A Resource Allocation Scheme for 5G C-RAN Based on Improved Adaptive Genetic Algorithm

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Abstract. Cloud-Radio Access Networks (C-RAN) is a novel mobile network architecture where baseband resources are pooled, which is helpful for the operators to deal with the challenges caused by the non-uniform traffic and the fast growing user demands. The main idea of C-RAN is to divide the base stations into the baseband unit (BBU) and the remote radio head (RRH), and then centralize the BBUs to form a BBU pool. The BBU pool is virtualized and shared between the RRHs, improving statistical multiplexing gains by allocating baseband and radio resources dynamically. In this paper, aiming at the problem of resource dynamic allocation and optimization of 5G C-RAN, a resource allocation strategy based on improved adaptive genetic algorithm (IAGA) is proposed. The crossover rate and mutation rate of the genetic algorithm are optimized. Simulation results show that the performance of the proposed resource allocation strategy is better than the common frequency reuse algorithm and the traditional genetic algorithm (GA).

Keywords: Cloud-Radio Access Network · Resource allocation · Improved adaptive genetic algorithm · Baseband unit · Remote radio head

1 Introduction

With the rapid development of fifth-generation mobile communications (5G), there is an increasing demand for higher-speed services and richer applications, such as enhanced mobile broadband services with higher speed and lower latency (Enhanced Mobile Broadband, eMBB), Massive Machine-Type Communication (mMTC) supporting massive user connections, and Ultra Reliable & Low Latency Communication (URLLC) for ultra-reliable and ultra-low latency. In response to the challenges from diverse application scenarios, rapidly growing business demands and uneven business distribution, major operators and their research organizations are looking for a new low-cost, high-efficiency method to achieve higher income. Among them, Cloud-Radio Access Network (C-RAN) has been introduced into 5G networks due to its high capacity, low latency,

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high energy efficiency and flexible deployment, and it is expected to become one of the most effective technical ways to face the above challenges [1].

How to realize C-RAN resource on-demand allocation and dynamic deployment is a key issue that needs to be solved urgently. Zhang et al. used the pure binary integer programming method for LTE uplink to search for the optimal resource allocation solution [2], which has lower complexity than the exhaustive search algorithm. Noh et al. used the Hungarian algorithm for multi-site OFDMA systems to match the balance between users and resource blocks [3], which has lower complexity too. In [4], Sahu et al. used the graph segmentation method to allocate base-band processing resources for the 5G cloud radio access network, which improved the system energy efficiency. In [5], the authors used heuristic search ant colony algorithm to the QoS-based spectrum resource allocation strategy. Genetic Algorithm (GA) is a kind of randomized search method that learns from the evolutionary laws of the biological world. It was first proposed by Professor J. Holland in the United States in 1975. It has inherent hidden parallelism and better global optimization ability than other methods. In [6], the authors conducted a preliminary study on the resource allocation algorithm based on GA for LTE systems.

In this paper, genetic algorithm is introduced into the resource allocation of 5G cloud radio access network. An improved adaptive genetic algorithm (IAGA) is proposed in the dynamic allocation and optimization strategy. The main contributions of this paper are as follows.

(1) Considering the 5G C-RAN architecture, genetic algorithm is introduced into the resource allocation of the C-RAN network, so that better dynamic resource allocation and optimization strategies can be obtained faster.
(2) An improved adaptive genetic algorithm is proposed to optimize the crossover rate and mutation rate. It has faster convergence and better stability than the traditional GA and frequency reuse algorithm.

This remainder of the paper is as follows. Section 2 presents the 5G C-RAN architecture and cell distribution model. Section 3 explains the resource allocation strategy based on GA and the improved adaptive genetic algorithm. Section 4 presents simulation results. Section 5 concludes the paper.

2 System Model

2.1 5G C-RAN Architecture

The concept of C-RAN was first proposed by IBM [7], which was named Wireless Network Cloud (WNC), and then it was derived from the concept of distributed wireless communication system [8], it is also known as "Centralized radio access network." The basic architecture is shown in Fig. 1.

The C-RAN architecture is characterized in that it geographically separates the base-band processing unit and the front-end wireless transmitting unit in the traditional base station. The two parts are connected by a low-latency, high-bandwidth preamble link to form a distributed radio head (RRH) combined with a centralized baseband processing unit (BBU) pool architecture. The core modules include:

(1) Radio frequency remote head (RRH), which mainly includes RF module, related amplifier/filter and antenna. It also includes digital signal processing, digital/analog conversion and other modules.
(2) The baseband processing unit (BBU) pool is shared and virtualized by all RRHs to implement baseband processing functions in the radio access network, such as modulation, coding, filtering and resource allocation.
(3) The pre-transmission link is used to ensure communication between RRH and BBU. Usually, it adopts the optical fiber link, and sometimes the Free Space Optical communication (FSO) or the microwave link may be used. The transmission distance is usually 20 km to 40 km.

