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5G heterogeneous network selection and resource allocation optimization based on cuckoo search algorithm

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ABSTRACT

In order to solve the problem of spectrum resource shortage and high-speed access in 5G network, the multi-agent system is embedded into the standard cuckoo algorithm, and the multi-agent cuckoo algorithm is proposed. Firstly, the spectrum information of network channel sharing available to users is obtained, and the cuckoo search algorithm is used to optimize under the condition of satisfying the quality of service (QoS) guarantee of users, and the optimal allocation scheme is obtained by iterating for many times. The use steps are illustrated by examples. Compared with the traditional genetic algorithm, the calculation complexity can be reduced, and it can also be extended to more users and networks. In this algorithm, each cuckoo represents an agent, and all the agents constitute a von-Neumann structure. Through the neighborhood competition cooperation operator, mutation operator, self-learning operator and the evolution mechanism of cuckoo algorithm, they can continuously enhance the energy and improve the adaptability, and can quickly and accurately find the optimal solution of the problem.

1. Introduction

Resource balance optimization is a discrete optimization problem with high dimension, non-linear and multi constraints. Scholars at home and abroad have proposed many methods to solve this problem, which can be roughly divided into three categories: accurate algorithm, heuristic algorithm based on priority rules, and intelligent algorithm [1–3]. The results of precise algorithm are accurate but very time-consuming, which is difficult to apply to large and complex problems; heuristic algorithm based on optimization rules is fast but the quality of optimization results depends on the merits of the rules and the universality of the algorithm is poor. Intelligent algorithm is a kind of meta heuristic algorithm which simulates the physical phenomena or biological evolution process in nature [4,5]. It has the characteristics of global, parallel, efficient and universal, and is a common algorithm to solve complex engineering optimization problems. 5G standard stipulates that 5G network peak transmission rate reaches 10 Gbit/s, traffic density reaches 10 TBPs / km^2, user experience rate reaches 0.1–1 Gbit/s, and connection density reaches 1 million sets/km2. The end-to-end delay reaches ms level, which can guarantee the user experience at the speed of 500 km/h, and greatly improves the energy efficiency, cost efficiency and spectrum efficiency [6]. At present, a large number of relevant workers are committed to research and develop the application of 5G network in Unmanned Aerial Vehicle (UAV), logistics, vehicle network, etc., and there will be more 5G network application scenarios in the future.

Cloud computing is a new computing mode based on parallel computing, distributed computing, network computing and other technologies. It is the development direction of computer computing. Resource allocation is an important topic in cloud computing, and its efficiency has a great impact on the performance of the whole cloud computing. Because the resource allocation problem is a typical NP complete problem, the traditional optimization method is difficult to solve. Intelligent optimization algorithm has unique advantages in solving this kind of problem. 5G heterogeneous cellular network has the advantages of high capacity, deep coverage, low cost, high energy efficiency and load balancing, which is considered to be the most critical technology to achieve 1000 times capacity improvement of wireless communication network. In addition to the traditional spectrum resources (channel, bandwidth and power), the resources of 5G heterogeneous cellular network include base station access point (small cell base station and relay, etc.), buffer and RF antenna [7–9]. The resource management of 5G heterogeneous cellular network is to reasonably adjust and allocate the above resources according to the needs and distribution of user services, to achieve the best match between user service needs and wireless communication services, to improve the utilization efficiency of various network resources, and to reduce the consumption costs (power and cost costs, etc.) generated by heterogeneous networks in the service process [10–12]. 5G heterogeneous cellular network resource management is facing many problems and challenges, including performance index, spectrum and interference management,

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network topology, base station load management, link management, active cache management, multi antenna and precoding management. According to the decision structure, 5G heterogeneous cellular network resource management decision can be divided into centralized decision, cluster decision (semi centralized decision) and distributed decision.

The residual of the paper is organized as follows: Section 2 devote to discuss related works of 5G heterogeneous network selection and resource allocation optimization. 5G heterogeneous network and system model was expressed in Section 3. Section 4 described the implementation of multi-agent cuckoo algorithm for resource balance optimization. Experimental results were discussed and analyzed in detail in Section 5. Finally, Section 6 concluded the work and proposed the outlook.

2. Related work

In recent years, the issues of user association in heterogeneous networks, massive multiple-input multiple-output networks, millimeter wave networks, and energy harvesting networks has become a hot topic in recent years. Many scholars have made great achievements in the field of 5G heterogeneous network selection and resource allocation optimization. Fadel et al. formulate an optimization problem for Heterogeneous Networks multi-user selection in a multi-input-multi-output and orthogonal frequency-division multiple access system, aiming to maximize the total system throughput [13]. Zhang et al. designed an optimization algorithm based on multi-objective discrete particle swarm optimization to provide guidance for users to select the optimal access network in heterogeneous wireless networks [14,15]. Hu et al. proposed a green collaborative heterogeneous network system framework, which aims at balancing and optimizing the spectrum efficiency, energy efficiency and service quality of heterogeneous wireless networks [16]. A taxonomy as a framework for systematically studying the existing user association algorithms has been proposed by Liu et al. [17].

