossRef Link)

[4] Liang Xiao, Tianhua Chen, Jinliang Liu, et al., "Anti-jamming Transmission Stackelberg Game With Observation Errors [J]," *IEEE Communications Letters*, vol. 19, no. 6, pp.949-952, 2015. Article (CrossRef Link)

[5] T.R.Newman. Multiple objective fitness for cognitive radio adaption [M].ProQuest,2008. Article (CrossRef Link)

[6] T.R.Newman, Rajbanshi, "Population adaptation for genetic algorithm-based cognitive radios[J]," *Mobile Networks and Applications*, vol. 13, no. 5, pp.442-451, 2008. Article (CrossRef Link)

[7] Xiaoming Dai, "Allele Gene Based Adaptive Genetic Algorithm to the Code Design[J]," *IEEE Transactions on Communications*, vol. 59, no. 5, pp. 1253-1258, 2011. Article (CrossRef Link)

[8] Guangming Lv, Xiaomeng Sun, Jian Wang, "A simulated annealing- new genetic algorithm and its application, Electronics and Optoelectronics (ICEOE)," in *Proc. of 2011 International Conference on*, vol. 3, no.1, pp.29-31, 2011. Article (CrossRef Link)

[9] Jin C, "Software reliability prediction based on support vector regression using a hybrid genetic algorithm and simulated annealing algorithm [J]," *Software, IET*, vol. 5, no. 4, pp.398-405, 2011. Article (CrossRef Link)

[10] Tzyy-Chyang Lu, Gwo-Ruey Yu, Jyh-Ching Juang, "Quantum-Based Algorithm for Optimizing Artificial Neural Networks[J]," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 24, no. 8, pp. 1266-1278, 2013. Article (CrossRef Link)

[11] Ho S.L, Shiyou Yang, Guangzheng Ni, et al., "A Quantum-Based Particle Swarm Optimization Algorithm Applied to Inverse Problems[J]," *IEEE Transactions on Magnetics*, vol.49, no.5, pp.2069-2072, 2013. Article (CrossRef Link)

[12] Shengbo Yao, Chaoyuan Yue, "Approach to stochastic multi-attribute decision problems using rough sets theory[J]," *Journal of Systems Engineering and Electronics*, vol. 17, no. 1, pp. 103-108, 2006. Article (CrossRef Link)

[13] Ikno Kim, Yu-Yi Chu, Watada J, et al., "DNA-Based Algorithm for Miniminzing Decision Rules:A Rough Sets Approach[J]," *IEEE Transactions on Nano Bioscience*, vol. 10, no. 3, pp. 139-151, 2011. Article (CrossRef Link)

Jin Hui received her B.E. degree in Information Engineering from Nanjing University of Aeronautics and Astronautics, Nanjing, China in 2016. She is now pursueing her M.S. degree in Communication and Information System at Nanjing University of Aeronautics and Astronautics. She is the holder of 1 patent. Her research interest is in the area of anti-jamming technology based on cognitive radio.

Song Xiaoqin received her Ph.D. degree in communication engineering from Southeast University, Nanjing, China in 2007. Before that, she has been worked with Hewlett-packard China and Siemens China, etc. engaged in the technical research of 3G mobile communication systems. She is now with the College of Electronic and Information Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, China. She authored more than 30 journal and conference papers and more than 20 patents. Her research interests mainly focus on cooperation communication and cognitive radio.

Wang Miao received her M.S. degree in Information Engineering from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2015. She is the author of 3 journal and conference papers, and the holder of 7 patents. Her research interest is in the area of anti-jamming technology based on cognitive radio.

Niu Yingtao received his M.S. degree from PLA Commanding Communication Academy, China, in 2005, and received his Ph.D. degree from Institute of Communication Engineering, PLA University of Science and Technology, China, in 2008. He is currently a senior engineer with Nanjing Telecommunication Technology Institute, China. He has authored more than 20 journal and conference papers. His main research interests are cognitive radio theory and techniques, with particular emphasis on communication signal sensing and communication decision-making algorithm in cognitive radio systems.

Li Ke received his Ph.D. degree in Information & Signal Processing from Southeast University, Nanjing, China in 2000. He has been with electrical and computer engineering dept. of Concordia University, Montreal, Canada, as postdoctoral research fellow during 2002~2003. He is now a full professor in telecommunication engineering at Beijing Union University since 2013. He is the (co-)author of more than 40 publications in scientific journals and conferences and more than 30 patents, in the area of signal processing, speech processing, mobile communications and data mining. His research interests are in the area of mobile big data, traffic and user behavior modelling, MIMO and cognitive radio.