Immune and Genetic Hybrid Optimization Algorithm for Data Relay Satellite with Microwave and Laser Links

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ABSTRACT

Aiming at the problem of oversubscription of data relay access request of user stars in future Space-Based Information System, the problem of resource scheduling optimization for data relay satellite system with microwave and laser hybrid links is studied. The characteristics of the hybrid links are analyzed. A multi-objective programming model on static resource scheduling constraint satisfaction problem is established, and a hybrid optimization algorithm integration of artificial immune strategies, niche ideas and improved genetic algorithm is put forward to solve the scheduling model. Simulation results show that the hybrid optimization algorithm optimizes the model quickly, and performs well in the ability of global optimization and convergence. The results validate that the static resource scheduling model could accurately describe the microwave and laser hybrid links relay satellite system resource scheduling problem with multi-tasking and multi-type antenna[1].

CCS CONCEPTS

• **Theory of computation → Theory of randomized search heuristics**; Optimization with randomized search heuristics;

KEYWORDS

Data relay satellite, resources scheduling, tabu search, niche, genetic algorithm

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1 INTRODUCTION

The construction of a space-based integrated information network is an important means for countries to compete for space resources and realize global investigation and imaging information. The data relay satellite system, as the main body of the future space-based integrated information network, directly determines the fostering processing capability of massive data information[1]. Increasing the data transmission capacity has become the urgent theme of the next data relay system development. The inter-satellite laser link is the solution proposed for the current data link capability of the microwave link. In recent years, countries around the world have carried out theoretical research and on-board demonstration verification of data relay satellite systems with inter-satellite laser links, and launched corresponding engineering verification plans[2], speeding up the pace of realization of inter-satellite high-speed laser transmission of capacity data. The coexistence of microwave and laser link has become an inevitable trend in the development of

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data relay satellite systems. In the hybrid link system, the relay satellite forms a data relay backbone network through the laser link, and provides multiple laser and microwave link access for the user satellite. With the continuous development of satellite imaging technology, the demand for large-capacity data relay will increase in the future, and the problem of over-rating of relay satellite resources will inevitably arise. The optimal scheduling of relay satellite resources is increasingly urgent and important.

At present, as for the problem of relay satellite resource scheduling, the literature [3] uses parallel machine scheduling theory to study, establishes a mixed integer programming model, considers the priority of the task, and uses the greedy random adaptive search algorithm to solve the model and obtain excellent results. The article studied the scheduling problem of no more than two time windows. In [4], a relay satellite scheduling algorithm based on task time flexibility is proposed. A scheduling example is validated and solved by the algorithm, and the initial scheduling scheme is obtained. The next step can further optimize the scheduling scheme. In [5], the dynamic clustering scheduling algorithm and the simulated degradation algorithm are used to solve the multi-satellite multi-circle observation scheduling problem. Literature [6] studies the observation satellite scheduling problem based on the time-order directed graph. In [7], a multi-satellite data transmission scheduling algorithm based on the smashing round optimization is proposed for the digital transmission scheduling technology in the earth observation system.

At present, the research on data relay satellites with optical terminals is at the experimental stage. Therefore, the problem of resource scheduling for microwave and laser hybrid links relay satellite system have not been studied intensively. Based on this, this paper mainly studies the resource scheduling problem of relay satellite system with microwave and laser hybrid links. First, for microwave and laser hybrid links, the characteristics of the resource scheduling problem have been studied and a static resource scheduling multi-objective constrained programming model have been established. Secondly, for the static resource scheduling model, a hybrid optimization algorithm combining artificial immune strategy, niche idea and improved genetic algorithm is proposed. Finally, the model and algorithm of this paper are simulated and verified in different scenarios.

2 RESOURCE SCHEDULING OF HYBRID LINKS RELAY SATELLITE SYSTEM

2.1 Scheduling Characteristics

In the future, the data relay system based on the hybrid links of microwave and laser is shown in Fig. 1. A data relay satellite can provide multiple laser and microwave links for the user satellite, when the data of the user satellite is difficult to directly return to the ground station. The data is forwarded to the ground station via the relay satellite using a microwave link or a laser link. The user satellite submits a data relay request to the dispatching center in advance according to its own mission plan, and reports the data capacity, priority, and time validity of the relay task to the dispatching center. The dispatching center adopts a certain global scheduling strategy according to all data relay requests of the user satellites, and realizes the maximum task scheduling amount under various constraints.

