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An Efficient Satellite Resource Cooperative Scheduling Method on Spatial Information Networks

Huilong Fan ^{1,2,3} , Zhan Yang ^{2,4} , Shimin Wu ^{1,2,3}, Xi Zhang ^{1,2,3}, Jun Long ^{2,4,*} and Limin Liu ^{1,2,3,*}

¹ School of Computer Science and Engineering, Central South University, Changsha 410075, China; hlfanpro@csu.edu.cn (H.F.); wsm19991031@163.com (S.W.); 3901160422@csu.edu.cn (X.Z.)

² Network Resource Management and Trust Evaluation Key Laboratory of Hunan, Changsha 410075, China; zyang22@csu.edu.cn

³ Joint Laboratory of Space Information System, Changsha 410075, China

⁴ Big Data Institute, Central South University, Changsha 410075, China

* Correspondence: junlong@csu.edu.cn (J.L.); liulimin@csu.edu.cn (L.L.)

Abstract: To overcome the low timeliness of resource scheduling problems in spatial information networks, we propose a method based on a dynamic reconstruction of resource request queues and the autonomous coordinated scheduling of resources. First, we construct a small satellite network and combine the graph maximum flow theory to solve the link resource planning problem during inter-satellite data transmission. In addition, we design a multi-satellite resource scheduling algorithm with minimal time consumption based on graph theory. The algorithm is based on graph theory to reallocate the resource request queue to satellites with idle processing resources. Finally, we simulate the efficient resource scheduling capability in the spatial information network and empirically compare our approaches against two representative swarm intelligence baseline approaches and show that our approach has significant advantages in terms of performance and time consumption during resource scheduling.

Keywords: collaborative scheduling; spatial information network; resource coordination; genetic algorithm; particle swarm optimization algorithm



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1. Introduction

A Space-Terrestrial Integrated Network (STIN) includes a space-based backbone network, space-based access network and ground-based node network. STIN is an essential national information infrastructure which closely integrates space, air, land, ship and island resources to achieve global reliable and efficient space-time data transmission capability. Spatial information network development needs to cross the sky and earth platforms to realize the integrated management and ample space and ground resources application in the future. With the gradually increasing dependence of industries on spatial information network services and increasing commercial and military demands, rapid response and efficient services have become the fundamental aspects of concern for various application fields.

However, the inefficient scheduling of storage resources in spatial information networks leads to extreme difficulties in rapidly allocating and efficiently utilizing resources. The communication between satellites and ground base stations is constrained by the visible time window resulting in relatively few resources available for satellites. When faced with multitasking and highly time-sensitive task scenarios, the limited storage resources cannot meet the demand. Therefore, how to solve the inter-satellite resource collaborative scheduling problem and realize the dynamic and rapid scheduling of spatial information network resources has become an extremely challenging and meaningful research direction on network resource management. The complex time-varying characteristics of spatial information networks make the collaborative resources scheduling extremely difficult.

Fortunately, researchers have studied resource scheduling problems and achieved results based on machine learning, reinforcement learning, and game theory methods. Such methods can learn independently, deeply mine data correlations, and integrate multiple factors for calculation. These methods offer significant performance advantages and significantly improve resource utilization. However, the space-time dynamic change characteristics of spatial information networks cause satellite and link resources to change dynamically over time. It is a challenge to know the state of resources at the next moment in the spatial information network. Unfortunately, the methods often cannot effectively schedule resources when facing a resource request queue with extensive data. Moreover, the methods may cause resource requests to have to wait a long time or to not achieve optimal overall resource scheduling.

Therefore, the cooperative scheduling of spatial information network resources still faces two challenges:

1. The existing satellite resource scheduling process requires a visible time window between the satellite and the ground station, which will lead to long waiting time costs and poor timeliness of resource scheduling. An essential issue for research is breaking through the barrier of ground base station control, coordinating the free satellite resources, and improving resource utilization [1].
2. In the spatial information network, the satellite task distribution is unbalanced, and reasonably reconfiguring the task queue and realizing the fast scheduling of satellite resources is an urgent problem [2,3].

