Research of Improved Genetic Algorithm for Resource Allocation in Space-based Information Network

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Abstract. Along with the expansion of space-based information network, the task cooperation and resource allocation of access nodes is important issues that need to be addressed in the context of multiple spacecraft access. For the problem of resource dynamic scheduling, based on the present situation and development trend of space-based information network construction, resource allocation on tasks is researched in this paper. Furthermore, network resource allocation model and method of resource dynamic allocation based on genetic algorithm are realized, comprehensively consider the consumption and profit of resources to meet the task demand. By establishing allocation model suitable for space-based network, and using simulated annealing process and adaptive method to design improved genetic algorithm, the advantages and disadvantages are analyzed and simulated. The simulation result indicated the algorithm has good result in improving effectiveness and timeliness of network resource scheduling.

Keywords: Space-based information network · Resource allocation · Genetic algorithm · Simulated annealing

1 Introduction

In the future space information system, there are a large number of spacecraft with complex types. In addition to the large-scale hybrid constellation network which constitutes the space backbone network system, there are still a large number of application spacecraft, such as remote sensing satellite, manned spacecraft, scientific test satellite, etc., which will be the basic unit of the space-based information network, and work together under the deployment of space-based management and control system as managed objects. With the development and scale expansion of this system in the future,

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the difficulty and complexity of space-based information network management are also increasing sharply. Therefore, it is necessary to carry out targeted network resource scheduling and network business management for a variety of space missions. The management of the managed objects in the network has gone far beyond the scope of the traditional equipment monitoring capability, and more emphasis is placed on the cooperative scheduling among multiple types of spacecraft under the unified task specification. In this scene, it is a feasible way to homogenize the functions of the deployable spacecraft into the available resources in the network, and to allocate the resources dynamically and cooperatively based on the mission requirements, so as to meet the requirements of real-time and effectiveness of space-based information network in the future.

The construction of space-based information network in China is conceived in reference [1–3], and aircrafts in different orbits, types and performances, corresponding ground facilities and application systems are described and constructed. Space-based information network has the ability of intelligent information acquisition, storage, transmission, processing, fusion and distribution, as well as high degree of autonomous operation and management capabilities. In reference [4], the architecture of space-based information port is described, and space-based information port satellite is defined as a complex system of "information + network". The multi-source information fusion problem is analyzed, and its process is defined as task planning and resource scheduling, data acquisition, basic algorithm and advanced application. Based on the above scene, the resource allocation problem in space-based information network is a multi-source and multi-type, task-based dynamic scheduling problem. The points of its model and algorithm construction are resource virtualization method, which can eliminate the differences of resource categories in modeling; and the fast dynamic task, resource allocation method to meet the timeliness and accuracy of space-based information network demand.

In terms of resource scheduling algorithm, the concept of satellite contribution degree is proposed in reference [5], and the contribution degree, observation switching rate and relaxation degree are taken as objective functions, and genetic algorithm is used to solve the satellite scheduling strategy; in reference [6], the mixed integer programming model of sensor scheduling is established for the multi-target tracking problem of low orbit early warning system, and the hybrid genetic simulated annealing algorithm is used to optimize the scheduling model In document [7], the problem model is established with the task execution efficiency as the objective function and solved by the quantum genetic algorithm; in document [8], the mathematical model is established with the goal of minimizing the mission completion time and solved by the adaptive genetic algorithm to dynamically schedule the battlefield resources to the platform; in document [9], the conflict resolution model in the satellite ground transmission, and data transmission in the ground transmission are built separately, then different scale scheduling tasks are generated, which are solved by the hybrid algorithm of dynamic programming and genetic algorithm. In reference [10], with the goal of earth observation task planning, the observation element and the receiver element tasks are taken as the way of gene expression, and solved by the genetic simulated annealing algorithm. In reference [11], a hybrid algorithm of genetic and local search is designed to solve the problem of satellite range planning and the matching between satellite task set and time window; in reference [12], a quantum heuristic genetic algorithm is proposed to solve the problem of multi-objective real-time task allocation in multi-sensor environment; in reference [13], a two-stage genetic annealing method is proposed to solve the problem of earth observation satellite scheduling, considering the search efficiency and global search ability of the solution. The above literature analyzes the scheduling and allocation of satellite resources, but its analysis object is mostly based on observation satellite, sensor resources and time window scheduling, not the analysis of space-based information network common resources, so it is not widely applicable.