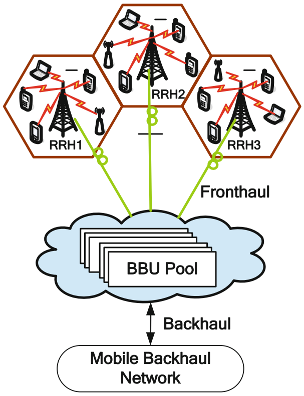

Fig. 1. Basic architecture of C-RAN

In addition, the BBU pool is connected to the mobile backhaul network through a backhaul link.

2.2 Advantages and Technical Challenges of the C-RAN Architecture

Compared with the traditional radio access network (RAN) architecture, the C-RAN architecture has many advantages as follows.

(1) Adapt to non-uniform services and different sized networks. The BBU resources in the C-RAN can be flexibly allocated and can be adaptively adjusted as the overall load in the system changes.
(2) It saves energy and cost. Research shows that C-RAN can save about 71% power consumption, 15% construction cost and 50% operating cost compared with traditional wireless access network [9, 10].
(3) Improve throughput and reduce latency. Signal processing for multiple cells can be finished in the BBU pool, which is easy to implement and reduces the latency in processing and transmission process.

(4) Easy network upgrade and maintenance. Virtualized BBU pools make software and hardware upgrades and maintenance more convenient, and software radio and other technologies can be used to software-configure new frequency bands and new standards.

The C-RAN architecture also brings some new technical challenges as follows.

(1) In the BBU pool, efficient BBU interconnection technology is required to support efficient baseband resource scheduling. The computing, communication, and storage resources for the BBU pool need to be virtualized to accommodate dynamic network load and achieve more flexible resource configuration.
(2) In terms of BBU pool and RRH connection, it is necessary to establish a transmission network that is fast, low-cost, and meets transmission delay and flutter delay.
(3) At the RRH end, the centralized processing architecture enables large-scale interference coordination and RRH cooperation, and thus it is necessary to solve problems such as efficient multi-antenna cooperation and joint radio resources scheduling.

2.3 5G C-RAN Cell Distribution Model

This paper conducts a radio access network consisting of 7-cell clusters (actual cells number in the cluster may not be 7). The cell distribution model is shown in Fig. 2.

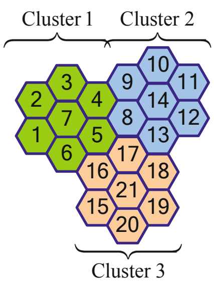

Fig. 2. C-RAN layout with a cluster of seven cells

Each cell (taking the cell No. 7 as an example) has two kinds of neighbors: a neighboring cell (cell No. 1–6) and a remote cell (such as cells No. 8, 9, 16 and 17). This paper only studies interference from neighboring cells.

In order to simplify the issue, this paper allocates resource block (RB) as the basic unit, and each RB contains all the related resources needed to provide services for one user. The system can flexibly adjust the bandwidth and allocate different numbers of RBs to different sizes of bandwidth resources. Assume that the actual available bandwidths are 3 MHz, 5 MHz, 10 MHz, 15 MHz and 20 MHz respectively, and the corresponding RBs are 6, 10, 20, 30, and 40 respectively. The goal is to find the optimal resource allocation strategy to minimize interference and optimize network performance.

3 Resource Allocation Strategy Based on IAGA

3.1 C-RAN RB Allocation Steps

Assume that each mobile user owns one RB, and the number of RBs is N_{RB}. The RB allocation consists of the following three steps:

(1) In each cluster shown in Fig. 2, the BBU pool collects user traffic and channel state information in the area covered by all RRHs. In order to simplify the issue, assuming there are no differences in user service requirements, and each user needs the same RB bandwidth and processing resources.
(2) The BBU pool uses GA to optimize the RBs allocation based on the user information fed back by each RRH, thereby improving the performance of the C-RAN system.
(3) The BBU pool sends a new optimal RB allocation decision to RRHs in each cluster to efficiently configure the mobile network.
(4) Periodically monitor the user information fed back by the RRHs and repeat steps (2) and (3) when the reallocation condition is satisfied.