In this paper, we propose a Resource request Queue Reconstruction and Collaborative Scheduling method (RQRCS) to remedy the poor timeliness of spatial information network resource scheduling. The method aims to solve the dynamic reconstruction of the global resource request queue and cooperate with idle satellite resources to complete the collaborative scheduling of spatial information network resources. RQRCS decomposes the cooperative scheduling problem of spatial information network resources into two sub-problems: the dynamic reallocation problem of the global resource request queue and the global optimization problem of inter-satellite resource link resources. First, we construct a satellite network graph based on the current satellite and its surrounding satellite resource status information. Then, we design the resource allocation algorithm with the least cost (time) consumption based on the graph theory. Moreover, according to the allocation result, we reallocate the resource request queue to the satellites with idle resources for processing. The satellite resources assigned to the resource request operation can meet the current resource demand, but there is still contention for inter-satellite link resources. The optimization of global link resources is proposed according to a tiny spatial information network and the maximum flow theory in the graph. Finally, we achieve the goal of minimizing the time consumption of task execution on spatial information networks.

Our contribution can be summarized as follows:

1. We propose the RQRCS method that mainly includes a multi-satellite resource scheduling model and algorithm based on the dynamic reconstruction of a multi-satellite cooperative resource request queue. We aim to minimize the execution time of the resource request queue and solve the problem of poor timeliness of spatial information network resource scheduling to achieve the goal of rapid response to the resource request of the task.
2. In order to prevent the resource scheduling process from relying too much on the ground-based stations and causing significant waiting time delays, we investigate an autonomous resource allocation strategy on satellites. First, we obtain information on the status of idle storage and observation resources on the neighboring satellites of the current satellite and construct a small-satellite network. Then, we construct a minimum cost flow calculation model for dynamic maps to calculate the mission data transmission route with the shortest time to solve the problem of fast and cooperative allocation of multi-satellite resources.

3. To solve the problem of contention for spatial information network link resources, we calculate the transmission route and the maximum data flow at the current moment according to the link resources usage and the amount of data to be transmitted. We transform the global link optimization problem from a small spatial information network to a multi-objective maximum network flow problem. Then, we design the maximum flow allocation of inter-satellite link resources algorithm to improve the utilization of link resources and reduce the time consumed by resource contention.

2. Related Work

In recent years, researchers have conducted in-depth research on the scheduling of spatial information network resources with the explosive growth of multimedia services and the continuous emergence of new space tasks. Presently, the scheduling methods of spatial information network resources are mainly based on machine learning, reinforcement learning, and game theory.

2.1. Resource Scheduling for Single Satellite

Researchers have conducted in-depth studies on the satellite resource scheduling problem and achieved specific results. In particular, the scheduling methods of single-star resources are studied [4,5], mainly on earliest mission priority, satellite resource scheduling mechanism, heuristic algorithms, high-level priority algorithms with time estimation and critical path algorithms [6–11]; these methods are the simplest, fast and effective resource scheduling methods. However, dealing with a large data volume of resource request queues, these methods often fail to schedule resources effectively and may result in many resource request tasks waiting for a longer time or failing to achieve the best overall resource scheduling.