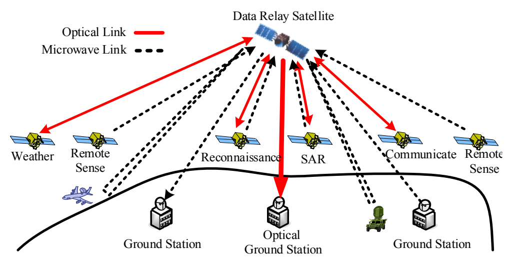

Figure 1: Data relay satellite system with microwave and laser hybrid links.

Since the resources of the data relay satellite system with microwave and laser hybrid links are limited, besides, the user satellite access to the relay satellite is subject to many restrictions, it is difficult to realize communication with the ground station at any time. Therefore, it is necessary to plan and schedule the resources of the relay satellites, and the resources are subjected to certain scheduling constraints.

2.2 Static Resource Scheduling Multi-Objective Constrained Programming Model

It can be seen from the above analysis that the resource scheduling problem of the hybrid links system is constrained by the visible time window, task priority, resource power consumption, etc. Therefore, the resource scheduling problem can be regarded as a kind of Constraint Satisfaction Problem (CSP). Constraint satisfaction is one of the core issues in computer science and artificial intelligence research. Many combinations in real life and scheduling optimization problems can be described as the CSP. A CSP consists of a set of variables, and a set of constraints that limit the value of the variable.

2.2.1 Resource scheduling constraints (where $i = 1, 2, ..., N$; $l = 1, 2, ..., n$)

1) The communication task set $J=\{J_1, J_2, \ldots, J_N\}$, N indicates the number of communication tasks that need to be scheduled.
2) The antenna resource set $M=\{m_1,m_2,\ldots,m_n\}$, where n indicates the number of antenna resources that can be scheduled.
3) The resource power set $PC=\{PC_1,PC_2 ,\ldots, PC_L\}$ represents the average power consumption of each antenna resource.
4) The task transmission time variable T_l^i represents the transmission time of task J_i on the l-th antenna.
5) The antenna switching time set $T_{l\text{-}switch}$ represents the switching time of the antenna l.
6) The task scheduling identifier set $Flag = \{flag_1, flag_2, \ldots, flag_N\}$, $f_i \in \{0,1\}$, $flag_i = 0$ or $flag_i = 1$ indicates that the communication task J_i is scheduled or not scheduled.
7) The priority of the task is $p_i \in \{1, 2, \ldots, p\}$, where p is a

positive number indicating the highest priority of the task.

8) Task J_i must satisfy the visible time window constraint when scheduling execution. The moment when the task starts executing is S_i, and the duration of the task is T_i. $STW_i^k \leq S_i \leq ETW_i^k - T_i$ indicates that the task J_i must be executed within its k-th visible time window $[STW_i^k, ETW_i^k]$. STW_i^k represents the start time of the k-th visible time window of task J_i, and ETW_i^k represents the end time of the k-th visible time window of task J_i. A task selects only one time window for transmission in all of its visible time windows.
9) Task J_i must be completed within its effective time frame. The end time of the task is (S_i+T_i), which must be within the valid time range $[t_{ai}, t_{bi}]$ of the task J_i.
10) $T_S \leq S_i \leq T_E$, $T_S \leq S_i+T_i \leq T_E$, indicating that all communication tasks must be scheduled within a given scheduling time period $[T_S, T_E]$. T_S represents the start time of the scheduling period, and T_E represents the end time of the scheduling period.

2.2.2 Constraint Planning Model Representation.

$$\begin{aligned}
&\text{Min } f_1 = \sum_{i=1}^{N} flag_i\, p_i \\
&\text{Min } f_2 = \sum_{l=1}^{L} \left[PC_l \sum_{i=1}^{N} (T_l^i + T_{l_{l-switch}}) \right] \\
&\text{Min } f_3 = T_e \\
&S.T.\ \ J = \{J_1, J_2, \ldots, J_N\} \\
&\qquad M = \{m_1, m_2, \ldots, m_n\} \\
&\qquad PC = \{PC_1, PC_2, \ldots, PC_L\} \\
&\qquad flag_i \in \{0,1\},\ \ i = 1,2,\ldots,N \\
&\qquad p_i \in \{1,2,\ldots,p\},\ \ i = 1,2,\ldots,N \\
&\qquad W_i \in \{W_1, W_2, \ldots, W_N\},\quad W_i = \bigcup_{k=1}^{TW_i} \qquad V_i^k] \\
&\qquad T_S \leq S_i \leq T_E,\ \ T_S \leq S_i + T_i \leq T_E,\ \ i = 1,2,\ldots,N \\
&\qquad \text{IF } (STW_i^k \leq S_i \leq ETW_i^k - T_i) \wedge (t_{ai} \leq S_i + T_i \leq t_{bi})
\end{aligned} \tag{1}$$

The objective function f_1 represents the goal of the scheduling is to ensure the priority of the unfinished tasks is as small as possible. That is, to complete as many high-priority tasks as possible. The objective function f_2 represents that the goal of scheduling to ensure that system resource consumption is minimized. The objective function f_3 represents the goal of scheduling to ensure that the system task scheduling completion time is the shortest.

