

## Research Article

# A Chaotic Hybrid Immune Genetic Algorithm for Spectrum Allocation Optimization in ICRSN

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The growing usage of the industrial cognitive radio sensor network (ICRSN) brings profound changes to the Internet of Things. The ICRSN is an emerging technique to transfer industrial data, which has strict and accurate communication requirements in a large number of areas such as environmental surveillance, building monitoring, control, and many other areas. The problem of maximizing the sum bandwidth by using a spectrum allocation algorithm has been extensively studied in this paper. Inspired by chaos theory and quantum computing, this work presents a new chaotic hybrid immune genetic algorithm (CHIGA). We then introduce a spectrum allocation model that considers both network reward, throughput, and convergence time. The improvement of CHIGA performance through experimental simulations is evaluated in terms of the sum network reward compared to methods based on simulated annealing (SA), ant colony optimization (ACO), and particle swarm optimization (PSO). Simulation results show that the CHIGA has a higher network reward and throughput existing optimized algorithms while maintaining total system throughput.

## 1. Introduction

In the past decades, information and communication technology is developing rapidly. Industrial wireless technology has become a new research hotspot in the field of industrial control [1, 2]. However, spectrum resources have become scarcer. A considerable number of frequency bands are not fully utilized. The currently adopted spectrum allocation strategy has caused some frequency bands to be crowded, while other frequency bands are extremely low. The problems of wireless spectrum resource shortage and spectrum utilization unevenness are studied. The research is focusing on developing new spectrum allocation schemes to maximize the network reward and improve the throughput in industrial cognitive radio sensor networks (ICRSNs) [3].

In general, ICRSNs have typically small devices that can only be equipped with a communication unit with limited communication capabilities [4]. Continuous industrial processes are sensitive to the quality of environmental data, especially in low-cost intelligent automation systems. In ICRSNs, different channels are assigned to users that will generate different channel rewards. The channel reward is generated

when a channel is allocated to a cognitive user. When all channels are assigned to cognitive users, the system will generate a network reward, which can be regarded as the sum of channel reward when all channels are allocated to the user.

Careful dynamic spectrum allocation (DSA) is an important sensor deployment means that has received considerable research interest for maximizing throughput and reward in the past [5, 6]. Although the spectrum resources are limited in ICRSNs, the utilization of spectrum resources can be improved by effective design and management.

In view of the shortage of spectrum resources faced by wireless sensor networks, the DSA technology in ICRSNs was applied to the wireless sensor networks, enabling that the spectrum can be used twice in wireless sensor networks. Hence, a new chaotic hybrid immune genetic algorithm (CHIGA) is proposed, which provides a solution to optimize the demand of users for limited channels in ICRSNs. One goal is to maximize the sum network reward, and the second objective that needs to be optimized is throughput. The spectrum allocation scheme-based CHIGA can make network reward lower and achieve the desired high throughput goals. By comparing the reward of various intelligent algorithms,

the proposed algorithm is introduced finally. It has an advantage in maximizing the network reward and achieving the desired high throughput of spectrum allocation.

## 2. Problem Statement and Our Contributions

Recently, the serious shortage of resources has attracted the attention of researchers [7–10]. They study the problem of wireless spectrum resource shortage and spectrum utilization unevenness. Research is focusing on developing new spectrum allocation schemes in order to maximize the network reward in ICRSNs. In this paper, the purpose of researching this problem is to optimize the network reward and increase the system throughput. In response to the above problems, the DSA technology in cognitive radio is applied in a wireless sensor network to improve system transmission efficiency and spectrum utilization. ICRSNs are, in general, composed of small devices that can only be equipped with a communication unit with limited communication capabilities. Careful dynamic spectrum allocation (DSA) is an important sensor deployment means that has received considerable research interest for maximizing throughput and reward in the past. Although the spectrum resources are limited in ICRSNs, the utilization of spectrum resources can be improved by effective design and management [11]. In [12, 13], the problem of spectrum allocation is proved to be an NP hard and can be solved with an optimized swarm algorithm. The problem of spectrum allocation is difficult to solve as it had been proved to be an NP hard. The system will be too complicated if considering the transmit powers. The spectrum allocation is solved by a simplified graph coloring model. The transmit powers are not considered in this paper, suppose that spectrum sensing is perfect.

Many heuristic-based approximation algorithms for the spectrum allocation problem are proposed [14–19]. A strategy of spectrum allocation that can trade-off between the computations as well as the network reward is researched using a genetic algorithm (GA) [20]. The proposed strategy makes use of a multi-population-based GA rather than a classic GA with one population. However, the rate of convergence could not reach an acceptable point. Researchers introduced particle swarm optimization (PSO) for increasing the total system throughput for better total system throughput in cognitive radio networks [21]. The authors' technique is not only higher throughput considerably but also reduces the computational difficulty. In [22], the ant colony optimization (ACO) is adaptable but affects the issue of a low convergence rate. For the cognitive radio spectrum allocation problem, the authors proposed a simulated annealing- (SA-) based spectrum allocation method, which is discovered to be more useful than PSO strategy [23]. Their work focused on improving the spectrum allocation scheme for sensor sets. But it also suffers from an excessive computational time requirement.

Recently, the immune theory has been proposed as a simple and alternative tool for solving optimization problems [24, 25]. Here, a chaotic hybrid immune genetic algorithm (CHIGA) is proposed to increase the total system throughput of the ICRSNs. In order to optimize the channel allocation

scheme, a fitness function to maximize the network reward of the ICRSNs is given as well as finds a chaotic sequence generator and immune clone operator to speed up the convergence rate.

The CHIGA is a novel framework that combines the characteristics of chaotic operation and immune clone operation in order to carry out effective optimization. The immune operator has an advantage of diversity. Clone and mutation contribute to the creation of new individuals. Immune operation speeds up the convergence of the algorithm. The chaotic operator uses the chaos principle to maximize the global search capability of the CHIGA. The chaotic operator is an effective method for improving global search capabilities. When the number of chaotic searches reaches a certain number, the chaos operator can avoid premature convergence, and the network reward optimized by the CHIGA is 10.61%, 16.14%, and 26.59% higher than ACO, PSO, and SA, respectively, when the number of channels is 20 and number of cognitive users is 40.

Simulations are executed to assess the overall performance of the proposed CHIGA against ACO, PSO, and SA. Simulation results demonstrate that the CHIGA has better consequences than ACO, PSO, and SA while taking the same computational complexity. Furthermore, the optimization employs a chaotic generator to initialize the parameters and avoid local optima effectively.