2.2. Resource Scheduling Method Based on Machine Learning

Based on the satellite time window characteristics, many researchers design algorithms to solve the scheduling problem of the visual time window constraints [12–14]. The resource scheduling process can generally be divided into task planning and resource allocation. Some scholars analyze the constraints and build corresponding models for these two aspects [15]. Paper [16] proposes an intelligent resource scheduling system based on the deep neural network (DNN, deep neural network) to solve the long solution time, low efficiency, and high computational cost problem of other scheduling algorithms. A study [17] proposes a learning-based approach (LBA, learning-based approach) to solve the problem of agile earth observation satellite in-flight scheduling. It uses offline training-on-board scheduling mode and uses a large amount of historical data to train classification on the ground offline. Moreover, it embeds the classifier into the onboard greedy construction algorithm. Researchers [18] studied the scheduling of Earth observation satellite tasks with specific time requirements, proposed an automatic scheduling algorithm for state equations based on linear temporal logic (LTL, linear temporal logic), and introduced LTL semantics to automate constraints and time specifications and to formulate the parameters of the task specification appropriately. The research [19] on small satellite networks expands the traditional dynamic programming algorithm based on it. It proposes a finite embedded infinite two-layer dynamic programming framework, transforming the scheduling optimization problem into a discrete Markov decision process (MDP). Papers [20–23] considered the complex constraints faced in the process of satellite resource scheduling, combined with computational geometry and other theories for modeling, and verified the effectiveness of the model based on data from many instances. Ref. [24] proposed a heuristic algorithm based on deep reinforcement learning which automatically learns multi-satellite scheduling strategies and problem representation. Ref. [25] proposes a graph-based joint scheduling strategy which combines the information in the sensing and transmission phases, makes full use of the satellite network's observation and transmission resources, and maximizes resource utilization.

Although machine learning methods have better resource scheduling performance, such methods usually incur high time consumption and require more computational resources during the learning process. The methods are difficult to adapt to the demand of high timeliness of resource-constrained spatial information networks.

2.3. Resource Scheduling Method Based on an Intelligent Optimization Algorithm

Researchers have studied the dynamic network characteristics based on game theory models to maximize the benefits of spatial information networks [2,3]. Dynamic graphs can represent the dynamic change characteristics of these networks. Therefore, researchers propose resource scheduling based on graph theory and design corresponding algorithms to solve resource scheduling problems [26]. The cooperative scheduling problem of spatial information network resources has achieved good results. Paper [27] proposed an on-demand learning resource reservation and scheduling algorithm (RODS). In RODS, resource requests are provided to the server through the terrestrial Internet. An improved maximum queue length algorithm is used to schedule reservation requests to generate an optimized scheduling plan. Paper [28] introduced an operational planning and scheduling strategy based on the time sequence availability of consumable and replenishable resources based on the analysis of satellite function and payload resource constraints, dividing the planning and scheduling cycle into several parts and combining them. Modeling optimization, a genetic particle swarm optimization algorithm (GPSO), is proposed. Researchers [29–32] proposed an ant colony optimization algorithm (ACO, ant colony optimization). Based on the observation that the problem's solution space is sparse, the ant colony algorithm is combined with the pheromone update method based on the guided solution. The basic idea of this method is that once the algorithm stops, the distribution of the pheromone trajectory can be changed by updating the pheromone trajectory with the guided solution. When the number of satellite observation task requests increases over time, the multi-satellite data downlink resource scheduling cannot be handled effectively [33]. One paper refers to a data downlink resource scheduling model that adapts to the observation task increment that is established to solve this problem. A new algorithm based on evolutionary calculation is proposed to quickly optimize the allocation and adjustment of data downlink resources to download high-priority observation data as soon as possible. Paper [34] proposes a fireworks algorithm (FWA, Fireworks algorithm), in which FWA is a swarm intelligence algorithm used to produce high-quality solutions to continuous optimization problems. FWA was first proposed in 2010 in [35] for the global optimization of complex functions. Papers [36,37] propose several improved models based on swarm intelligence algorithms to improve the overall benefits of resource scheduling. Some researchers [38] also regard data transmission task scheduling as a combined optimization problem between satellite data transmission requirements, visible time windows, and ground station resources and propose a satellite data transmission scheduling algorithm based on the framework of differential evolution algorithm. In the process, the individual evaluation process is improved by an improved method based on 0/1 knapsack. One paper [39] formulates the data exchange between the ground station and the satellite as a multiprocessor task scheduling problem and proposes a fixed and relaxed heuristic algorithm based on the Lagrangian version to overcome the inability of standard integer programming to resolve complex technical constraints procedures. One study [40] abstracted and simplified the multi-satellite resource scheduling problem and established a mathematical model combined with the design idea of a genetic algorithm, and proposed an improved genetic algorithm for population disturbance elimination.

However, intelligent optimization algorithms have enumeration properties, and the computation time is difficult to estimate. It is challenging to meet the stability requirements of dynamic network resource scheduling.