Cuckoo search algorithm (CSA) is a new intelligent algorithm proposed by Yang et al. It is an intelligent algorithm developed by simulating the breeding habits of cuckoo in nature and the flight characteristics of levy. It has the advantages of less parameter setting, fast convergence speed and strong global search ability, and the test results show that it has higher optimization performance than genetic algorithm, particle swarm optimization algorithm and firefly algorithm [18–20]. In view of this, Yang et al. Introduced the concepts of dominance relationship and non dominance set into the cuckoo algorithm, constructed a multi-objective cuckoo algorithm (MOCS), and extended the algorithm to the field of multi-objective optimization. The multi-objective algorithm inherits the excellent characteristics of the algorithm. In the benchmark function and engineering optimization test, it is found that the algorithm is more close to the real Pareto solution set than the traditional SPEA (strength Pareto evolutionary algorithm) and VEGA (Vector Evaluated Genetic Algorithm) [21–23]. Leandrodos et al. Improved the setting of the control step, used the Duffing oscillator chaotic mapping to adjust the step dynamically, improved the multi-objective cuckoo algorithm, and used it to estimate the parameters of the Jiles–Atherton hysteresis model. Hanoun et al. Applied the multi-objective cuckoo algorithm to solve the multi-objective workshop scheduling problem, and the results also showed the effectiveness and superiority of the multi-objective cuckoo algorithm.

Spectrum sharing can use discontinuous spectrum, so it can expand system capacity, support a large number of device connections, and improve system throughput. Georgios et al. Put forward that the key points of spectrum allocation are dynamic spectrum allocation, spectrum aggregation and spectrum movement. We need to select available spectrum parts to provide services for secondary users (SU). This allocation is the output of a complex process, often considering multiple network and quality of service (QoS) parameters. Using swarm intelligence optimization algorithm to solve the spectrum allocation problem, taking the network efficiency and user fairness as the index to measure the superiority of the algorithm, the evolutionary idea of crossover operation and mutation operation in genetic algorithm is embedded in particle swarm optimization algorithm, and the linear inertia weight function is introduced to improve the spectrum resource allocation problem of the two algorithms. Some scholars have studied a network selection and channel allocation mechanism, using genetic optimization algorithm to minimize system interference and maximize benefits by accommodating more subscribers and ensuring their QoS. In this paper, we propose a method of heterogeneous network selection and resource allocation based on cuckoo search algorithm (CS), which aims to minimize system interference and output the optimal allocation scheme through multiple iterations on the premise of ensuring user QoS.

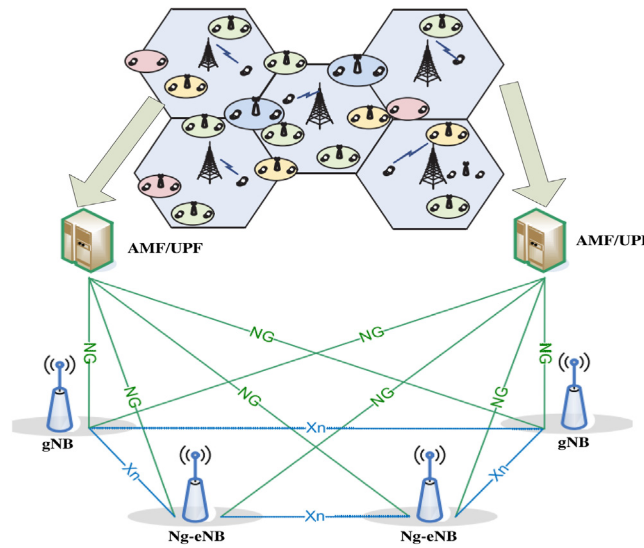

Fig. 1. Schematic diagram of 5G heterogeneous cellular network.

3. 5G heterogeneous network and system model

3.1. 5G network topology

An obvious difference between 5G heterogeneous cellular network and traditional macro cellular network is the network topology and cell coverage distribution. In the traditional macro cellular network, the base stations are evenly distributed, usually on the hexagon grid, and the service area corresponds to the hexagon in the grid [24]. In 5G heterogeneous cellular network, the small cell base station is irregularly distributed, and its service area is also uneven. As shown in Fig. 1, in general, small cell base stations are scattered or clustered in the macro cell network to supplement and support communication services in the edge area or hot spot area.

Because the deployment information of small cell base station is difficult to obtain, the spatial model of base station distribution in 5G heterogeneous cellular network is still an open problem. Although people can build a series of overlapping grids with different densities, the previous grid models are no longer suitable for multi-layer 5G heterogeneous cellular networks. In the absence of prior information of user traffic distribution, the deployment of small cell base stations is generally considered to be uniformly distributed, corresponding to a Poisson point process in two-dimensional plane, which is a completely random distribution model [25,26]. The Poisson distribution of 5G heterogeneous cellular network in some scenarios has been confirmed by field experiments and data simulation. The base station distribution model of Poisson point process has the following characteristics:

(1) When a new base station is added to the network, although the new base station will generate interference, due to the increase of the

base station, the average distance between the user and the adjacent base station will be reduced, and the strength of the corresponding target signal will be increased, so the interference impact of the new base station can be completely offset.

(2) When the small cell base station is added, the overall SINR of the 5G heterogeneous cellular network remains unchanged, while the congestion degree of the network decreases and the overall capacity of the network increases.