2.2.3 Multi-objective problem handling

In the resource scheduling problem of relay satellite system with microwave and laser hybrid links, the priority sum, the resource and the time consumption are the target parameters of different dimensions. In order to obtain the optimized scheduling result, the target parameters are first dimensionlessly standardized. Then, according to the fuzzy preference, the weighting coefficient is determined separately for the optimization target. Finally, based on the analysis of each objective function, the linear objective method is used to construct the single objective function by multi-objective function weighting operation, and the multi-objective problem is transformed into Single goal optimization problem. Expressed as

$$\min f = \sum_{i=1}^{k} w_i f_i \tag{2}$$

Where: w_i is the weight, generally taken $\sum_{i=1}^{k} w_i = 1$; f_i is the objective function (where i = 1, 2, …, k); k is the number of objective functions.

2.2.4 Weight determination based on preference relationship

The scheduling problem with three objective functions is studied in the paper, $F=\{f_1, f_2, f_3\}$, constructing equivalence classes: $c_1=\{f_1\}$, $c_2=\{f_2\}$, $c_3=\{f_3\}$, $C=\{c_1, c_2, c_3\}$, where $c_i \in C_i$, $1 \leqslant i \leqslant 3$. The preference relationship is: $c_1 \prec\prec$, $c_3 \prec\prec c_1$, $c_3 \prec c_2$. According to the preference relationship[8], the normalized weights are obtained: $w(f_1)$=0.54, $w(f_2)$=0.33, $w(f_3)$=0.13. Therefore, the individual fitness value is:

$$Fitness = \sum_{i=1}^{k} w_i f_i \tag{3}$$

3 HYBRID OPTIMIZATION ALGORITHM

The relay satellite resource scheduling problem is a complex combinatorial optimization problem. Unlike the traditional combinatorial optimization problem, the relay satellite resource scheduling problem has unique visible time window constraints and task time validity constraints. The relay satellite resource scheduling problem has been proved to be an NP-hard problem. The solution space of the problem is extremely large, which is a typical high-dimensional multi-peak problem. Therefore, it is easy to fall into local optimum for optimization. On the other hand, the program evaluation calculation time of the general task amount can reach the order of milliseconds, and the calculation amount is large. When the tasks and resources increase, the solution space and the program evaluation calculations increase exponentially. Therefore, the key to solve relay satellite resource scheduling optimization problem is to reduce the probability of falling into local extremum and reduce the search volume of the algorithm.

In view of the complexity of the problem, this paper proposes an adaptive genetic algorithm with elite retention as the basic algorithm, and a hybrid optimization algorithm combining artificial immune strategy and niche ideas. The genetic algorithm has been widely used in combinatorial optimization, constraint satisfaction and other issues, and has achieved good results. Therefore, the genetic algorithm improved by the elite retention strategy is used as the basic algorithm of the hybrid optimization algorithm to enhance the local search ability and accelerate the convergence speed of the algorithm. The adaptive crossover and mutation operator are used to enhance the algorithm to jump out of the local optimal ability. Introduce niche ideas in the basic algorithm to reduce the probability that the algorithm falls into local extremum. Artificial immune strategy is adopted to reduce the algorithm's repeated calculation of some better solutions in the search process, thereby reducing the computational complexity of the algorithm. The specific design is as follows.

3.1 Hybrid Optimization Algorithm Flow

Genetic Algorithm (GA)[9] is an evolutionary algorithm proposed for discrete problems. It has a strong global search ability, and its idea comes from the natural law of "natural selection, survival of the fittest". Each individual in the algorithm represents a solution to the problem, called a chromosome, and the quality of the solution is evaluated by the fitness value. Each solution to the scheduling problem is a scheduling scheme with N decision variables, i.e. N genes of the chromosome. Each coding gene is designed to be $\boldsymbol{x}_i = [x_{ai}, x_{bi}]$, x_{ai} and x_{bi} are the scheduling order of the tasks and the selected antenna resource sequence, respectively. The general flow of hybrid algorithm is shown in Fig. 2. The algorithm is mainly composed of five major function modules: main function module, Compute Fitness Value of Individual, Niche Idea, Adaptive GA with Elitism Strategy and Artificial Immune Strategy.