3.2 GA-Based RB Allocation Algorithm

According to the principle of GA, the RB resource allocation algorithm includes the following steps:

(1) Establishing a chromosomal expression on the RB allocation problem.
(2) Genetic operations are performed on the parent population (The initial population can select a set of chromosomes in which the solution may be concentrated) to generate a new RB configuration scheme, and the next generation population is generated according to the fitness evaluation function on the new configuration scheme.
(3) Repeat the operation in 2 until the GA convergence condition is met, and an approximately optimal RB allocation scheme is obtained.

Chromosome Expression. The chromosomes represent the correspondence between RBs (numbered 1 to N_{RB}) and 7 cell users in each cluster. The RB allocation in each cluster is represented by a single chromosome, which can be represented by Ch, which is a matrix of $7 \times N_{\mathrm{RB}}$. The row number of each chromosome matrix indicates the cell number N_{C} in the corresponding cluster, and the column number of the matrix indicates the user serial number N_{U}. The matrix item indicates the k-th RB for the i-th user in the j-th cell. Figure 3 shows an example of a chromosome expression with an N_{RB} of 6. In the figure, $\mathrm{Ch}(3, 5) = 4$, which means that the fifth user of the third cell is assigned the RB number of 4. Assume that the initial population contains N_{I} chromosomes.

Genetic Manipulation. Genetic manipulation involves three operations: selection, crossover, and mutation. The first step is to choose, the BBU pool selects N_k chromosomes in the parent population according to the individual evaluation function to remain in the next generation. Followed by crossover, the goal is to generate new chromosomes based on the retained chromosomes. The crossover operation is shown in Fig. 4.

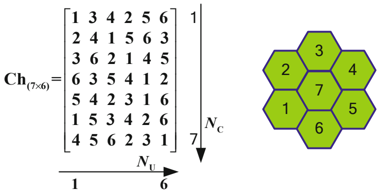

Fig. 3. Illustration of chromosome representation

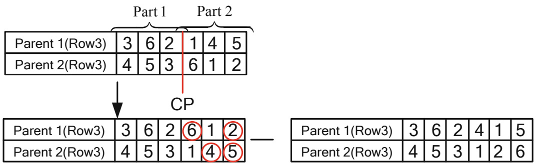

Fig. 4. Crossover operation

The new chromosomes are generated line by line. As shown in Fig. 4, the parental chromosomes are divided into two parts with the third line as the example from the parental 1 and 2 chromosomes, randomly selecting the crossover point (CP). The first step in the intersection is to connect the first part of the parent 1 and the second part of the parent 2 to form the child 1, and the first part of the parent 2 and the second part of the parent 1 are connected to the child 2. Then we find that the RB numbers 6 and 2 in the child 1 are repeated, and the RB numbers 4 and 5 in the child 2 are also repeated. On the other hand, RB numbers 4 and 5 do not appear in child 1, and RB numbers 2 and 6 do not appear in child 2. In order to obtain the final chromosomal expressions in progeny 1 and progeny 2, in step 2, namely the crossover operation, the repeated numbering is replaced with the number that does not appear.

Finally, the mutation, the BBU pool randomly selects two positions on the same line of the chromosome and exchanges their values, according to the mutation probability, and the goal is to add a certain change in the next generation population.

Evaluation Function. The evaluation function, also named the fitness function, it is the basis for the selection operation. This paper defines the evaluation function for a single cluster as

$$C_{BW}=\frac{\sum_{p=1}^{7}\sum_{i} BW_{\mathrm{RB}}\log_2\left(1+10^{\mathrm{SINR}_i^p/10}\right)}{BW_{N_{\mathrm{RB}}}} \tag{1}$$

Where BW_{RB} is the bandwidth of each RB (taken as 500 kHz), $BW_{N_{\mathrm{RB}}}$ is the total bandwidth of the system (3 MHz, 5 MHz, 10 MHz, 15 MHz or 20 MHz), and SINR_i^p is the signal to noise ratio when the i-th RB is allocated in the cell numbered p. The evaluation function represents the total user capacity in the cluster divided by the total bandwidth that is the spectral efficiency in the cluster.

3.3 Improved Adaptive Genetic Algorithm

To improve the convergence accuracy of the GA and accelerates the convergence speed, an improved adaptive genetic algorithm is designed by adjusting the genetic parameters adaptively. Nowadays, a large number of improved algorithms simulate the biological evolution more vividly according to the characteristics of biological evolution, so that the algorithm can converge to the optimal solution with a large probability. GA crossover and mutation are the key steps to affect the GA operation and performance.