(3) In the interference limited network, if the user can access the base station with the best signal (Open Access), add any type of small cellular base station (different transmission power), and do not change the SINR distribution of the downlink, the downlink power control is no longer a very serious problem.

The traditional distribution model based on grid is a kind of fully determined distribution of planning. The distribution of cellular base stations in 5G heterogeneous cellular network is between the two extreme distribution models of grid distribution and Poisson process distribution [27,28]. In fact, the distribution of small cell base stations is not completely independent. Due to the strong assumption that the base station distribution is completely independent, the Poisson distribution model of 5G heterogeneous cellular network is not applicable in many cases.

3.2. System model

Considering the 5G heterogeneous network composed of N main networks, there are primary users (PU) and secondary users (SU) in the main network, and there can be as many primary users in the main network. The maximum number of channels owned by each primary network is recorded as Cmax, but the channels that can be reused by secondary users depend on the number and status of PU. Suppose there is a cognitive network operator (CNO) to manage all the secondary users SU to be accessed and collect the channel state information (CSI) of all the primary networks, as shown in Fig. 2. In the figure, 5G heterogeneous network centered on cognitive network operators, including the main network composed of base station, wireless access point and ENB. There are main users using the network in each main network, and there are secondary users to be accessed.

Note $\left\{U=\left\{u_1,u_2,\dots,u_m\right\}\right\}$, indicating the set of secondary users SU to be accessed, $N=\{1,2,\dots .M\}$, indicating the set of primary networks, assuming that each network has the same number of channels. Note that the maximum transmission rate of the ith channel of the mth network is $V_{i,m}^{\max}$, then the transmission rate $V_{i,m}$ depends on the channel state of the mth network. If the jth sub-user is going to enter the system, it needs to calculate its own location, and provide information such as the minimum transmission rate demand RJ, the maximum price that can be paid to operators $p_j^{\max}$ to cognitive network operators. When the ith channel of the network m is allocated to the jth secondary user, the expense that SU needs to pay is P_m. It is recorded that the interference of the secondary user to the primary user PU is $I_{j,m}$, and the total interference depends on the channel state. In order to ensure the QoS of the primary user, the total interference in the M network should not exceed the threshold ε_m; the secondary user should also meet their own requirements, that is, the minimum transmission rate requirements, lower than the maximum price requirements. Assuming that the pricing strategy of each primary network is different, the cost of the jth secondary user accessing the mth network is recorded as $P_{j,m}$.

The goal of this paper is to minimize the interference of secondary users to primary users under the condition of guaranteeing the QoS of secondary users.

Therefore, the total objective function is:

Minimize:

$$H(x)=\sum_{i=1}^{n}\sum_{n=1}^{M} I_{in}x_{in} \tag{1}$$

Subject to:

$$\sum_{n=1}^{M} x_{in}=1, \forall j=1,2,\dots,M \tag{2}$$

$$x_{in}\in\{0,1\} \tag{3}$$

Where (1) H (x) is the total objective function, which represents the sum of the total interference of all Su to Pu after joining each main network. Constraint (2) indicates that at a certain time, a channel of a main network is intelligently assigned to an SU. The constraint (3) indicates that it is 1 when the j channel of network m has been allocated, otherwise it is 0.

4. Implementation of multi-agent cuckoo algorithm for resource balance optimization

4.1. Standard cuckoo algorithm

In the algorithm, the feasible region is regarded as the nest for laying eggs, and the global optimal solution is regarded as the best host. The whole iterative optimization process simulates the process of finding the most ideal nest of cuckoo, and establishes the corresponding relationship between the problem solution set and cuckoo. Cuckoo algorithm is a natural heuristic algorithm developed by Xin She Yang and suash DEB in 2009. CS is based on the parasitic brooding behavior of cuckoo. In addition, the algorithm can be enhanced by the so-called Levy flight instead of simple isotropic random walk. The research shows that this algorithm may be more effective than genetic algorithm, PSO and other algorithms. In order to simulate the behavior of cuckoo in nature more simply and effectively, and at the same time to solve optimization problems, cuckoo algorithm sets the following three ideal states:

(1) Each generation of cuckoo produces only one egg and hatches in its nest randomly;

(2) Greedy selection strategy, cuckoos always keep the best nest as the host before finding a better nest;

(3) The number of bird's nests available for each generation is fixed, and the probability of finding parasitic eggs of host birds is Pa.

For a given scheduling task, taking cost and time as optimization objectives, the cuckoo search algorithm is used to optimize the problem, and the calculation flow is shown in Fig. 3.

The pseudo code of the algorithm is as follows:

Step 1: Define the objective function $f(X)$, initialize the function, and randomly generate the initial position $X_i\,(i=1,2,\dots,n)$ of n bird's nests. Parameters such as population size, problem dimension, maximum discovery probability P and maximum iteration times are set;

Step 2: The fitness function is selected and the objective function value of each nest position is calculated to obtain the current optimal function value;

Step 3: The optimal function values of the previous generation were recorded, and the position and state of other nests were updated;

Step 4: Comparing the existing position function value with the previous generation optimal function value, if it is better, the current optimal value will be changed;

Step 5: After position updating, the random number $r\in[0,1]$ is compared with P. if $r>P$, x^{t+1} is changed randomly, otherwise, it is unchanged. Finally, the best nest location $y_i^{t+1}$was reserved;

Step 6: If the maximum number of iterations or minimum error requirements are not met, return to step 2; otherwise, continue to the next step;

Step 7: Output the global optimal position.