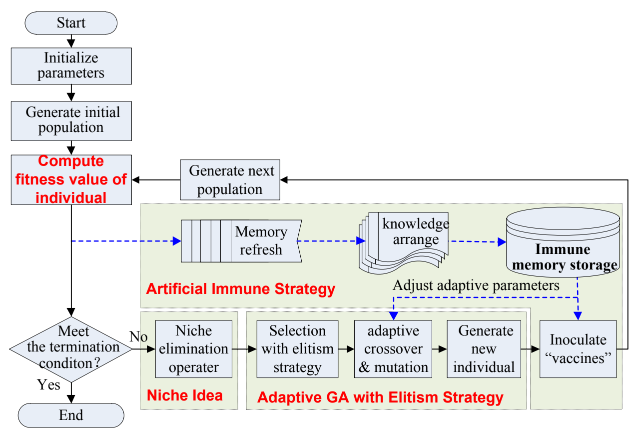

Figure 2: Hybrid optimization algorithm flow.

The main function module is mainly responsible for the various parameter setting and genetic control of the algorithm, and finally ends the algorithm, generates a scheduling sequence and an unfinished scheduling task set. The parameters set include initial population size, maximum number of genetic iterations, adaptive crossover and mutation parameters, niche related parameters and the capacity of the immune memory. The main functions of the other modules are described in the following sections.

3.2 Compute Fitness Value of Individual

Based on the CSP model, the scheduling process mainly includes two operations of "Ascertain Current Mission Scheduling Time" and "Refresh Latter Mission Time-Window", as shown in Fig. 3.

Each scheduling scheme has N decision variables, and different decision variable values will have different scheduling effects. How to quickly obtain the scheduling result of the task, that is, the rapid evaluation of the generated new individuals (different decision variables), is the key to improving the efficiency of the algorithm. The complexity of the resource scheduling problem of the hybrid links relay satellite system is mainly: a time period in which a task occupies resources, which will affect the available time window of subsequent scheduled tasks. Therefore, this paper adopts a loop iteration algorithm based on time window update, so as to quickly obtain the scheduling result of the task. Firstly, according to the different antenna resources selected by the tasks, the tasks are divided into different sets, and then according to the scheduling order of the tasks, the CSP model is used to judge, obtain the scheduling identifier and execution time of each task, and finally calculate the individual fitness value according to equation (3).

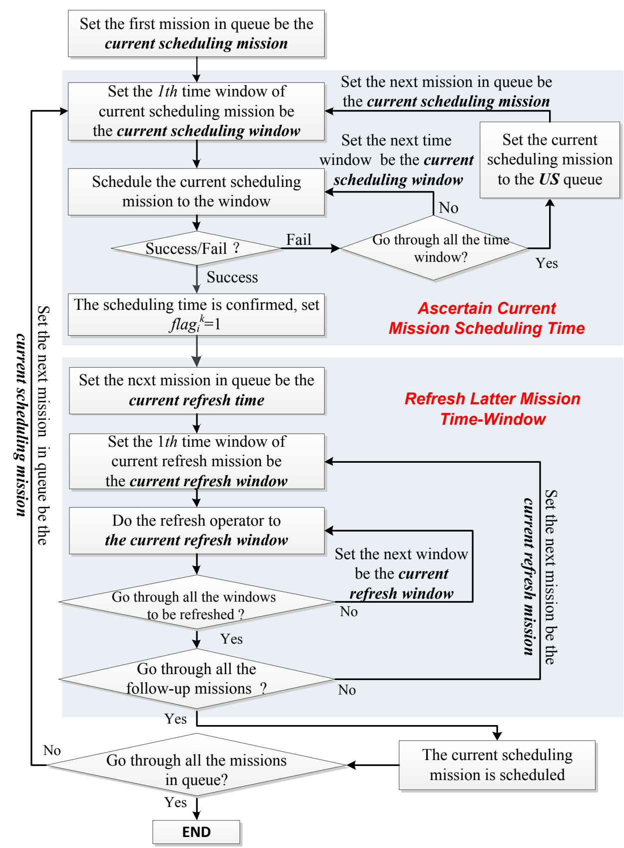

Figure 3: Process of mission scheduling.

3.3 Niche Idea

In order to avoid population aggregation near local optimal values to maintain population diversity, improve algorithm search efficiency and global optimization ability, this paper introduces the niche idea and uses the dynamically changing niche distance parameter to search for the neighborhood near the optimal value[10]. The superior individual performs a penalty (the fitness value is multiplied by a number far less than 1), thereby reducing the probability that the individual is selected to the next generation in the vicinity of the local optimum.