## 3. System Model

The model of spectrum allocation with limited communication capabilities and spectrum is described. ICRSNs are composed of a quantity of sensor nodes. The structure of ICRSNs is generally composed of three components, namely, a sensing node, a sink node, and a user management center. The transmission of information in the ICRSNs is transmitted and received by the terminal nodes in the network. When these nodes are in the working state, each node transmits the collected information to the sink node. After that, it will be transmitted to the user management center and user terminal through the network [26].

Spectrum allocation technology is a cognitive radio-based spectrum switching technology. The two most important features of ICRSNs are the spectrum sensing and spectrum reconfiguration in the physical layer. The spectrum sensing technology can detect which channel is idle in the current state. All busy and idle states can be recorded and shared.

In each cycle, the system parameters are adjusted. If there is a free channel, users need to be assigned in time. When spectrum allocation is performed by cognitive users, it is necessary to detect whether there is a free spectrum or whether the authorized user is in a free state. The above-mentioned allocation methods are dynamically utilized to maximize the utilization of the spectrum.

In the ICRSN system, the bandwidth, user location, and the number of channels are not fixed. DSA can adjust the spectrum allocation strategy according to user requirements. It improves the flexibility of the system and avoids waste of spectrum holes. Spectrum allocation has a good advantage to solve the problem of sharing spectrum resources.

Cognitive users obtain the available spectrum by the technology of spectrum sensing but cannot directly use spectrum. The spectrum needs to be allocated to users reasonably. Otherwise, there are conflicts between adjacent cognitive users. The technology uses the model of color-sensitive graph coloring (CSGC) which includes channel available matrix, channel reward matrix, interference constraint matrix, and allocation matrix [27]. It has become mature after years of research. Particularly in the era of mobile cellular communications, it can be used to analyze the frequency planning and spectrum allocation of cells. However, when using the model to allocate spectrum to ICRSNs, it is necessary to consider the real-time changes of the main user and other environments. So clear constraints and allocation targets are needed.

A typical spectrum allocation scheme in the ICRSN is studied in [28]. The researchers gave a spectrum allocation method with a limited amount of nodes.

In Figure 1, the graph coloring model is regarded as a network topology, which is composed of authorized users and cognitive users. Four circles represent a sensing range of authorized users, and five pentagrams represent cognitive users. The channels used by authorized users (I-IV) are C, B, A, and B, respectively. The connection between two pentagrams indicates that interference will be produced when two cognitive users use the same spectrum at the same time, which has an effect on the communication. If the cognitive user is located in the coverage of the authorized user, it cannot use the same channel as the authorized user; otherwise, the communication of the authorized user will be affected. For example, cognitive user 3 which is located in the overlapping coverage range of two authorized users (II and III) cannot use channel B and spectrum A. Therefore, channel C can be only selected by cognitive user 3.

In this paper, we adopt the network reward definition given in [29]. Consider an ICRSN system with  $I$  spectrum channels and  $J$  secondary user nodes in the simulation area. Like other models, we consider the channel availability matrix  $T = \{t_{j,i} | t_{j,i} \in \{0, 1\}\}_{J \times I}$ . The channel availability matrix represents the free channel that is available to the user.  $t_{j,i} = 1$  represents that the  $i^{\text{th}}$  channel can be allocated to the  $j^{\text{th}}$  user. If  $t_{j,i} = 0$ , the channel is unavailable.

In the first phase, the channel reward matrix  $R = \{r_{j,i}\}_{J \times I}$  is set to calculate the channel reward. The channel reward represents the reward that users can attain when a channel is assigned to it.  $r_{j,i}$  represents the reward that the  $i^{\text{th}}$  spectrum can be allocated to the  $j^{\text{th}}$  cognitive user.

The interference constraint matrix is  $E = \{e_{j,k,i} | e_{j,k,i} \in \{0, 1\}\}_{J \times J \times I}$ . The interference constraint matrix represents whether two users use one spectrum resource simultaneously impact on other users. If  $e_{j,k,i} = 1$ , the  $i^{\text{th}}$  channel cannot be assigned to the  $j^{\text{th}}$  user and the  $k^{\text{th}}$  user at the same time. If  $e_{j,k,i} = 0$ , there is no interference between the  $j^{\text{th}}$  user and the  $k^{\text{th}}$  user. The  $i^{\text{th}}$  channel can be assigned to the  $j^{\text{th}}$  user as well as the  $k^{\text{th}}$  user simultaneously. If  $j = k$ ,  $e_{j,j,i} = 1 - t_{j,i}$ .

The optimization variable is the allocation matrix. Then, by determining the allocation matrix  $C = \{c_{j,i} | c_{j,i} \in \{0, 1\}\}_{J \times I}$ ,

the sum reward of the network can be maximized while ensuring that all channels have no conflicts. The assignment matrix represents that the channel is allocated to the user without any interference.  $c_{j,i} = 1$  represents that the  $i^{\text{th}}$  spectrum can be allocated to the  $j^{\text{th}}$  cognitive user.  $c_{j,i} = 0$  represents that there is no allocated relationship between the  $i^{\text{th}}$  channel and the  $j^{\text{th}}$  cognitive user.

If a conflict does not exist, the reward of the  $j^{\text{th}}$  user can be represented as  $D = \{d_1, d_2, \dots, d_J\}$ , where  $d_j = \sum_{i=1}^I c_{j,i} r_{j,i}$ . Our goal is to maximize the network reward  $F$  of a system, which can be represented as

$$F(C) = \sum_{j=1}^J d_j, \quad (1)$$

with the constraint

$$r_{j,i} r_{j,k} = 0, \quad \text{if } e_{j,k,i} = 1. \quad (2)$$

Formula (2) ensures that no communication conflicts occur.

$$c_{j,i} \leq t_{j,i}. \quad (3)$$

Formula (3) ensures the spectrum availability of the spectrum assignment matrix.

The second objective that needs to be optimized is throughput, which can be calculated by the formula (4). In this paper, a fixed transmission rate was considered. We consider the throughput weight matrix  $W = \{w_{j,i}\}_{J \times I}$ . The throughput can be evaluated as follows:

$$G(C) = \sum_{j=1}^J \sum_{i=1}^I c_{j,i} w_{j,i}. \quad (4)$$

#### 4. CHIGA for Spectrum Allocation in ICRSNs

Generally speaking, the iterative and hill-climbing algorithms can be mostly converged to a local minimum. In this paper, the spectrum allocation problem in ICRSNs can be turned into a mathematical model; after that, it can be solved by the CHIGA.