On this basis, the exploratory path of cuckoo is as follows:

$$W_i^t=Y_i^t+\alpha\oplus L(\gamma) \tag{4}$$

Among them, Y_i^t represents the position of the ith bird's nest of the t-generation; W_i^t represents the position of the ith exploratory bird's

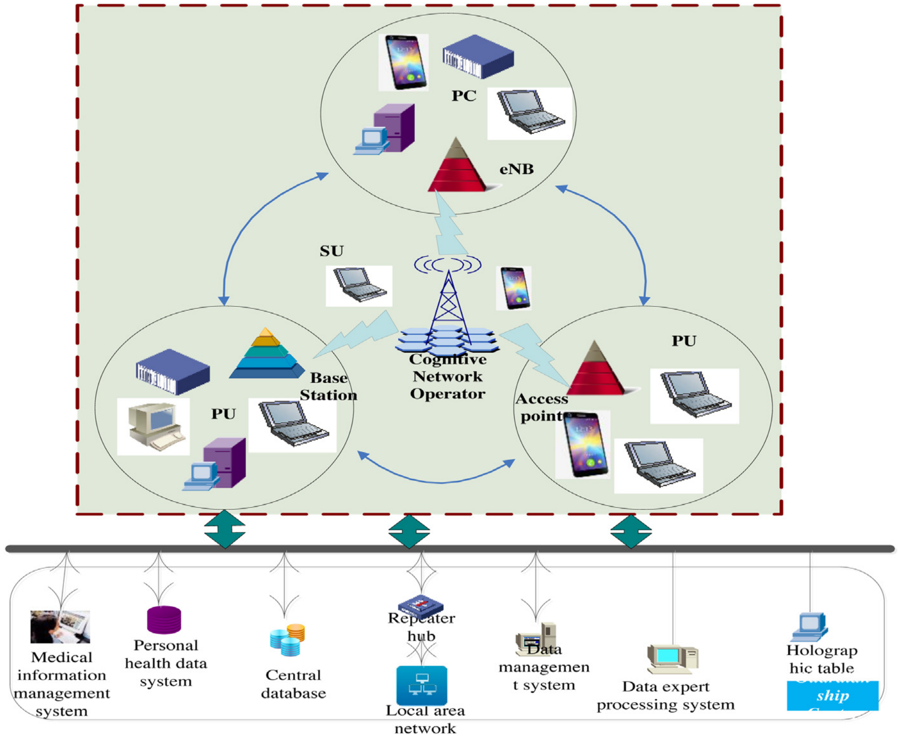

Fig. 2. 5G heterogeneous network diagram based on cognitive network operators.

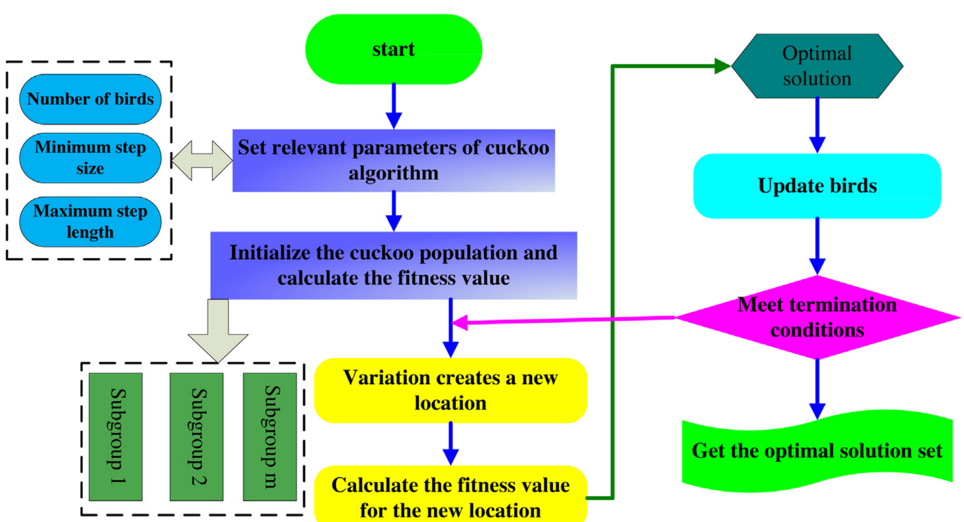

Fig. 3. Algorithm flowchart of cuckoo.

nest of the t-generation based on Y_i^t; α is the control step size, which can be set according to the solution problem; $\oplus$ is the point-to-point multiplication; $L(\gamma)$ is the random search path, whose walk length follows Levy distribution. Levy distribution has the feature of heavy tail. In Levy flight, short-distance step and long-distance step alternate, which is more efficient than Brownian motion in unknown or large space. The cuckoo algorithm uses Levy flight principle to update the candidate population, which can expand the search range, increase the diversity of the population, and effectively avoid the phenomenon of "premature".