Definition 1: Let the minimum Euclidean distance between individual $\boldsymbol{x_i}$ and all individuals in the population be the difference $\boldsymbol{D_i}$ between the individual $\boldsymbol{x_i}$ and the population, as shown in equation (4), Where the variable N_{scale} is the population size:

$$\begin{aligned} D_i &= \min_{j\neq i}\left\|x_i - x_j\right\| \\ &= \min_{j\neq i}\frac{1}{2N}\sqrt{\sum_{l=a,b}\sum_{k=1}^{N}\left(x_{li}^k - x_{lj}^k\right)^2} \quad i=1,2,\cdots \end{aligned} \tag{4}$$

Definition 2: Let N_{niche}'s optimal individual and the average difference in the population be the niche distance L of the population. When the average difference is less than 1, take the niche distance L=1, as shown in equation (5).

$$L = \max\left\{ \underset{i\in idx\_niche}{\text{mean}}\{D_i\}\ ,\ 1 \right\} \tag{5}$$

3.4 Adaptive GA with Elitism Strategy

The paper adopts the genetic algorithm of elite retention strategy, which is to directly inherit the best individual in each generation to the next generation. Therefore, the fitness function only needs to reflect the merits of the individual, and the target value can be directly used.In the hybrid algorithm, the P_c and P_m are the crossover and mutation probabilities, respectively. When the population is trapped in the local optimum, even after the niche is eliminated, the new individuals may surround the niche and the population diversity is poor. Therefore, selecting larger P_c and P_m at this time can increase the generation of new individuals, which is beneficial to jump out of local optimum. When the initial stage of the algorithm or the population fitness value is dispersed, selecting smaller P_c and P_m is beneficial to retain the elite individual, which can speed up the convergence of the algorithm. Therefore, adaptive crossover probability and mutation probability are calculated using equations (6) and (7):

$$P_c = \begin{cases} k_1 & f_c < f_{avg} \\ \dfrac{k_2\left(f_{max} - f_c\right)}{f_{max} - f_{avg}} & f_c \geq f_{avg} \end{cases} \tag{6}$$

$$P_m = \begin{cases} k_3 & f_m < f_{avg} \\ \dfrac{k_4\left(f_{max} - f_m\right)}{f_{max} - f_{avg}} & f_m \geq f_{avg} \end{cases} \tag{7}$$

In the formula, the parameters k_1, k_2, k_3 and k_4 are variables between 0 and 1, and their sizes will be adjusted according to the case of "Artificial Immune Strategy (Section 3.5)" during the search. f_{avg} and f_{max} are the average and the maximum fitness value of the population, f_c is the average fitness value of the cross individual, f_m is the fitness value of the individual to be mutated.

3.5 Artificial Immune Strategy

The simulation of the discrete problem shows that the algorithm will frequently generate the same individuals that have been searched in the late stage after genetic algorithm converges to local optimum. For this kind of computationally expensive scheduling, not only the computational resources are wasted, the calculation time is delayed, and the optimization ability of the algorithm is also reduced. In response to this problem, the algorithm refers to the artificial immune strategy[11]. Usually, the artificial immune algorithm takes the optimal individual in the solution space as the "antibody", and calculates the new individual's fitness value to determine its appetency with the "antigen". The algorithm of this paper references its idea, but the algorithm remembers the easy-to-repeat individuals (always with the better fitness value) that have been searched in history as "antibodies", and the new generated individuals are regarded as "suspected antigens". After the new individuals are compared with the "antibodies", the suspects are eliminated or when it is characterized as "antigen", the "release" or "phagocytosis" operation is taken respectively. When a "phagocytosis" operation is performed, a new individual is regenerated by the "immune-cloning" method to replace the individual. When implementing the "immune-cloning" operation to generate a new individual, the adaptive mutation probability is calculated using equation (7).

3.5.1 Vaccination

As the algorithm searches deeper, the distribution of individual populations will gradually converge to one or several local extremes. Concentration is conducive to the convergence of the algorithm, but too concentrated or maintained concentration will affect the global optimization ability of the algorithm. In this paper, the hybrid optimization algorithm introduces the artificial immune idea to avoid the repeated calculation of the individual's fitness function and improve the computational efficiency. It can prevent the population from being too concentrated, and avoid the algorithm falling into local optimum.