In the recent time, it has been known that a hybrid immune operator based on GA has a wide space-search capability [30]. The hybrid algorithm can explore the search space with better solutions within a short span of time. In this paper, we propose a CHIGA for the spectrum allocation problem in ICRSNs which can enhance the network reward. It can also maintain no communication conflicts in the area.

In the CHIGA, the chaotic operator and immune operator are combined to carry out effective optimization. The immune operator has an advantage of diversity. Clone and mutation contribute to the creation of new individuals. Immune operation speeds up the convergence of the algorithm. A chaotic operator is an effective method for solving global optimization of no convex optimization problems.

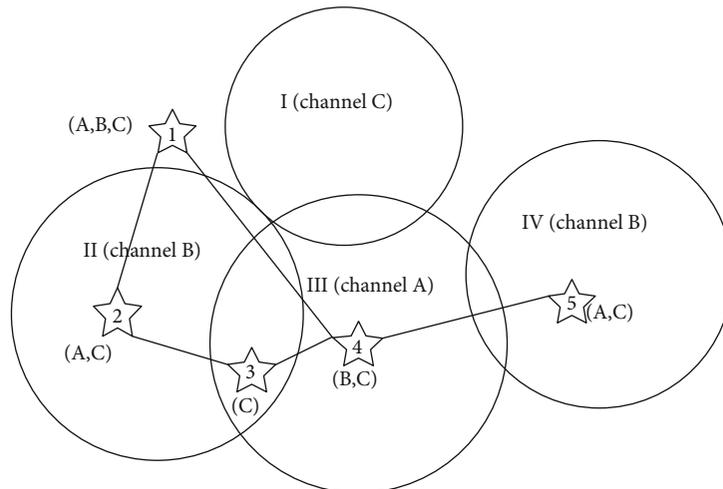


FIGURE 1: Topology of a graph coloring model.

When the number of chaotic searches reaches a certain number, the chaos operator can guarantee the convergence of the CHIGA, and the computational efficiency is typically improved. The CHIGA combines a chaotic operator and immune operator to assess the overall performance.

The traditional genetic algorithm can easily fall into premature convergence in the problem of spectrum allocation [31]. It is hard to close to the optimal reward after the finite iterations. The CHIGA is a heuristic algorithm. In the heuristic algorithm, the optimal solution can be gradually approached after a finite number of iterations. The CHIGA algorithm, which is typically an intelligent optimization scheme, starts from the initial solution and gradually improves the current chromosome by iteratively until the maximum generation is approached.

After a large number of tests, PSO, ACO, and SA find the near-optimal solution after iterations. The immune operator was added based on the traditional genetic algorithm. The performance of the above algorithms was compared. After that, the chaos operator was added to compare network reward. After many experiments, by combining the immune operator and chaotic operator, the overall performance and relevant parameters of the CHIGA are analyzed. The cooperation on the network reward and throughput of the CHIGA, ACO, PSO, and SA is compared and analyzed in section IV.

The simulation results show that the CHIGA can improve network reward and throughput. During each generation in the CHIGA, we create a new population by genetic processes. We first generate a fixed quantity of original individuals with a chaotic generator, in which almost all individuals have poor fitness; this set of individuals is described as the initial population. After that, the main loop was performed in the algorithm. Each one goes as follows: we choose parent individuals in the population in accordance with their relative fitness. Then, the selected individuals are merged by partially mixing their factors to develop new individuals, called offspring. The immune mutation is carried out. The offspring is developed employing a clone operator. Once the offspring fulfills some conditions, it changes some individuals in the population. Then, the fitness of offspring can

be evaluated. The loop will be done over and over again until the breaking condition is fulfilled.

The execution process of the genetic algorithm is a typical iterative process. The main steps are as follows:

*Step 1.* Construct chromosomes that satisfy the conditions. Firstly, binary substrings are concatenated to stand for a chromosome. Secondly, the chromosomes of our CHIGA can be described as a  $J \times I$  binary matrix. Since the CHIGA cannot directly deal with solutions in the space of solution, the solution must be represented in an appropriate form by encoding. The chromosomes of the actual problem have multiple encoding methods, and the selection of the chromosome encoding method should be as close as possible to the problem constraint; otherwise, it will affect the calculation efficiency.

*Step 2.* The initial population is randomly generated. The initial population is a set of chromosomes at the beginning of the search. The number of chromosomes should be appropriately selected.

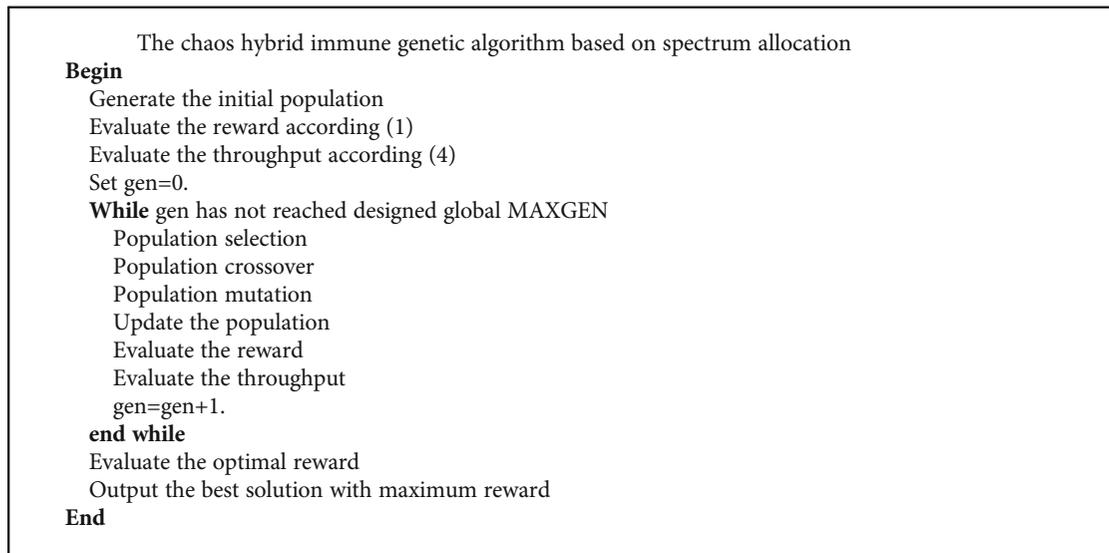
*Step 3.* Calculate the fitness of the chromosomes. Fitness is an indicator of the merits of a chromosome. The CHIGA needs to find the optimal chromosome.

*Step 4.* Produce subpopulations by using a selection operator, crossover operator, and mutation operator.