The cuckoo uses the greedy selection strategy to test the one-to-one competition between W_i^t and Y_i^t in the bird's nest. Only the individuals with high adaptability can survive. The selection rules can be expressed as follows:

$$Y_i^{t+1} = \begin{cases} W_i^t, f\left(W_i^t\right) > f\left(Y_i^t\right) \\ Y_i^t, f\left(W_i^t\right) \leq f\left(Y_i^t\right) \end{cases} \tag{5}$$

After the above selection operation, some individuals with poor fitness will move their positions randomly if they are found, in order to find a nest with better adaptability and improve the quality of the population.

4.2. Coding scheme

The intelligent algorithm mainly uses the coding scheme based on the start time or the floating working hour rate in solving the resource balance problem. In this paper, we choose a coding scheme based on start time without decoding operation. According to the principle of resource balance optimization, the feasible solution of resource optimization problem is regarded as an agent's n-dimensional search space, where n represents the number of tasks in the network plan. Where $Lt_{ij} = \{lt_1, lt_1, \ldots, lt_n\}$ represents the actual start time of the k-dimensional task of agent $Lt_{i,j}$ in the t-generation. Due to the constraints of time sequence relationship between the work in the network planning chart, the start time of an operation can only be determined after all the urgent tasks of an operation are reasonably arranged. Therefore, this paper arranges the tasks referred to in each dimension according to the topological sorting order, so that the tasks that affect the start time of any task are located in front of the task, and all the tasks affected by the task are ranked next, so that it is convenient to initialize or check and correct the values of each dimension of $Lt_{i,j}$ from left to right. The steps to generate topology sorting are as follows:

(1) The starting tasks in the network graph are put into the partial topological ordering sequence;
(2) Check the unsorted tasks, and put the tasks that have been arranged before the urgent tasks into the partial topological sorting sequence;
(3) Repeat step (2) until all tasks in the network plan are arranged to form a complete topological ordering sequence.

The coding scheme based on the start time is illustrated with Fig. 4 as an example. According to the topological method, a topological ordering chain 1→4→2→3→5→6→7 of network planning graph is generated. Then the corresponding relationship between the individual vector $Lt_{i,j} = \{lt_1, lt_1, \ldots, lt_7\}$. lt_1 refers to the start time of work 1, lt_2 refers to the start time of work 4, and so on. Fig. 4 describes the single code network structure. Of course, there are other forms of network. Only Fig. 4 is taken as an example to illustrate the coding scheme based on the start time. Other forms of network structure will not be discussed.

4.3. Discretization of values and modification of illegal individuals

Because the standard multi-agent cuckoo algorithm is designed for the continuous optimization problem, it is necessary to improve the cuckoo search path and location updating formula, neighborhood competition cooperation operator and self-study operator to meet the needs of discrete value when it is used to solve the discrete optimization problem of resource balance optimization. At present, there are two common improvement methods: the first is to use binary coding, the second is to directly round floating-point numbers. The second method is simple and easy to use.

The multi-agent cuckoo algorithm is a random optimization method. The coding scheme based on the start time will generate illegal solutions that violate the timing constraints in the evolution process. Therefore, it is necessary to test the legitimacy of the new individuals formed by evolution and correct the illegal individuals. The test correction operation is: recalculate the value range (FS_j, LS_j) of the start time of the jth dimension task from left to right. If the value of the jth dimension of the new individual is not in this range, it will be determined as illegal individual, and then it will be corrected by randomly taking integer in(FS_j, LS_j).

The process of multi-agent particle swarm optimization for resource balance optimization is as follows:

Step 1: Set parameters. Set the scale of agent system $M \times N$; number of iterations N discovery probability P_a; scale of self-learning agent system $L_{size} \times L_{size}$.

Step 2: Multi agent initialization. Randomly generate $M \times N$ bird nests (initial value of multi-agent), determine the neighborhood of each agent, calculate the corresponding objective function value, and record the current optimal solution $F_{\min}$.

Step 3: Determine whether the end condition is met. If yes, the optimal solution $F_{\min}$ will be output at the end of iteration, otherwise, turn to step (4).

Table 1
Pareto frontier obtained by multi-objective cuckoo algorithm.

No.	R1	R2	R3	T1	T2	T3	T4	T5	T6	T7	T8
1	14.968	9.197	12.398	1	8	11	3	1	4	6	10
2	16.213	9.912	8.912	1	7	11	3	1	5	8	10
3	17.355	8.483	7.483	1	6	11	3	1	4	9	8
4	18.498	10.197	9.197	5	8	11	1	1	3	9	6
5	20.784	4.954	4.954	1	4	8	3	1	7	9	10
6	20.784	7.954	7.498	1	6	11	1	5	7	9	9
7	21.927	6.954	8.641	5	8	11	1	2	6	8	10
8	22.968	5.669	7.784	5	8	11	1	1	6	9	8
9	22.968	3.483	5.573	3	6	11	1	1	6	9	8

Step 4: Nest location update. A new generation of candidate bird's nest is formed by updating the position. Compared with the previous generation of bird's nest, the better one is kept as the current bird's nest, and the best solution $F_{\min}$ is updated.