This algorithm defines the memory process of the easy-to-repeat individuals (always with the better fitness value) becoming the "antibodies" as the "vaccination". Individuals that are easy-to-repeat are defined as "vaccines". At different stages of the search, the "vaccines" inoculated and the total size of "antibody" (ie, "immune memory" size) are dynamically changed. Usually at the beginning of the algorithm, the individual repetition rate is low. At this time, in order to improve the search efficiency, a small amount of the "vaccine" inoculated should be controlled. As the search progresses, the probability of individual repetition increases, and the number of "vaccines" inoculated should gradually increase. Since the new individuals are required to compared with the "antibodies" (i.e., "immune memory"), the amount of calculation is directly proportional to the number of "antibodies", so the size of the "immune memory" cannot be increased indefinitely, otherwise the optimization efficiency of the algorithm will be reduced.

Therefore, the algorithm adopts a growth strategy in which the number of the "antibodies" is dynamically increased, and sets the maximum size

1) At the beginning of the algorithm, the "immune memory" capacity is initialized to a population size.

2) In the search process, when no "antigen" is found (i.e., no new individual repeats with the individuals in the "immune memory"), then keep the "immune memory" capacity unchanged, only dynamic update "immune memory" individuals (i.e. vaccinate the new "vaccine"). Vaccinate of a new "vaccine" means replacing the "immune memory" individual with a better new individual. If the new individual is superior to the worst one in the "immune memory", then use the "dichotomy" to compare the individual in the "memory" with the new ones, so as to obtain the ranking position of the new individual fitness value, and discard the worst individual.

3) In the search process, when the "antigen" is found, the "immune memory" capacity is expanded. All individuals in the current population superior to the "immune memory" worst individuals are all added to the "immune memory". If the "immune memory" capacity reaches its maximum size, it will no longer increase, and only dynamic update "immune memory" individuals.

In the process of search, the variation parameters in the adaptive genetic algorithm are adjusted according to the repetition rate of the individual population of the current generation. When a repeating individual occurs, the mutation parameter is updated as follows:

$$k_i := (k_i)^{\beta} \quad , \quad i = 3,4 \tag{8}$$

Among them, the variable β is an amplification factor, usually taking a decimal between 0.9 and 1, and the smaller the β, the faster the variation parameter is amplified. When there are more individuals, the amplification of the variation parameters can increase the diversity of the population and reduce the appearance of repeated individuals.

3.5.2 Memory knowledge organization

Although computer memory has been rapidly developed in terms of capacity and access speed, it takes a long time for each new individual to use the global polling comparison method to determine whether genes are consistent, which will seriously affect the efficiency of the entire optimization algorithm. Therefore, the knowledge in the "immune memory" needs to be sorted according to a certain strategy.

In the search process, new individuals need to be compared with "antibodies". If they are directly compared one by one, the algorithm will be very computationally expensive. Therefore, it is necessary to organize the individuals (immune knowledge) in the memory to establish an index of the individual genes of the memory; when the new individual is compared with it, the "dichotomy" search can be used to reduce the amount of calculation to an exponential level. If the simple sorting method is adopted, when the memory individual is updated, there will be a large number of individual sorting sequence numbers that need to be updated, and when there are many individuals, the algorithm will be very computationally expensive. Therefore, this paper draws on the sorting method of "dictionary order". First, the solution space is meshed, and each dimension is divided into 2^n cells. As shown in Fig. 4, if the solution space is a two-dimensional space, it can be divided into 16 cells, and the memory banks are placed in the corresponding grid. When the new individual is compared with the memory individual, it is only necessary to locate the grid to which the new individual position belongs, and then compare the individual with the grid one by one, and the calculation amount of the comparison is still controlled in a small range, and at the same time, the calculation of sorting is significantly reduced.

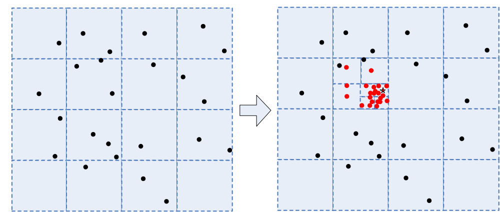

Figure 4: knowledge index.

In addition, in the search process of the algorithm, as the memory capacity becomes larger, more and more individuals are more and more concentrated in a certain grid, as shown in the right figure of Fig. 4. At this point, the grid can be further subdivided until the number of individuals in a single grid is small.

4 SIMULATION AND RESULTS ANALYSIS

4.1 Simulation Scenario

Many aerospace and astronomical institutions in the world provide orbital parameters for the orbiting satellites. The selection of relay satellites that are located at 10° east longitude. According to the ESA's European Data Relay Satellite (EDRS)[2]. Set there are three single-address antennas on the relay satellite. The antenna types are S-band, Ku-band and optical antenna. Set the terminal specific parameters as shown in Table 1. The simulation period is 00:00:00~06:00:00, and the user satellites parameters are imported in STK. The data is shown in Table 2. Using the STK to analysis the visibility of the user satellites, the visible time windows between the relay satellite and the user satellites are shown in Table 3. It is assumed that a total of 64 tasks of the user satellites need to be scheduled, each task has a different priority, and the task priority is a uniform random number of [0, 10].