In order to meet the needs of dynamic resource allocation of space-based information network in the future, this paper studies the cooperation mode and resource allocation method of different types of spacecraft in collaborative tasks. Considering the consumption and profit of resources to meet the needs of tasks, a dynamic resource allocation model of space-based information network is established. According to the characteristics of this model, genetic algorithm and its improved algorithms are used to discuss their application schemes of information network resource allocation.

2 Resource Allocation Model of Space-Based Information Network

The basic architecture of the space-based information network is shown in the figure below. As the control node of the space-based information network, the GEO communication satellite constitutes the space-based backbone network. Other satellites, including remote sensing satellite, navigation satellite, meteorological satellite, communication satellite constellation, as well as various types of spacecraft, such as space station and space telescope, are connected through the inter satellite link as the access node of the backbone network. Other access users also include those operating in the near earth space For example, near space vehicle, airship, UAV, etc. The space-based information network establishes a communication link with the ground station through the GEO communication satellite and communication satellite constellation, and connects to the ground processing center to realize the information interaction with the ground communication network and the ground Internet (Fig. 1).

There are different types of nodes in space-based information network, and the load carried by the nodes has different functions. The backbone network node has strong data processing ability and storage space. By carrying intelligent algorithm, data from other function nodes can be preprocessed. According to the different functions of spacecraft, there are some differences in the types and quantities of resources it can provide. For example, remote sensing satellite has image acquisition and preprocessing functions, communication satellite has communication functions with ground users or other satellites, navigation satellite can provide positioning information, etc. The task is initiated by the ground processing center and sent to the control node of the space-based information network. In the scheduling, different types of spacecraft are required to provide corresponding resources according to their own functions, participate in the task and cooperate to complete it. For example, if the meteorological satellite or remote sensing satellite finds that there is a disaster in a local area by collecting images, the corresponding data will be transmitted to the backbone node of the space-based information network. The backbone node preprocesses and transmits the data on the satellite, then transmits the

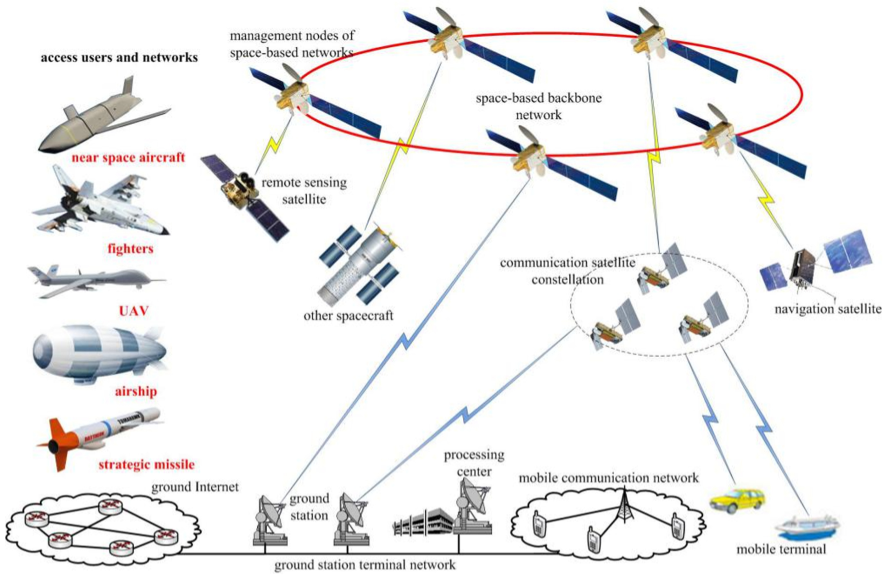

Fig. 1. Space based information network architecture

broadcast information to the communication satellite covering the disaster area, and then broadcasts the disaster details to the ground users through the communication load.