Step 5: Random migration. According to the probability P_a, a new group of bird's nests can be obtained by random migration of bird's nests. The best nest is kept and the best solution is recorded.

Step 6: Neighborhood competition, cooperation and variation. Perform neighborhood competition and cooperation operation and mutation for each agent in turn, update bird's nest position and optimal solution $F_{\min}$.

Step 7: Self learning operation. Perform self-learning operation on the optimal agent (cuckoo), update the optimal bird's nest and the optimal solution $F_{\min}$, and turn to step (3).

5. Experiment and analysis

The hardware environment of this experiment is Intel Core i5, 2.3 GHz CPU, memory is 4 GB DDR3, the program is realized by MATLAB 2019. There are three sub groups with a total scale of 10 iterations 1000 times, generating 30000 scheduling times. Therefore, this paper sets a population scale of 30, the maximum number of iterations 1000, non-uniform variation Pa = 0.86, cross probability CR = 0.86, scaling factor F = 0.4, and compares the operation results of each algorithm under the same scheduling times. The operation results of standard and improved multi-objective cuckoo algorithms are shown in Table 1. The Pareto front in Table 1 is listed in ascending sequence according to the variance of resource 1, and nine Pareto optimal solutions are found in the multi-objective cuckoo algorithm. The single objective cuckoo algorithm is used to optimize the three resources independently. The minimum variance of R1, R2 and R3 is 134.868, 3.483 and 4.578, as shown in Fig. 5. By comparing the dominating relations of the solutions in Table 1, it can be found that the solutions from No. 7 to No. 8 obtained by VEPSO-BP algorithm are pseudo Pareto solutions, which are all dominated by Pareto optimal solutions of No. 9. In addition, through comparison, it can be seen that the sequence number 3 to 5 found by VEPSO-BP algorithm are also pseudo Pareto optimal solutions, which only obtain four Pareto solutions of sequence number 1, 2, 6 and 7. According to the operation results of the two algorithms, it can be found that the multi-objective cuckoo algorithm has more reliable global convergence performance than VEPSO-BP algorithm in dealing with multi-resource balance optimization.

(1) Algorithm validation

According to the dimensionality of each resource and the parameters after index transformation, the basic cuckoo algorithm (CS), the adaptive cuckoo algorithm (ACS) and the multi-agent cuckoo algorithm (MACS) are used to solve the optimization and selection model of resource allocation. Set the initial population number as n = 30, the global iteration number as iteration = 160, and find the probability of bird's nest as Pa = 0.25, and the number of function parameters as $n_d = 8$. The maximum value of scale factor is 0.5, the minimum value of scale factor is 0.05, the initial temperature q = 500, and the cooling coefficient a is 0.5. After the MATLAB operation, the change curve of fitness value is shown in Fig. 6.

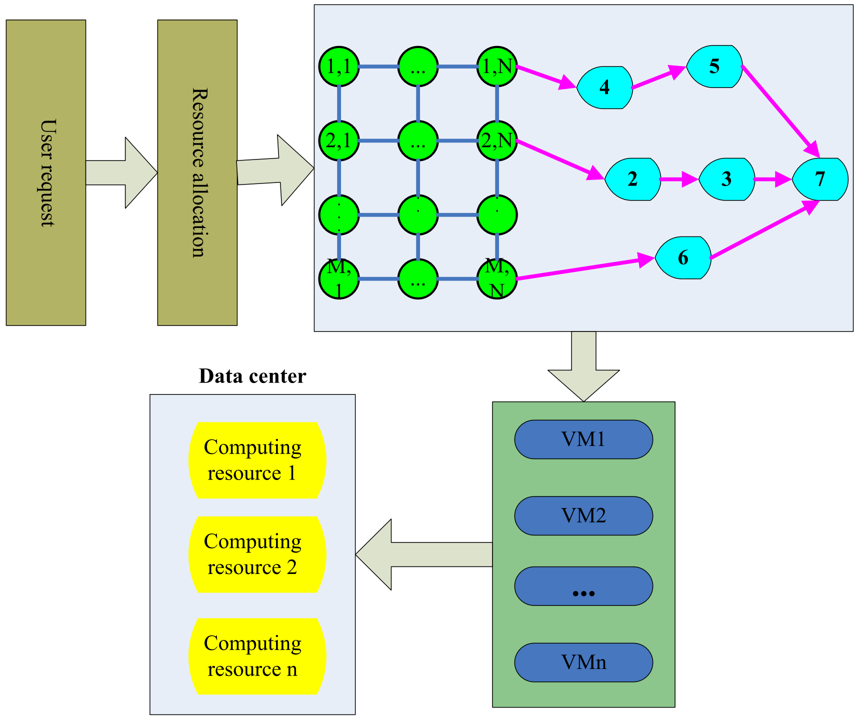

Fig. 4. Single code network diagram.