Table 1: Key Performance Parameters of the Antenna

Antenna	S	Ku	Optical
Data Rate	10Mbps	200Mbps	1.8Gbps
Power Consumption	500W	500W	100W

Table 2: Basic Situation of User Satellites

Satellite	LEO 01	LEO 02	LEO 03	LEO 04
Altitude	400km	1000km	2000km	3000km
Orbit inclination angle	35°	95°	115°	115°

Table 3: The Visible Time Windows Between Relay Satellite and User Satellites

LEO 01 (400km)	LEO 02 (1000km)	LEO 03 (2000km)	LEO 04 (3000km)
00:00:00--00:48:25	00:02:56--01:09:15	00:00:00--01:06:04	00:00:00--00:07:07
01:31:04--02:26:00	01:48:34--02:53:41	01:45:10--03:08:38	00:45:04--02:49:09
03:08:40--04:03:47	03:32:42--04:39:43	03:46:45--05:13:47	03:30:14--05:44:53
04:46:25--05:42:26	05:14:26--06:00:00	05:42:02--06:00:00	05:54:58--06:00:00

4.1 Analysis of results

The scheduling problem is optimized with the hybrid optimization algorithm proposed in this paper and the standard genetic algorithm, and the search process of the two algorithms is compared and analyzed. Both populations have a population size of 80, an iteration number of 100, and a mutation probability of 0.5. The adaptive cross mutation probability parameters are 0.5, 0.25, 0.05, and 0.025, respectively. The magnification factor β = 1.05. Since the algorithm performs Dimensionless Normalization processing with the fitness value distribution generated by the algorithm, different algorithm cannot be directly compared by the fitness value. Since the scheduling problem is most concerned with priority-weighted task completion, the following simulation mainly compares the completion of priority-weighted tasks of the two algorithms. Fig. 5 is a comparison of repeated experiments of the two algorithms. Fig. 6, Fig. 7 and Fig. 8 are respectively a search process of the two algorithms.

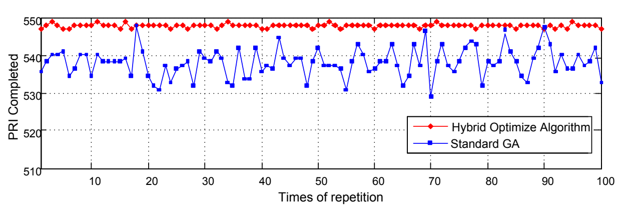

Figure 5: Repeated tests for two optimization algorithms.

In Fig. 5, the 98% result of the hybrid optimization algorithm is superior to the standard genetic algorithm, and only two results are comparable. This is because the hybrid optimization algorithm adopts the idea of introducing niche and artificial immunity. After the algorithm converges, it has the strategy of actively improving the diversity of the algorithm and the operation of jumping out of the local extremum, which indicates that the algorithm is suitable for such complex high-dimensional multi-peak problem.

Comparing the single experiments in Fig. 5 and Fig. 6 shows that the optimal value found by the standard genetic algorithm is 539; and the optimal value of the hybrid optimization algorithm is 549, which is obviously superior to the standard genetic algorithm. It can be seen from the partial enlarged view of Fig. 9 that the algorithm has a small jump after convergence, indicating that the hybrid optimization algorithm can still jump out of the local extremum after convergence. There is a greater gap between the population mean and the optimal value of the hybrid optimization algorithm, which indicates that the hybrid optimization algorithm introduces niche idea, immune strategy and adaptive genetic operators to improve the diversity of the population.

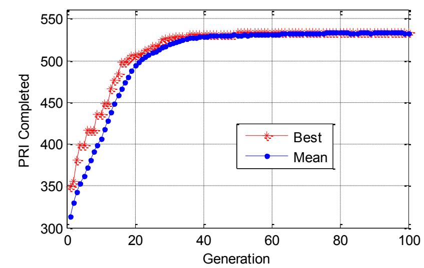

Figure 6: Search process of genetic algorithm.

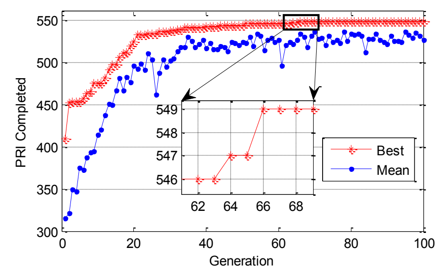

Figure 7: Search process of hybrid optimize algorithm.