*Step 5.* Repeat Step 3 and Step 4 until the termination condition is satisfied.

The pseudocode for CHIGA is presented in Algorithm 1. The related source code can be found at [https://www.researchgate.net/publication/344213166\\_GA-optimization-\\_reward](https://www.researchgate.net/publication/344213166_GA-optimization-_reward).

*4.1. Population Encoding.* In the CHIGA, a solution symbolizes a chromosome and the value of fitness at a solution is the objective function value. Because the steps of the CHIGA rely on the theory of biological evolution, we need to translate the



ALGORITHM 1: Algorithm flow ([https://www.researchgate.net/publication/344213166\\_GA-optimization-\\_reward](https://www.researchgate.net/publication/344213166_GA-optimization-_reward)).

actual problem into the form of strings in the progress of a genetic operation, which is named encoding of the chromosome. Chromosome encoding can solve the problem through the form of arranging and combining the gene points of the chromosome to obtain more different forms of chromosomes. A good coding method is very important for solving practical problems.

The CHIGA has two encoding methods, which include binary as well as decimal encoding. The decimal encoding holds a string with  $J$  decimal figures. Each digit in the string is coded ranging from 0 to  $2^I$ . Binary substrings are concatenated to stand for a chromosome which is made up of  $J \times I$  Boolean variables stating whether the spectrum is assigned in the related user or not. This kind of encoding scheme has a positive effect in searching for better individuals, because it can accelerate the optimization speed. Here, the chromosomes of our CHIGA can be described as a  $J \times I$  binary matrix, where  $J$  is the quantity of users and  $I$  is the amount of available spectrum channels. In other words, the  $j^{\text{th}}$  column in the matrix corresponds to user  $J$ . As noted, the quantity of all possible combinations is  $2^{J \times I}$ . Each chromosome in the population can be transformed into a group of selected spectrum channels.

In Figure 2, the mapping process of a chromosome is shown with 5 cognitive users and 6 channels. The  $t_{j,i}$  in the channel availability matrix  $T$  is 1, which represents that the  $i^{\text{th}}$  channel can be allocated to the  $j^{\text{th}}$  secondary user. At the position where the element of channel availability matrix  $T$  is 1, the chromosome  $S$  is a chromosome, which can be mapped to matrix  $C$  with the same underlined position in  $T$ .

**4.2. Generation of Initial Population.** In the CHIGA, a chaotic mutation operator is employed to solve the problem of spectrum allocation. In order to optimize an objective function, the traditional mutation operator is developed by a chaotic mutation operator and employed in the CHIGA. In the cha-

otic mutation operator, the binary individual is applied with a mutation possibility. Unlike traditional mutation operators, if the new binary individual has a lower network reward, the binary individual will not be substituted by a new individual.

A logistic map is applied in the CHIGA. A random mutation bit of random can be obtained by a logistic map. The logistic map was expressed by formula (5) which can obtain chaotic variables. The logistic map is employed to create a random sequence.  $a_k$  represents a chaotic variable between 0 and 1;  $k$  represents iteration ( $k = 1, 2, \dots$ ). The control parameter is 4, which represents the system is completely chaotic. It is demonstrated in (5).

A population of the CHIGA consists of a fixed number of solutions. In this paper, the initialization method used by the CHIGA is as follows. In the first phase, the preliminary population is generated by the chaotic generator randomly and the chromosomes in the current population have a specific chance to recreate their offspring. In expression (6), if  $a_k > 0.5$ ,  $c_{j,i} = 1$  represents that the  $i^{\text{th}}$  spectrum is allocated to the  $j^{\text{th}}$  secondary user. If  $a_k \leq 0.5$ ,  $c_{j,i} = 0$  represents that there is no allocated relationship between the  $i^{\text{th}}$  channel and the  $j^{\text{th}}$  user. Each bit  $c_{j,i}$  in the string can be generated with a logistic map, which can be shown by formula (6).

$$a_{k+1} = 4a_k(1 - a_k), \quad (5)$$

$$c_{j,i} = \begin{cases} 0, & a_k \leq 0.5, \\ 1, & a_k > 0.5. \end{cases} \quad (6)$$

For the spectrum allocation problem in ICRSNs, each chromosome in the population can be regarded as a set of randomly chosen allocation schemes. For each chromosome, a random value can be chosen based on the sum network reward of a solution. If the network reward of a solution is low, a random Boolean matrix is picked from the chaotic generator. This procedure will be repeated  $n$

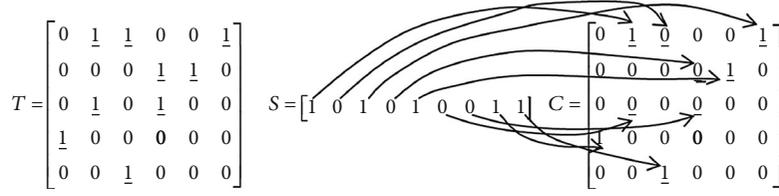


FIGURE 2: Mapping process of a chromosome.

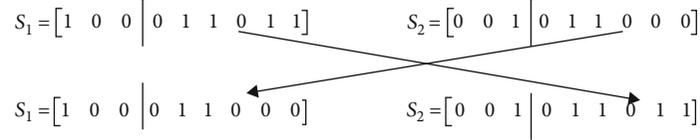


FIGURE 3: Crossover.

times except when the chromosome turns into feasible before  $n$  times. After that, the initial population is produced. In this way, the initialization procedure runs at random so that the variety of initial chromosomes can be well maintained.

**4.3. Selection.** Firstly, each individual performs the selection operation. The process of selecting superior individuals from the group and eliminating inferior individuals is called selection, also known as replication. The selection operation can be used to determine which individual will be inherited from the parent population to the next generation. The decision of the operator immediately has an effect on the outcomes of the CHIGA.

In each generation of the CHIGA, there will be a quantity of parents that were chosen from the current chromosomes to build the newly generated one. The chromosomes will have a higher possibility to be chosen if their fitness value is high. The roulette wheel strategy is applied for the selection possibility of each solution. The individuals can be selected according to the reward of the solution.

$$p_j = \frac{F(j)}{\sum_{j=1}^J F(j)} \quad (j = 1, 2 \dots \dots J), \quad (7)$$

$$P_j = P_{j-1} + p_j \quad (j = 1, 2 \dots \dots J), \quad (8)$$

$$P_{j-1} < \text{rand} < P_j \quad (j = 1, 2 \dots \dots J). \quad (9)$$

The principle of roulette wheel strategy can be shown in formula (7), (8), and (9),  $J$  is the number of chromosomes,  $F_j$  is the reward of the  $j^{\text{th}}$  individual, and  $p_j$  is the ratio of the reward of the  $j^{\text{th}}$  individual to the total reward.  $P_j$  is the sum probabilities of the first  $j$  individuals.  $\text{rand} \in (0, 1)$ . The  $j^{\text{th}}$  chromosome will be picked when the  $\text{rand}$  is between  $P_{j-1}$  and  $P_j$ .