If the number of tasks to be executed sent from the ground is set to M, the task set containing M tasks is set to $T = \{T_1, T_2, \cdots, T_M\}$, and there is N nodes providing resources for task completion as $S = \{S_1, S_2, \cdots, S_N\}$. The $m \times n$ matrix can be used to represent the allocation relationship between resources and tasks. Defined $X = \{x_{ij}\}_{m\times n}$, $x_{ij} = 0/1$ as assignment matrix, we have

$$\sum_{i=1}^{m} x_{ij} = 1 \tag{1}$$

That is, at the same time, each resource can only be allocated to one task. And to ensure that all the proposed tasks be allocated resources to, we have

$$\sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij} = n \tag{2}$$

The process of allocating resources to tasks needs to consider the benefits and consumption of resources, as well as the time held by resources. The use of resources is a unified allocation process, so there is no gain for the spacecraft that provides resources; therefore, the gain is defined as a combination of priority scheduling and the state of the resource-occupying node. The higher the priority of the task, the more necessary it is for the resource-occupying node to participate in the task. At the same time, the working state of the node itself will also affect the effect of participating in the task. For example, if a node acts as resource to provide distributed computing capability, and most of its processor resources have been occupied by other tasks, it may not have enough sufficient computing power to participate in tasks, thus affect the execution of tasks. When task priority is defined as $H = \{H_1, H_2, \cdots, H_M\}$ and node resource occupancy rate is defined as $p = \{p_1, p_2, \cdots, p_N\}$, the benefit of using resources is as follows:

$$a_{ij} = H_i(1 - p_j) \tag{3}$$

About the cost of resource allocation, it is necessary to consider the energy consumption of nodes and the resource occupancy time. The longer the task occupies the resource means resource will be occupied by a specific task, and the lower the probability that the resource will be used by other tasks. Therefore, the energy consumption of a task should be set by the node to prevent it from resource-free state for a long time; at the same time, the longer the occupation time, the higher the cost of using resources. Define the total energy consumed by a node to accomplish a task as e_j, and the cost of using resources is

$$b_{ij} = H_i k_j e_j (1 - c_j^{-t}) \tag{4}$$

k_j is the parameter for node j as energy upper limit and satisfy $H_i k_j \leq 1$, which indicates that the node determines the upper limit of energy consumption according to the priority of the task. c_j is the time attenuation for node j and $c_j > 1$, which are used to express the impact of resource occupancy time to other tasks. The larger of c_j means the resource have stronger timeliness and should be used in shorter time.

In summary, the benefit function of allocating resources to tasks is $f_{ij} = a_{ij} - b_{ij}$, in which the benefit and consumption are the result of normalization of proportion. The goal of optimization is to maximize the total benefit of the allocation relationship between resources and tasks.

In the process of allocation, we need to consider the following situations: 1. the amount of resources provided to a task should be limited; otherwise a task with high priority will incur more overhead, which will block the use of other tasks. Therefore, there is

$$\sum_{j=1}^{n} b_{ij} x_{ij} \leq r_i \tag{5}$$

And r_i is upper limit for a task. When a task uses the resources provided by the node i exceed this limit, it cannot continue to occupy more resources.

2. Some resources need not be used in the execution of certain tasks. For example, in the image acquisition-disaster prediction scenarios illustrated above, it's not need to use the resources provided by reconnaissance satellites, communications satellites that do not cover the communication area. Correspondingly, in the gain function matrix F from resource to task, the corresponding allocation item should be set to 0 to avoid unnecessary resource occupation.

Based on the above constraints, the dynamic resource allocation model of space-based information network can be described as:

$$\max f = \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} x_{ij}$$

$$s.t. \sum_{i=1}^{m} x_{ij} = 1$$
$$\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} = n$$
$$\sum_{j=1}^{n} b_{ij}x_{ij} \le r_i \tag{6}$$

3 Solution Algorithm of Model

The resource allocation model established above can be classified as an unbalanced assignment problem due to the unequal number of resources and tasks allocated. It belongs to the problem category of linear programming. Hungarian algorithm (HA) is the basic algorithm for assignment problem. However, a large number of data experiments show that time-consuming of HA is unstable in solving different problems. Even when dealing with some special data, it cannot find its optimal solution because of its non-convergence. At the same time, the Hungarian algorithm has low computational efficiency because of low speed and holding large storage space. For the above reasons, genetic algorithm as substitute algorithm has been widely used.

The main characteristics of genetic algorithm are that it can directly operate the structure object without the limitation of derivation and function continuity; it has the inherent implicit parallelism and better global optimization ability; the probabilistic optimization method can adaptively adjust the search direction without the need of certain rules. At the same time, there are some disadvantages of genetic algorithm: genetic algorithm is a random search method, a large number of calculations take a long time, and it is difficult to meet the scene with high real-time requirements; on the other hand, when the convergence speed is high, it is easy to cause "early-maturing" phenomenon, that is, it may converge to the local optimal solution rather than the global optimal solution, so as to reduce the quality of solution.