The crossover probability is adjusted with the evolutionary process adaptively. At the beginning of evolution, the crossover probability is chosen to be larger. Such a rough search process is conducive to maintaining the population. Diversity, and in the later stages, detailed search is needed to prevent the optimal solution from breaking down and speed up the convergence.

Adaptive mutation is the process by which the probability of variation varies according to the evolutionary characteristics of the population. The general mutation probability is selected within 0.01, the mutation probability is too large, and the destructiveness to the solution is relatively large. It is easy to make the optimal solution to be lost, the mutation probability is too small, and it is prone to premature phenomenon. Therefore, the adaptive mutation probability generally takes a large to small change. In this way, extensive search at the beginning can maintain the diversity of the population, and careful search at the end will prevent the optimal solution from being destroyed. In addition, in the optimization process, the operation from extensive search to detailed search is performed multiple times. This method can make the algorithm not only ensure the comprehensiveness and accuracy of the search, but also quickly jump out of the local optimum. Quick convergence to the global optimal, experimentally proved that this mutation method has a great improvement in convergence speed and convergence precision compared with the previous adaptive algorithm, especially for multi-peak functions.

Therefore, a nonlinear adjustment to the adaptive crossover rate and mutation rate was made. First, compare the individual fitness function with the average value of the present population, and then calculate the individual's crossover rate and mutation rate by combining the best and the worst individuals. In the evolution of population, the model of excellent individuals is effectively preserved, and the ability of variation of poor individuals is enhanced, so that the algorithm can jump out of the local optimal solution and overcome the premature point. Compared with GA, the new algorithm is simpler and memorizes less. The old individual can adaptively adjust its crossover rate and mutation rate according to the adaptability of surrounding individuals. Experiments show that the new algorithm converges faster and has better stability.

The adaptive crossover rate and mutation rate are shown in formula (2) and (3).

$$P_c = \begin{cases} \frac{P_c\max - P_c\min}{1+\exp(A(\frac{2(f' - f_{\text{avg}})}{f\max - f_{\text{avg}}} - 1))} + P_c\min & f' \geq f_{\text{avg}} \\ P_c\min & f' < f_{\text{avg}} \end{cases} \tag{2}$$

$$P_m = \begin{cases} \frac{P_m\max - P_m\min}{1+\exp(A(\frac{2(f' - f_{\text{avg}})}{f\max - f_{\text{avg}}} - 1))} + P_m\min & f' \geq f_{\text{avg}} \\ P_m\min & f' < f_{\text{avg}} \end{cases} \tag{3}$$

Where $f^{'}$ is the fitness function of a single individual in a population, f_{avg} is the average fitness function of the population under the present iteration, $f_{\max}$ is the best fitness function for the population under the present iteration, the maximum value of the crossover rate $P_{c\max} = 1.0$, the minimum value of the crossover rate $P_{c\min} = 0.75$, the maximum value of the mutation rate $P_{m\max} = 0.25$, the minimum value of the mutation rate $P_{m\min} = 0.05$, and $A = 9.903438$.

Based on the above analysis, a GA/IAGA-based C-RAN resource allocation flowchart as shown in Fig. 5 can be obtained. Where g represents the number of iterations, and G represents the maximum number of iterations to ensure GA convergence, which is also known as GA convergence parameters. The initial population construction is randomly selected in a possible solution set.

4 Simulation Results

The simulation parameters settings are shown in Table 1.

Table 1. Simulation parameters for RAWGA in C-RAN

Parameter	Value
Bandwidth of each RB	500 kHz
Total bandwidth in the system	5 MHz
Number of cells in per cluster	7-cell
User distribution	Random uniform distribution
Number of RBs for per user	1

Figure 6 shows the curve indicating the evaluation function C_{BW} as a function of the iterations number g. In the figure, a 7-cell cluster model (Fig. 2) is used, and each cell has 20 users. The initial population has a chromosome number N_{I} of 30, the number of available RBs is 30, and the maximum number of iterations is G = 80. The crossover probability and mutation probability are respectively 0.75 and 0.05. It can be seen from the figure that as the g increases, the evaluation function increases and quickly converges to a stable value.

With the same parameters, based on IAGA, the curve of evaluation function C_{BW} as a function of the iterations number g is shown in Fig. 7. Obviously, it can be seen that the GA originally oscillates the optimal value around 50 generations. Now in Fig. 7 after only 20 generations can converge to the sub-optimal value and 30 generations can get the optimal value.