**4.4. Crossover.** The CHIGA performs crossover operation after the above several processes. Its main function is to exchange chromosomes based on the crossover probability to generate new chromosomes. A suitable crossover proba-

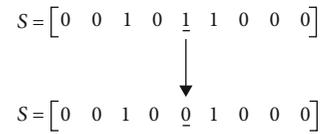


FIGURE 4: Mutation.

TABLE 1: Parameters of the CHIGA.

	Number of iterations	Population size	Gap	Crossover probability	Mutation probability
CHIGA	100	40	0.9	0.8	0.05

bility has advantage to produce a good chromosome and increases the diversity of chromosome produced in the population. However, if the crossover probability is too large, the CHIGA could fall into a completely random search process. The parameter of crossover probability is selected based on the experience. In general, the crossover probability is selected between 0.6 and 0.9. When the optimized problem is changed, the crossover probability may not optimize the objective function suitably. Crossover operations have single-point crossover operation, multipoint cross operation, etc. Single-point crossover can be described as that the two chromosomes are randomly selected in a population with a crossover probability, and the selection of a gene point on the chromosome as an intersection to cross and remove the repeated gene points.

The principle of crossover is that it cannot destroy the well-behaved individuals but produces some new good individuals. The crossover operation mainly produces some solutions with new features and expands the search range of the solution in the process of evolution, so the near-optimal individual could be obtained while analyzing the solutions of different features.

The crossover operation can be described as creating a new solution which is produced simply by the random combination of the partial characteristics of two parent chromosomes. A large amount of variations on crossover operation are put forward. Here, the principle of the crossover operation is given.

TABLE 2: Parameters of the ACO.

	Number of iterations	Population size	Pheromone volatilizing coefficient	Weight of pheromone	Weight of heuristic information
ACO	100	40	0.98	2	2

The crossover operation of the CHIGA is a genetic operator to generate offspring by combining two sections of chromosomes of the parent individuals. Figure 3 shows the process of crossover. The crossover needs to swap the segments of selected chromosomes by generating a random crossover point. The left elements of the first chromosome are inherited from the left elements of the first parent. The remaining elements of the first chromosome are inherited from the right elements of the second parent which do not appear in the first parent. The left elements of the second chromosome are inherited from the left elements of the second parent. The remaining elements of the second chromosome are inherited from the right elements of the first parent which do not appear in the second parent. All components of chromosome inherit from the parents that must keep the sequence as they appear in parents.

**4.5. Mutation.** The mutation operation simulates gene mutations in nature, and the population undergoes crossover operation to achieve gene recombination. After the new gene pattern is generated, the value of gene positions is changed by the mutation operation. Thereby the individuals can be changed. For chromosomes encoded with 0 and 1, the mutation is to reverse the gene values at a certain location, i.e., 0 to 1 and 1 to 0. For other encoding methods of chromosomes, it is possible for a mutation to change the value in a certain location. The mutation operation in the CHIGA improves the quality of the solution after the global search.

The mutation operator can be demonstrated in Figure 4, which indicates the principle of crossover. The mutation operation randomly mutates one point in chromosome  $S$ . The 5<sup>th</sup> element of the parent chromosome is mutated to 0.

The mutation operation of the CHIGA is to replace the value with another randomly selected value in the chromosome. The idea of mutation operation in the CHIGA is produced from the convex set theory. A mutation is a significant operation for the spectrum allocation problem. The number of spectrums and users is randomly selected. A mutation rate governs the possibility that each element has an exact chance of being replaced with a new randomly chosen binary generated by the chaotic generator.

The mutation operation randomly mutates one or more gene points of a chromosome by a mutation probability. The mutation probability is selected based on the experience. In general, the mutation probability is selected between 0.1 and 0.001. When the optimized problem is changed, the mutation probability is not suitable to optimize the objective function. When the real scenario is changed, the parameters may not optimize the objective function suitably.

Mutation has the advantage to produce a good chromosome. However, the mutation operation has both good and bad aspects. The bad aspects are as follows. It destroys the original gene sorting combination in the population and increases the instability of the population; the good aspect

TABLE 3: Parameters of the PSO.

	Number of iterations	Population size	The maximum velocity	The cognitive and social parameters ( $c_1$ and $c_2$ )
PSO	100	40	4	2

TABLE 4: Parameters of the SA.

	Number of iterations	Population size	The initial temperature	The annealing temperature coefficient
SA	100	40	200	0.85

is to increase the diversity of chromosomes produced in the population.

A mutation rate is designed to regulate the possibility of the mutation. Lower mutation ranges are appropriate for a more local search. However, higher mutation ranges are greater for introducing diversity. If the precision of the value of a solution is too low, a random value is picked from discrete values. Nevertheless, if an individual generates a high-precision value, then, a random value is picked from either discrete values or the regular distribution. It will be demonstrated in Section 5 that mutation operation benefits in reaching greater solutions.

**4.6. Clone Operator.** A clone operator is an intelligent search method in the CHIGA. It is a heuristic random search algorithm that combines determinism and randomness [32]. In the clone operator, the optimized objective function is regarded as the antigen. The possible individual is regarded as the antibody, and the quality of the possible individual is regarded as the affinity of the immune cell and the antigen. The optimization process of the problem in the CHIGA can correspond to the process of the biological immune system which includes recognition of antigen and realization of the evolution of the antibody. The steps of the clone operator in the CHIGA mainly include antigen recognition and initial antibody production, antibody evaluation, immune manipulation, etc.

## 5. Simulation and Results

The reward and throughput of the CHIGA are analyzed and tested in this section. We compare it against the ACO, SA, and PSO for the problem of maximizing the network reward using spectrum allocation. Then, we show the performance of the CHIGA by means of simulations. As mentioned in Section 3, the objective fitness demonstrates the effectiveness of schemes in maximizing the network reward under multiple constraints in simulation.