Because of the above defects, this paper uses genetic simulated annealing algorithm (GSA) and self-adaptive genetic algorithm (SGA) to solve the problem of resource allocation in space-based information network, compares and analyzes the advantages of the two improved algorithms and the original algorithm. The starting point of simulated annealing algorithm is based on the similarity between the annealing process of physical solid matter and the general combinatorial optimization problem, using the Metropolis criterion to accept the deteriorating solution with probability, so as to avoid the problem of local optimization; but at the same time, substituting the annealing process increases the time of global convergence. The hybrid genetic simulated annealing algorithm combines the advantages of both and improves the efficiency. Unlike traditional genetic algorithm, adaptive genetic algorithm adjusts the probability of adaptation. The goal of this adjustment is to ensure the diversity of the population on the one hand, on the other hand, keep the excellent individuals in the population from being destroyed, avoid the problem that the original algorithm is easy to fall into the local optimization, and improve the global search ability of the algorithm.

(1). Chromosome coding
In the process of assigning resources to tasks, the number of resources is more than the number of tasks, so as to ensure that multiple resources are used by the same task, without the situation that a task cannot be carried out due to no resources available. Therefore, an allocation scheme is defined as an individual in GA, which is an ordered sequence $D = \{D_1, D_2, \cdots, D_j, \cdots, D_N\}, j \in [0, M]$ of N integers to allocate resources j to tasks D_j. If the value of D_j is 0, the resource is not used in the allocation scheme.

(2). Fitness function
The benefit function of resource allocation is selected as the individual fitness function, and the fitness function of the dth individual is expressed as

$$F_d = f_d - f_G \tag{7}$$

Among them, f_G it is the smallest benefit function value of the individual in the current evolution, and the benefit function value f_d is that of the dth individual in the current generation. If the individual benefits greatly, the advantage with the individual of least benefit in the current generation is larger, and the fitness function value is larger.

(3). Individual choosing
The algorithm uses roulette with quintessence selection strategy to simulate natural selection. In order to ensure that the evolution process will not destroy the obtained optimal solution, the strategy of keeping the optimal solution is added on the basis of roulette. This part of the algorithm is described as follows:

Algorithm 1 Individual Choosing Algorithm

For $n = 1 : siz$ **% the number of individual**

Calculate $F_n^{(G)}$, F = **sum**($F_n^{(G)}$); **%** G means generation

end

$F_1^{(G+1)}$= **max**($F_n^{(G)}$);

$P_1 = F_1^{(G+1)}/F$;

For $j = 2 : siz$;

For $i = 2 : siz$

$r = rand(1)$;

$P_i = P_{i-1} + F_i^{(G)}/F$;

if $P_i > r$

$D_j^{(G+1)} = D_i^{(G)}$;

else $D_j^{(G+1)} = D_1^{(G+1)}$;

end

end

(4). Genetic manipulation
Genetic manipulation includes crossover and mutation. Crossover refers to the generation of new individuals by the exchange of the parent individuals' genes in the population, that is, the half of the individuals are crossed with random probability; mutation refers to the random disruption and recombination of their genes, that is, the partial sequences of individuals are replaced with each other with random probability. From the coding design, it can be seen that the target sequence of an individual represents the process of allocating resources to a task, while the total benefit of the allocation scheme is the result of the interaction of the allocation sequence and the benefit function, which has reflected whether a resource can be used for a specific task, so the change of the allocation sequence will not affect the result of whether the node providing the resource is available.

(5). Sampling by Metropolis criterion
In GSA algorithm, the change of individual fitness before and after genetic operation is calculated, and the retention probability is defined as

$$p_{save} = \exp((F^{(G+1)} - F^{(G)})/t) \tag{8}$$

Where T is the current temperature. If $p_{save} > rand(1)$, the new individual is accepted as the current individual. Otherwise, the parent individual is retained as the current individual. At the same time, the operation of $t^{(G+1)} = \alpha t^{(G)}$ as desuperheating is used with the rate of desuperheating α.