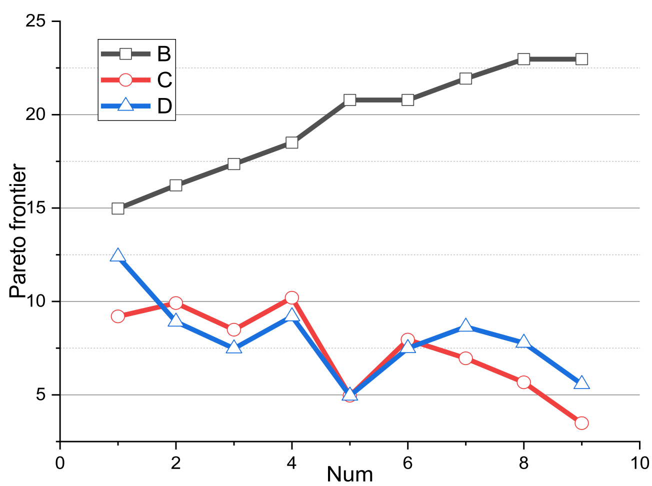

Fig. 5. Variance frontier of three resources R1, R2, R3.

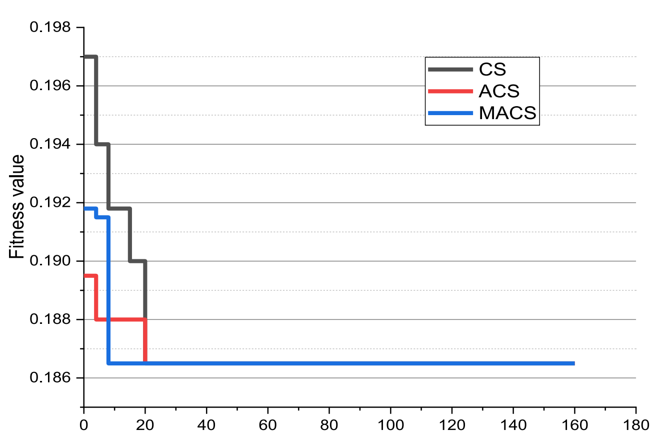

Fig. 6. Comparison of fitness curve of algorithm.

Table 2
Comparison of calculation accuracy and number of iterations required for convergence.

Algorithm	Accuracy of solution	Minimum number of iterations	Average number of iterations
CS	92	22	92
ACS	98	19	57
MACS	99	10	48

It can be seen from Fig. 6 that the population fitness value tends to be stable after about 30 generations. Finally, the minimum fitness value is 0.1864, and the maximum maxz of the total objective function is 5.3648. The corresponding optimal resource combination scheme is: resource $N1M3$, resource $N2M3$, resource $N3M4$, resource $N4M3$, resource $N5M1$, resource $N6M3$, resource $N7M2$, resource $N8M2$. The total time to complete the total task is 35.56h, and the total cost to complete the total task is 2932 yuan. The experiment fully proves that the improved adaptive cuckoo algorithm is feasible and effective in solving the cloud manufacturing resource allocation model.

(2) Algorithm accuracy verification

According to the parameters after de-dimensioning and index transformation of each resource in Table 2, under the conditions of the same population size n = 50, the same iteration number iteration = 200 and the same problem size $n_d = 8$. The basic cuckoo algorithm (CS), adaptive cuckoo algorithm (ACS) and multi-agent adaptive cuckoo algorithm (MACS) are respectively used to solve the selected mathematical model for 100 times, and the accuracy of the new algorithm is compared and explored. The results are shown in Table 2 and Fig. 7.

From the comparison results in Table 2 and Fig. 7, it can be seen that the accuracy of MACS solution is significantly higher than that of the other two algorithms, and under the same conditions, the number of iterations of MACS is less than that of other algorithms. Therefore, the improved adaptive cuckoo algorithm is more accurate in solving the cloud manufacturing resource allocation model. The fitness of MACS algorithm is stable at the earliest stage because it can get better results after less iterations, so it seems to be stable in the early stage.

(3) Algorithm efficiency verification

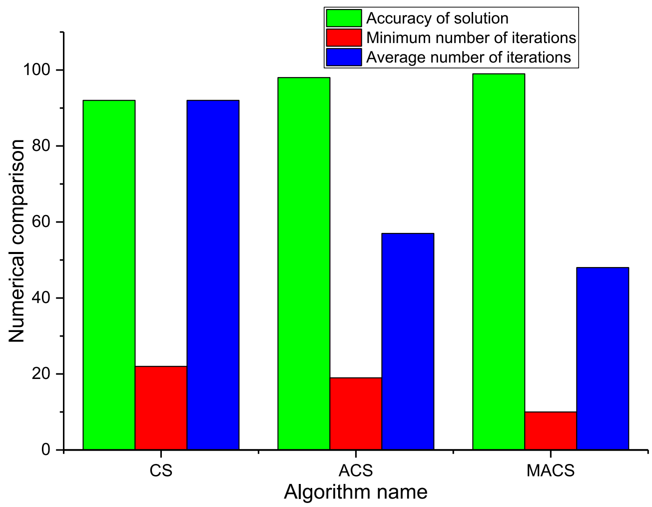

Fig. 7. Comparison of calculation accuracy and number of iterations required for convergence.