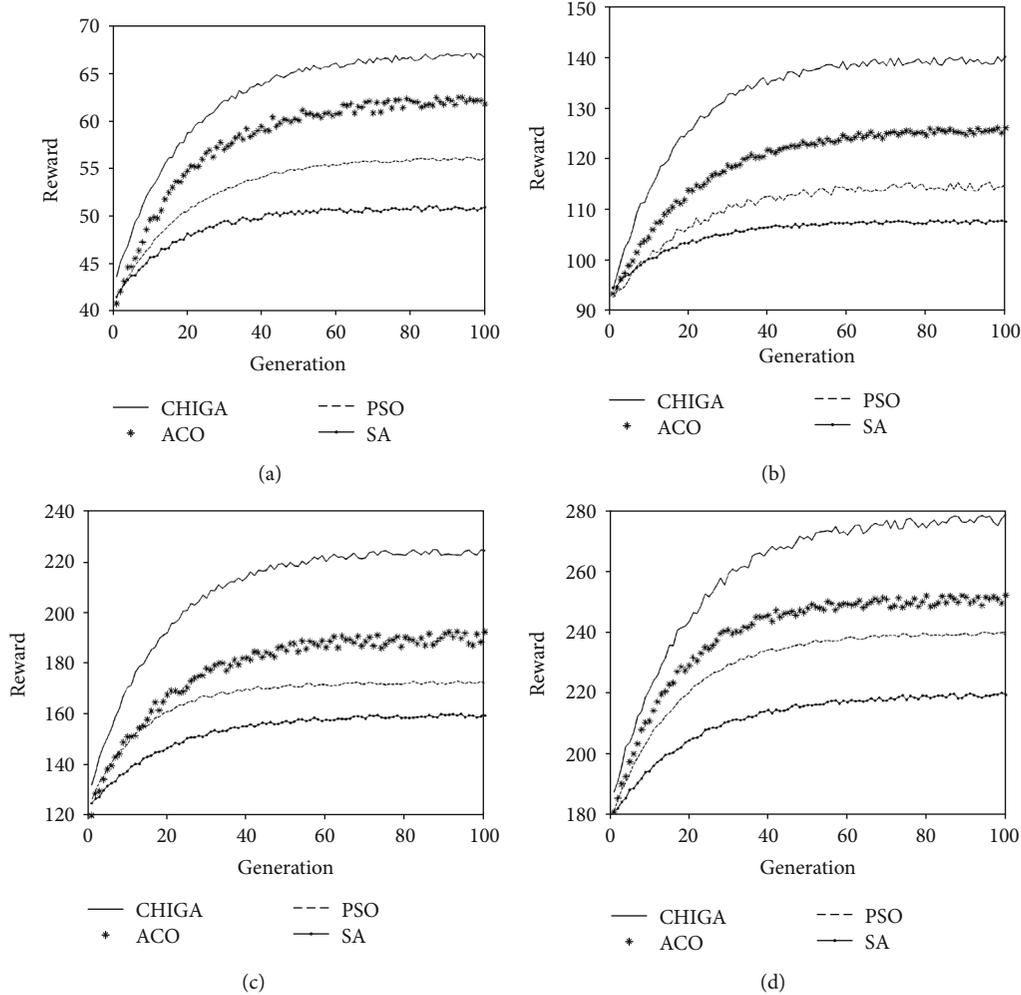


FIGURE 5: (a) 5 channels and 10 cognitive users; (b) 10 channels and 20 cognitive users; (c) 15 channels and 30 cognitive users; (d) 20 channels and 40 cognitive users.

All comparisons between CHIGA, ACO, PSO, and SA were reported using the same number of iterations and population size. The parameters of the CHIGA, ACO, PSO, and SA are described in Tables 1–4, respectively.

In the CHIGA, we investigate that the population size is 40 that ensures a specified quality of the solution. The likelihood of crossover and mutation have an influence on the convergence of the CHIGA. The bigger probability of crossover and mutation are given, the faster the new individual is generated. Different mutation probabilities and crossover probabilities were tested during the execution of the algorithm. The values of the optimal probability of crossover and mutation were tested and simulated by comparing the network rewards. They are given in Table 1.

In the ACO, the larger the pheromone weight is, the ants prefer to toward the path that they have traveled before. The larger the weight of heuristic information is, the ants prefer to toward the optimal reward. If the pheromone volatilization coefficient is too large, the speed of pheromone volatilization becomes faster. The values of parameters are tested during

TABLE 5: Improvement percentage of network reward optimized by the CHIGA compared with the other three algorithms.

Number of channels and cognitive users	ACO	PSO	SA
5 channels and 10 cognitive users	7.41%	19.44%	31.57%
10 channels and 20 cognitive users	11.13%	21.54%	30.23%
15 channels and 30 cognitive users	17.00%	30.29%	40.54%
20 channels and 40 cognitive users	10.61%	16.14%	26.59%

the run of the algorithm. The best parameter is chosen to calculate the reward. In the ACO, they are given in Table 2.

In PSO, the maximum velocity determines the maximum moving distance of a particle in a generation. The value of maximum velocity is tested during the execution of the algorithm, the optimal maximum velocity is chosen to calculate the reward. In PSO, the maximum speed is 4. The cognitive value and social value are  $c_1 = c_2 = 2$ .

In SA, the annealing temperature coefficient determines the rate of temperature drop. The value of the annealing temperature coefficient is tested during the run of the algorithm;