(6). Adaptive crossover and mutation
In SGA algorithm, the crossover probability and mutation probability of the population are related to the evolutionary generation. In the early stage of the algorithm, the larger crossover probability and mutation probability are guaranteed to improve the search ability of the optimal solution; in the late stage of the algorithm, the lower probability is to protect the better individuals from being destroyed. Therefore, sine function is introduced into the probability of crossover and mutation to adjust it adaptively, so as to avoid the stagnation of update caused by entering the local optimization when approaching the maximum fitness value. When using SGA algorithm, the crossover probability is defined as:

$$p_{cross}^{(G+1)} = \begin{cases} \frac{(p_{cross1} + p_{cross}^{(G)})}{2} - \frac{(p_{cross1} - p_{cross}^{(G)})}{2} \times \sin(\frac{\pi}{2} \times \frac{F - F_{ave}}{F\max - F_{ave}}), F \geq F_{ave} \\ p_{cross1}, F < F_{ave} \end{cases} \tag{9}$$

And the mutation probability is:

$$p_{vari}^{(G+1)} = \begin{cases} \frac{(p_{vari1} + p_{vari}^{(G)})}{2} - \frac{(p_{vari1} - p_{vari}^{(G)})}{2} \times \sin(\frac{\pi}{2} \times \frac{F - F_{ave}}{F\max - F_{ave}}), F \geq F_{ave} \\ p_{vari1}, F < F_{ave} \end{cases} \tag{10}$$

Where p_{cross1} and p_{vari1} are parameters that vary with evolution generation G:

$$p_{cross1} = p_{cross} + \frac{1}{2 + \lg G} \tag{11}$$

$$p_{vari1} = p_{vari} + \frac{0.1}{2 + \lg G} \tag{12}$$

Where p_{cross} and p_{vari} are the convergence limits of the crossover probability and the mutation probability.

(7). Algorithm flow
The flow chart of GSA and SGA optimization algorithm is as follows (Fig. 2):

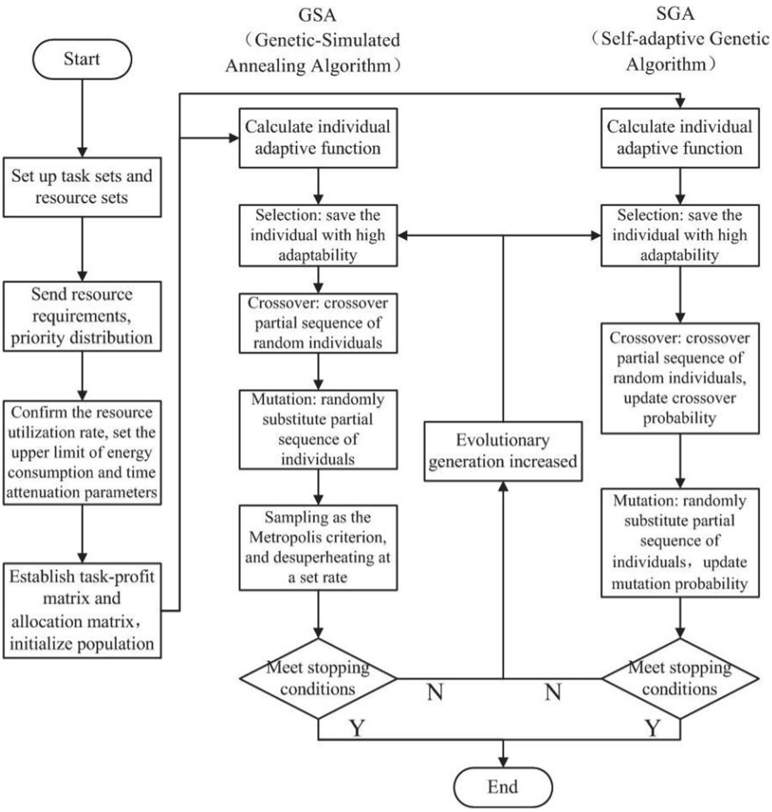

Fig. 2. Improved genetic algorithm process

4 Simulation Results

In the simulation scene of this paper, M cooperative tasks are sent at one time in the space-based information network, N resource nodes are involved in collaboration, the convergence limits of crossover probability and mutation probability are set to =0.6 and =0.8, respectively, the number of individuals is set to 100, the maximum evolution generation is set to 100, the initial temperature is set to 2000, the desuperheating rate is set to 0.95, the upper limit of energy consumption is set to 0.8, the time decay parameter is set to 1.05, and the priority is divided into nine levels.