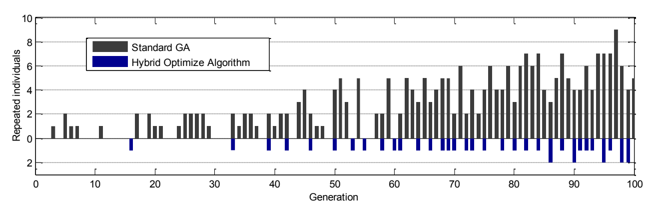

Figure 8: Repeated individuals in each generation of two optimize algorithms.

Fig. 8 records the number of individual instances of the newly generated individuals and historically searched individuals for each of the two algorithms. It can be seen from the figure that the repeated optimization of the hybrid optimization algorithm is kept below 2 (2.5%); while the genetic algorithm is in the late stage of the search, the average number of individuals is between 6-8 (the repetition rate is close to 10%). This is because the hybrid optimization algorithm adopts an artificial immune strategy. When the population has repeated individuals, the adaptive mutation parameters are adjusted to increase the diversity of the population, thereby controlling the individual repetition rate and forming a negative feedback mechanism.

Fig. 9 shows the specific time and scheduling sequence of task scheduling on three antenna resources. Different color blocks represent different tasks, and the color block length represents the length of the task transmission time. The labels on the color blocks represent the task number and priority respectively. Due to the high data transmission rate of the laser link and the low power consumption of the optical antenna, the optical antenna has more transmission tasks arranged and higher resource utilization.

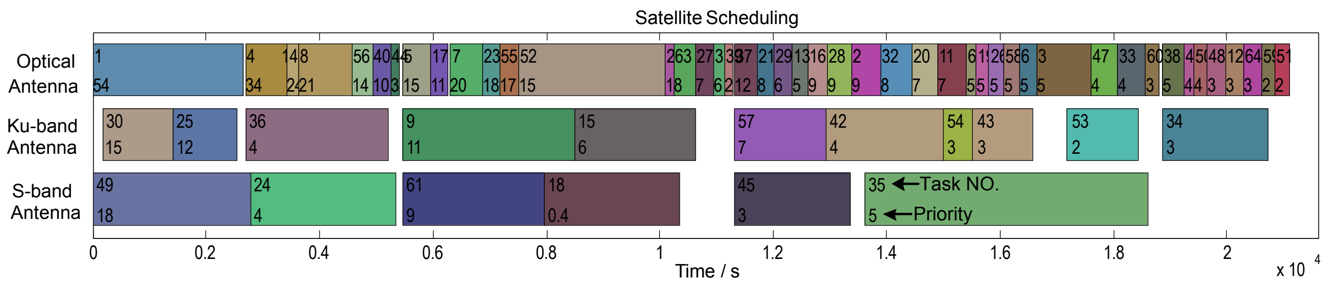

Figure 9: Gantt Chat of scheduling result.

In the scheduling result of Fig. 9, the scheduling time period is 21600s (6 hours), and the total scheduling execution completion time is 21089.786s. Task 41 and 10 failed to be scheduled due to resource conflicts, with priority weights of 10 and 1, respectively. The task completion rate was 96.875%. The ratio of the total priority weight of the scheduled tasks is 98.03%. The resources utilization is 97.63%. Considering that the task must arrange scheduling within a specific visible time window, the scheduling result shows that the scheduling algorithm has advantages in convergence speed and scheduling efficiency, and is suitable for multi-task, multi-antenna microwave and laser hybrid links data relay satellite system resource scheduling.

5 CONCLUSIONS

In summary, the efficient and reliable data relay satellite system resource scheduling in the future is a key technology for the construction of the space-based integrated information network. In this paper, the data relay access request oversubscription problem of the user satellite in the future space-based information system is oversubscribed, and the resource scheduling problem of data relay satellite system with microwave and laser hybrid links is studied. A multi-objective constrained programming model for static resource scheduling is established. The hybrid optimization algorithm based on artificial immune strategy, niche idea and improved genetic algorithm is used. The scheduling model is solved to obtain the best solution for static resource scheduling. Simulation experiments show that the proposed hybrid optimization algorithm can quickly optimize the model, and the hybrid optimization algorithm introduces niche idea, immune strategy and adaptive genetic operators to improve the diversity of the population, and is suitable for multi-task, multi-antenna microwave and laser hybrid links data relay satellite system resource scheduling.

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