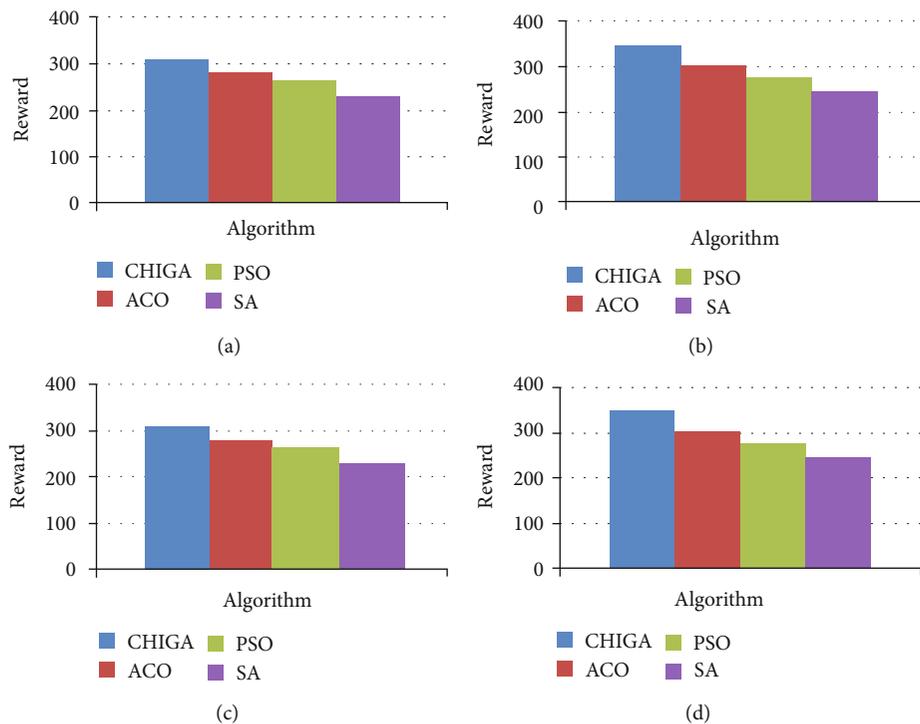


FIGURE 6: (a) 50 cognitive users and 5 channels; (b) 50 cognitive users and 10 channels; (c) 50 cognitive users and 15 channels; (d) 50 cognitive users and 20 channels.

the best annealing temperature coefficient is chosen to calculate the reward. The value of the original temperature is defined as 200, and the value of the annealing temperature is defined as 0.85.

The immune operator is generated, and the position of the hybrid operator is randomly specified within the square area. In Figure 5, we set the numbers of users as 5, 10, 15, and 20, respectively. The numbers of channels are 10, 20, 30, and 40, respectively. For comparison purposes, the results of ACO, PSO, and SA are also given.

Figure 5 shows the convergence and change of solutions for the CHIGA, ACO, PSO, and SA, respectively. In (a), it demonstrates evidently that the CHIGA has a better reward compared with ACO according to the convergence speed with 10 users and 5 channels. In (a), at the beginning of the iteration, the performance of SA is poor and the reward of PSO is higher compared with SA; the performance of ACO is better than PSO. The performance of the CHIGA is more effective than PSO. In the first 60 generations, the speed of the CHIGA surge with the development of the iterations. On the other hand, ACO has a lower performance of convergence than the CHIGA. After 60 generations, the reward of the CHIGA is 67.27; the network reward of ACO is 62.63; the reward of PSO is 56.32, and the reward of SA is 51.13. Furthermore, the CHIGA has a better performance compared with ACO, SA, and PSO.

In (b), (c), and (d), the similar results can be obtained with 10, 15, and 20 cognitive users, respectively, and 20, 30, and 40 channels, respectively. In (b), the rewards of the CHIGA, ACO, PSO, and SA with 10 channels and 20 users

TABLE 6: Reward optimized by the CHIGA, ACO, PSO, and SA with 50 users.

Number of channels	CHIGA	ACO	PSO	SA
5	259.43	230.40	211.84	193.03
10	286.98	267.11	224.64	210.93
15	310.43	281.16	265.20	228.58
20	345.68	302.11	276.20	245.41

TABLE 7: Improvement percentage of reward optimized by the CHIGA compared with the other three algorithms with 50 cognitive users.

Number of channels	ACO	PSO	SA
5 channels	12.60%	22.47%	34.40%
10 channels	7.44%	27.75%	36.05%
15 channels	10.41%	17.05%	35.08%
20 channels	14.42%	25.16%	40.86%

are 140.54, 126.46, 115.63, and 107.92, respectively. In (c), the rewards of the CHIGA, ACO, PSO, and SA with 15 channels and 30 users are 225.86, 193.04, 173.35, and 160.71, respectively. In (d), the rewards of the CHIGA, ACO, PSO, and SA with 20 channels and 40 users are 279.26, 252.47, 240.46, and 220.59, respectively. Improvement percentage of network reward optimized by the CHIGA compared with the other three algorithms is given in Table 5.

TABLE 8: Reward optimized by the CHIGA, ACO, PSO, and SA with 50 cognitive users.

Number of channels	10 users				20 users			
	CHIGA	ACO	PSO	SA	CHIGA	ACO	PSO	SA
5	67.27	62.63	56.32	51.13	116.80	104.43	99.83	85.78
10	98.08	88.52	75.62	74.74	140.54	126.46	115.63	107.92
15	115.25	106.22	98.28	88.51	174.14	156.60	132.01	123.21
20	139.85	134.14	121.10	108.26	192.60	166.70	154.55	148.67
25	162.80	151.23	133.59	131.13	210.14	187.96	173.07	164.38
30	180.61	166.76	155.67	149.23	231.77	219.77	200.78	169.83
35	215.81	190.74	184.52	162.98	273.66	233.01	207.46	187.14
40	229.31	214.15	199.55	185.26	283.03	255.63	224.82	220.74
45	262.80	251.69	223.65	195.55	319.80	297.70	251.11	242.34
50	287.10	272.55	225.42	216.92	349.46	305.80	286.40	257.92

Number of channels	30 users				40 users			
	CHIGA	ACO	PSO	SA	CHIGA	ACO	PSO	SA
5	168.64	153.66	135.22	125.28	220.61	199.60	182.68	153.14
10	185.11	172.33	160.39	140.20	249.84	208.60	206.08	169.45
15	225.86	193.04	173.35	160.71	268.63	248.56	211.95	187.53
20	228.95	218.29	194.88	177.85	279.26	250.47	240.46	220.59
25	265.47	251.16	218.01	200.75	317.13	297.70	250.04	229.11
30	280.00	253.95	248.04	214.36	318.54	300.99	273.87	236.51
35	321.33	272.34	259.15	227.93	363.36	341.92	308.93	273.92
40	333.28	319.14	262.32	236.89	377.90	350.96	315.90	288.04
45	353.83	328.68	288.43	275.16	388.98	360.29	338.90	291.40
50	374.02	334.06	301.29	279.43	416.48	373.66	343.62	304.05