In order to evaluate the impact of the size and load of space-based information network on the performance of the algorithm, the performance of GSA and SGA are investigated in the scene of task and resource changes. The higher the number of tasks, the higher the load of space-based information network; and the higher the number of resources, the more resources are available, which can better meet the needs of task allocation. Therefore, when the resources can meet the needs of the task, the profit shows an upward trend; if there are more unused resources, the profit will decrease. It can be seen that in terms of profits, GSA is the best, SGA is the second, and GA is the last. With the increase of scale, the gap between algorithms tends to decrease. In terms of algorithm time, GA is the best, GSA is the second, and SGA is the last. Because every generation needs to calculate the probability of crossover and mutation, SGA takes 1.3–1.8 times of the other two algorithms, and GSA takes 10–20% more time than the original GA.

The following simulation is carried out in the scene of. As shown in Fig. 3, in the case of randomly generating a set of task and resource allocation relationship and benefit matrix, the total profits of the original genetic algorithm GA, SGA and GSA are compared and simulated as the number of iterations increases. It can be seen that the total profits of GSA algorithm and SGA algorithm are greatly improved compared with the original algorithm, which shows that the algorithm is optimized to prevent premature convergence, so that the optimal allocation scheme can not be obtained. In this case, GSA is better than SGA. And GSA is better than SGA in most control data.

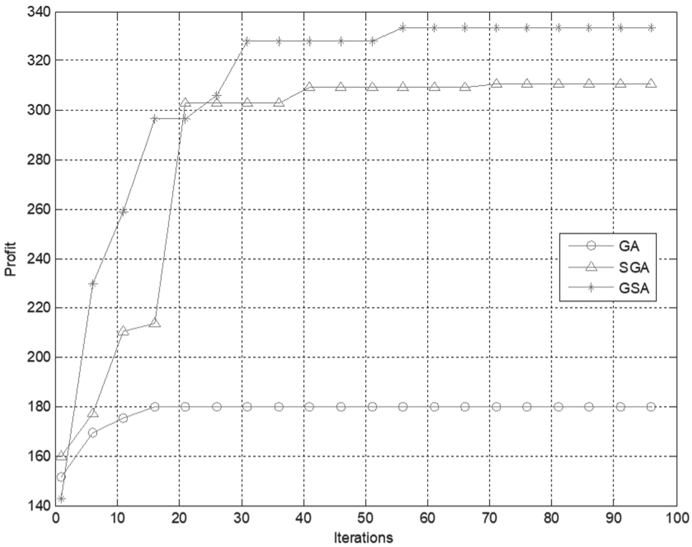

Fig. 3. Profits of GSA and SGA algorithm allocation schemes under different iterations

The simulation in Fig. 4 is the result of adding and averaging 100 randomly generated resource allocation relationships and profit matrices. It can be seen that the total profit of GSA is better than that of SGA.

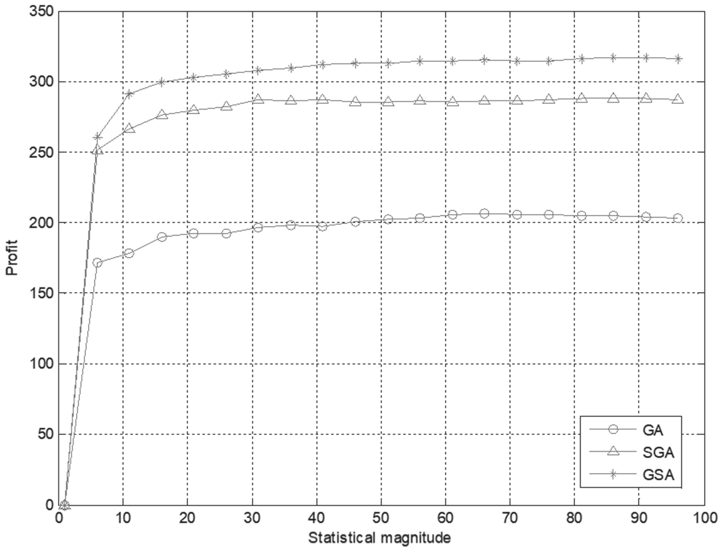

Fig. 4. The profits of GSA and SGA algorithm allocation schemes in random scenes

Figure 5 shows the influence of the range of change on the two improved algorithms after adjustment in the range of profit matrix. By adjusting the upper limit of energy consumption and time decay parameters, the range of energy consumption is adjusted. When the change range is 40 W, the performance of GSA is better than that of SGA; with the decrease of the change range, the performance improvement is gradually reduced, and the performance gap between the two algorithms is also reduced. It can be seen that GSA performance is better for scenes with large energy consumption changes. The energy consumption of space-based information network also fluctuates because of the differences in function and performance of the nodes. In this scene, the adaptability of GSA is better than that of SGA.