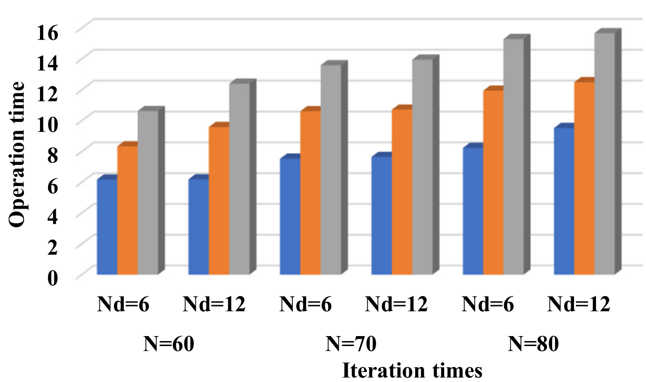

Fig. 8. Macs operation time.

Table 3
Macs operation time.

		600	800	1000
N=60	Nd=6	6.18	8.34	10.63
	Nd=12	6.19	9.59	12.39
N=70	Nd=6	7.53	10.62	13.59
	Nd=12	7.65	10.72	13.95
N=80	Nd=6	8.24	11.95	15.29
	Nd=12	9.53	12.49	15.67

According to the parameters of each resource de-dimensioning and index transformation, the improved adaptive cuckoo algorithm is used to solve the selected mathematical model under the conditions of different population scale, different iterations and expansion of the problem scale, and the solution efficiency of the new algorithm is explored. The results are shown in Table 3 and Fig. 8.

It can be seen that with the unilateral change of population size, problem size and iteration times, the operation time of MACS basically changes linearly. In addition, it further shows the feasibility and efficiency of the improved adaptive cuckoo algorithm in solving various scale problems. After 50 iterations, the multi-agent cuckoo algorithm can basically converge to the optimal solution, while other algorithms need about 200 iterations to converge to the optimal solution. Although the single iteration of the multi-agent cuckoo algorithm has the highest time complexity, the solution efficiency is the fastest. Fig. 9 shows the optimization process of the algorithm. This is mainly because the multi-agent cuckoo algorithm well realizes the complementary advantages of the multi-agent system and the standard cuckoo algorithm, and the neighborhood competition cooperation operator in the algorithm makes up for the lack of information exchange in the standard cuckoo algorithm. The mutation operator perturbs the population randomly, which enlarges the search range, while the self-learning operator improves the precision of the algorithm by small-scale search technology. At the same time, the efficient search mechanism of Levy flight can also expand the search space, increase the diversity of the population, and jump out of the local optimal solution. Thus, the algorithm can converge to the global optimal solution at a faster rate.

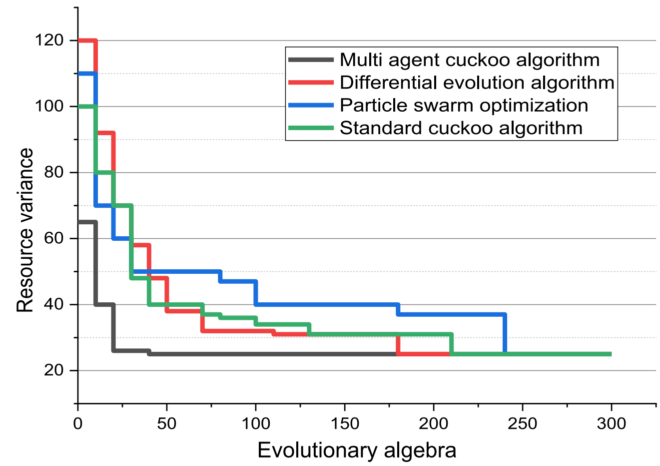

Fig. 9. Optimization process chart.

6. Conclusion

In order to solve the problem of spectrum resource shortage and high-speed access in 5G network, this paper proposes a cuckoo search optimization method. Firstly, the spectrum information of network channel sharing available to users is obtained, and the cuckoo search algorithm is used to optimize under the condition of satisfying the QoS guarantee of users, and the optimal allocation scheme is obtained by iterating for many times. The use steps are illustrated by examples. Compared with the traditional genetic algorithm, the calculation complexity can be reduced, and it can also be extended to more users and networks. The simulation also proves that the multi-agent cuckoo algorithm has better global optimization performance than the standard cuckoo algorithm, particle swarm optimization algorithm and differential evolution algorithm, and is a feasible and effective method to solve the resource balance optimization problem. The simulation test results show that in the field of multi-resource equilibrium optimization, the multi-objective cuckoo algorithm can converge to a better Pareto optimal solution than VESPO-BP algorithm, and has a stronger global convergence performance. At the same time, the convergence accuracy of the improved multi-objective cuckoo algorithm is greatly improved, and the convergence speed is significantly improved, which is a feasible and efficient method. However, in the heterogeneous network scenario, the network is complex and changeable, as well as the continuous change of user's QoS, and now most devices are mobile, so the future research should also consider the network switching and distribution in the mobile state of devices. The improved multi-objective cuckoo algorithm provides a set of Pareto optimal solutions. With the continuous change of user quality and the existence of mobile devices, future research should also consider the problem of network handoff and allocation in mobile state. How to select a solution that meets the actual engineering needs as the construction scheme will be the focus of the next research work.

CRediT authorship contribution statement

Ning Ai: Data analysis. **Bin Wu:** Formal analysis. **Boyu Li:** Validation. **Zhipeng Zhao:** Wrote the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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