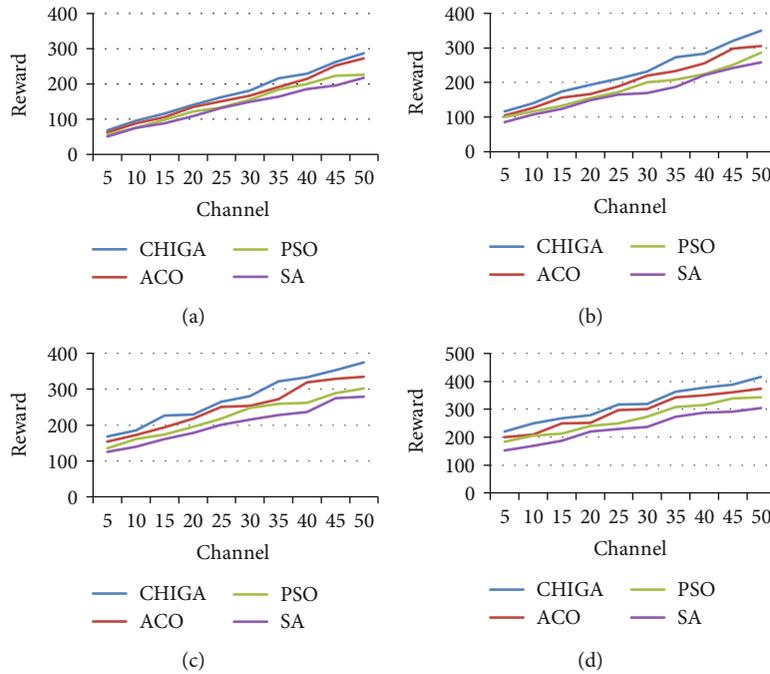


FIGURE 7: (a) 10 cognitive users; (b) 20 cognitive users; (c) 30 cognitive users; (d) 40 cognitive users.

TABLE 9: Convergent time.

	CHIGA	ACO	PSO	SA
Convergence time	1.61 s	7.42 s	9.51 s	11.23 s

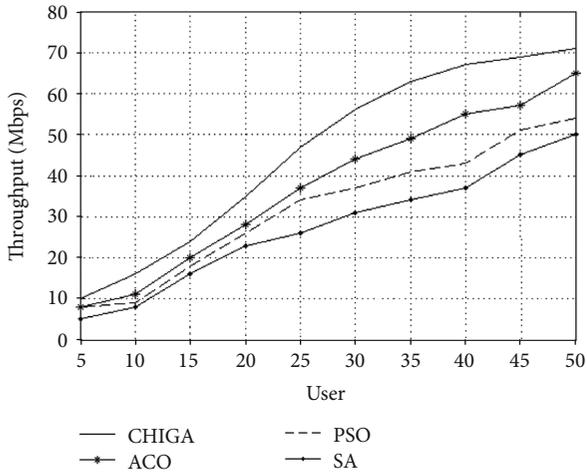


FIGURE 8: Comparison of four algorithms based on throughput.

Overall, the CHIGA is more appropriate for spectrum allocation than ACO, PSO, and SA. Moreover, similar results can also be attained from the simulations that the CHIGA provides a better optimum solution than ACO, PSO, and SA.

In Figure 6, the rewards of the four algorithms are compared when the quantity of users is 50 and the numbers of channels are 5, 10, 15, and 20, respectively. In (a), the reward of the CHIGA is 259.43 with 5 channels after iterations, while the solution for spectrum allocation in ICRSNs of ACO, PSO, and SA is 230.40, 211.84, and 193.03, respectively. As (b), (c), and (d) show, it can be obviously found that the CHIGA can obtain better solutions than ACO, PSO, and SA. The experimental data of reward with 50 cognitive users and different numbers of channels are given in Tables 6 and 7.

The experimental data in the above tables demonstrate a genetic algorithm combined with a chaotic operator and immune operator that is an effective method for improving global search capabilities. When the number of chaotic searches reaches a certain number, the chaos operator can avoid premature convergence; the utilization of spectrum resources can be improved by effective design and management. The spectrum allocation scheme-based CHIGA makes network reward lower and achieves the desired high throughput goals in the following table.

The network reward optimized by the CHIGA, ACO, PSO, and SA with a different number of channels and users is given in Table 8 and Figure 7. In Figure 7, as (a), (b), (c), and (d) show, it can be obviously found that the CHIGA can obtain even better solutions than ACO, PSO, and SA after 200 iterations. The figures show the reward when the numbers of users are 10, 20, 30, and 40, respectively, with different channels. (a) shows the rewards of the CHIGA, ACO, PSO, and SA converge after 100 iterations when the number of users is 10. The comparison results show that the reward of the CHIGA is better than ACO, PSO, and SA.

After the iterations, individuals of the CHIGA have faster convergence and the reward is better than three other algorithms. Moreover, the effectiveness and superiority of our proposed CHIGA are better than ACO, PSO, and SA when the numbers of users are 10, 20, 30, and 40, respectively. Similar conclusion can be obtained in (b), (c), and (d) in Figure 7.

In Table 9, the average convergence time of four algorithms is computed, respectively, to compare the performance after 100 iterations. The convergence times of the four algorithms with 5 cognitive users and 20 channels are compared. Results show that the average time of convergence of the CHIGA, ACO, PSO, and SA after 100 generations. The CHIGA is 1.61 s (second); ACO, PSO, and SA are 7.42 s, 9.51 s, and 11.23 s, respectively. Table 9 shows that the convergence time of the CHIGA is better than that of ACO, PSO, and SA. It is obvious that the CHIGA has a better performance compared with ACO, SA, and PSO.

Figure 8 shows the performance comparison of four algorithms based on throughput when the numbers of users are different and the number of channels is 10. Throughput can be calculated according to the formula (4). To evaluate our design, the throughput increases with the number of users. Moreover, the throughput of the CHIGA is better than ACO, PSO, and SA. It is obvious that the CHIGA has a better performance compared with ACO, SA, and PSO.

## 6. Conclusions

In this paper, a new chaotic hybrid immune genetic algorithm is introduced in an effort to make the complex channel management possible and optimize the wireless spectrum resource shortage issue. It has advantages in maximizing the network reward and achieving the desired high throughput goals of spectrum allocation. Genetic algorithm is an existing method that has been studied by researchers for many years. Different from a traditional genetic algorithm, the CHIGA combines some advantages of a chaotic operator and immune operator. The advantages of operators and traditional genetic algorithms were combined. The new CHIGA is designed to optimize the spectrum allocation scheme. By comparing with other algorithms, the proposed algorithm performs better and it is more suitable for solving the problem of spectrum allocation.

Hence, the proposed CHIGA approach effectively develops the network reward in ICRSNs. It has typical advantages in the environments, which have a great deal of monitoring nodes required in the industrial application. By introducing the CHIGA into the spectrum allocation, an objective function that evaluates the reward of spectrum allocation is created to improve the network reward for ICRSNs. Extensive simulations are executed to validate the throughput and the effectiveness gain according to spectrum allocation efficiency when compared with the other three algorithms. Simulation results indicate that network reward and throughput optimized by the CHIGA are higher than the ACO, PSO, and SA approach, particularly for ICRSNs with a large number of users and channels.

## Data Availability

The authors declare that the data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declared that they have no conflicts of interest to this work.

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