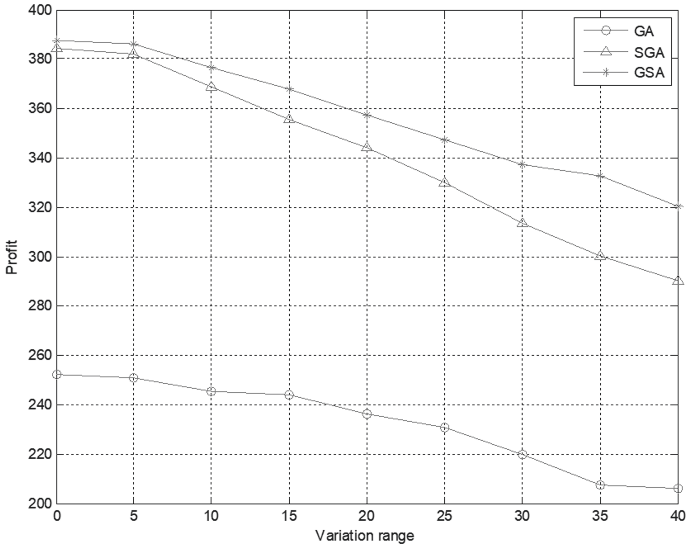

Fig. 5. Profits of schemes under different energy consumption constraints

Figure 6 is the simulation result of the average time of the algorithm execution. It can be seen that SGA has a lower convergence rate because of the dynamic adjustment of crossover and mutation probability in every loop of the algorithm, and its operation time is longer than GSA.

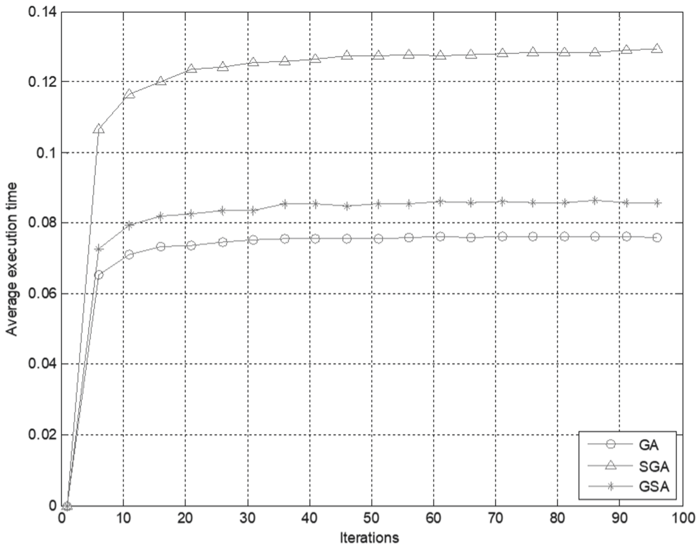

Fig. 6. Operation time of schemes under different iterations

5 Conclusion

In the construction of space-based information network in the future, as the management and control center of space-based information network, GEO satellite constitutes the space-based backbone network, realizes the access of other satellites and spacecraft to the space-based information network, and constructs integrated space-terrestrial information system. This architecture determines that there are many nodes and networks of different types and architectures in the space-based information network. The collaborative tasks initiated on the ground need to realize the dynamic allocation of multi-source and multi-type resources. The virtualization design of resources and the fast resource allocation algorithm are the basis of realizing the rational allocation of resources. Based on the above requirements, this paper studies the application of genetic algorithm in the task resource dynamic allocation of space-based information network. Considering the consumption and profits of resources to meet the task requirements, a dynamic resource allocation model is established. According to the characteristics of the model, the dynamic resource allocation scheme is designed by using improved genetic algorithm And the simulation of scene implementation and algorithm effect is carried out. The results show that the algorithm proposed in this paper has a good effect on improving the timeliness of resource allocation and utilization.

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