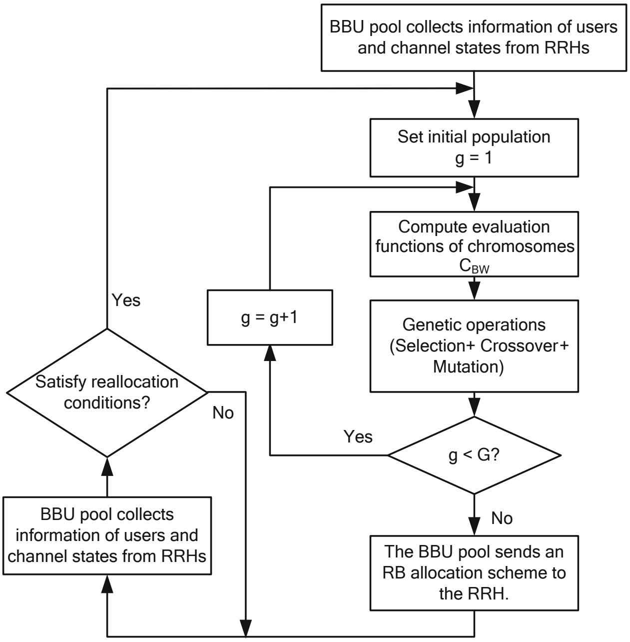

Fig. 5. Flowchart of the RB allocation with GA/IAGA in C-RAN

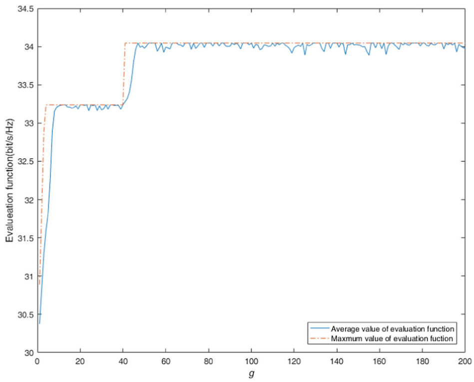

Fig. 6. Evaluation function C_{BW} change with g (GA)

Figure 8 gives the final optimization results based on IAGA, GA and the Universal Frequency Reuse (UFR) rules. It shows that the spectral efficiency of the RB allocation algorithm based on IAGA/GA has been improved evidently. And the closer the spectrum resource is to the number of users, the more advantage the optimization result of the IAGA/GA algorithm is. And the IAGA algorithm is greatly improved compared with the GA algorithm, except for the case of cell users equals 30. The reason why the IAGA is slightly worse than the GA when the number of cell users is equal to 30 is that the IAGA

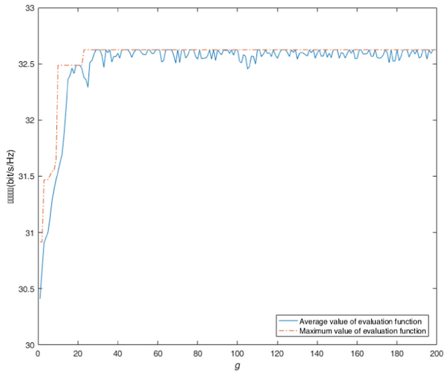

Fig. 7. Evaluation function C_{BW} change with g (IAGA)

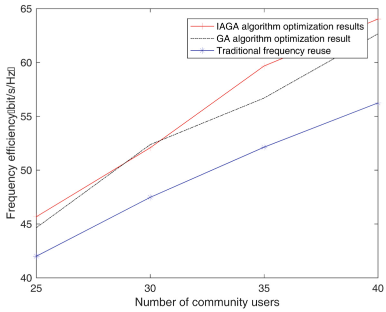

Fig. 8. Comparison between IAGA, GA and UFR

converges to an acceptable suboptimal solution at this point, and the GA converges to the optimal solution. This is inevitable in the course of the algorithm work, but it is acceptable under the condition that the overall performance of the algorithm is better than GA.

5 Conclusion

Resource allocation strategies based on GA and IAGA for 5G C-RAN are investigated. Firstly, collect the user information and CSI from the RRHs. Secondly, the BBU pool uses the IAGA/GA to obtain the optimal resource allocation scheme based on the collected user information. Then, send the obtained optimal resource allocation decision result to the RRHs for each cluster. Finally, it periodically monitors the RRH user and channel state information, and reallocates resources as the network changes. The performance of the proposed scheme is superior to the UFR algorithm, especially IAGA. In the future, we will optimize the resource allocation for the cloud radio access network and further improve the network performance by combining the differences in user service requirements, the virtualization implementation of the BBU pool, the intelligent network environment awareness, and the limitations on the preamble links.

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