2.4. Resource Scheduling Method Based on Game Theory

Paper [41] proposes a resource allocation method based on multi-layer matching game theory, which mainly solves the problem of resource allocation in multi-user scenarios. Researchers [2] consider the service quality requirement as the constraint condition, study the access control strategy based on the penalty function, and propose a cooperative game satellite bandwidth resource allocation algorithm. Paper [42] proposes a bargaining cooperative game model based on the Nash equilibrium and proves the effectiveness of this method in time complexity. One study looked at [2] the problem of joint transmission power and bandwidth allocation and proposed a combined resource management method based on game theory. Researchers [43] analyzed the similarities between mobile and complex satellite services based on the main characteristics of the millimeter-wave spectrum and proposed a new cooperative scheduling algorithm based on a game-theoretic framework.

In summary, the approaches based on machine learning, reinforcement learning, or game theory ensure the maximization of resource utilization. However, the time complexity of the algorithms is slightly higher, which increases the occupation of valuable satellite computing resources and needs to be calculated on ground-based base stations. The establishment of communication links between ground-based stations and satellites will consume a large amount of time. The resource scheduling algorithms start from the perspective of task execution gain, thus ignoring the time consumption of the algorithms, and the efficiency of resource scheduling still needs further research.

Therefore, we propose a coordinated resource scheduling method from the perspective of efficient scheduling of spatial information network resources to solve these problems quickly and efficiently.

3. Satellite Resource Scheduling Problem Formulation

3.1. Preliminaries

To provide a clear description of the data model, we present a list of the main variables used in the paper. As shown in Table 1.

Table 1. List of variables.

Variables	Description
T	Discrete time
t	Slot time
S	Satellites
Q	Task queue
τ	Time Slice
$c(u, v)$	Time consumption from node u to v
$f_s^r(t)$	The amount of resource
$sours$	Source Node Satellite Collection
nei	Neighborhood Nodes
K	Request tasks
s_{source}	The source satellite
s_{sink}	The sink satellite
(u, v)	The edge from u to v
$f_{u,w}^r(t)$	The data amount on the edge (u, w)
$g_q(t)$	The time cost which consumed to complete a request
Φ	The waiting delay and the corner time of antenna equipment
$f_s(x)$	The time consumption for all tasks performed on satellite s
$U_s^r(t)$	The time cost consumption for the resource request
$l_{s,s'}^{\max}$	Link bandwidth
V	Nodes in a network representing satellites
E	Edge in a network representing an inter-satellite link
G	The spatial information network

3.2. Problem Formulation

The traditional satellite resource scheduling method solves the satellite resource scheduling plan at the ground base station and then transmits it to the satellite for execution.

As shown in Figure 1, the network operation control center is the central hub of satellite work and the command post of ground control satellites. Its role is to send specific instructions after mission planning to the satellites. We can express the command set received by satellite in the form of a queue. If there is a visible time window between the satellite and the ground station, the ground station can receive the data sent by satellite. The satellite executes the instruction process sent by the ground station and the relationship between the satellite and the ground base station. The function $g_q(t)$ represents the time cost of the satellite s_i to respond to a specific resource request task at a slot t and complete the resource scheduling. The function $f_s(x)$ represents the time consumed to meet resource scheduling for all resource request operations received by satellite s . The function $f_s(g_q(t))$ represents the time required for all satellite resource requests for job scheduling in a discrete time period $T = \{1, 2, \dots, \tau\}$. To improve resource utilization and achieve efficient resource scheduling effects, we need to solve the minimum value of the function under the complex constraints in the spatial information network to reach the minimum time consumption. The model is established as Equation (1),

$$\begin{aligned} & \min \sum_{t=1}^{\tau} \sum_{s=1}^S \sum_{q=1}^Q f_s(g_q(t)) \\ & \text{s.t.} \\ & \text{C1: } \sum_{t=\sigma}^{\delta} c_s(t) \leq 1, \forall \sigma \in R^*, \forall s \in \xi, \forall \delta < S, \\ & \text{C2: } \sum_q w_q(u, v) \leq c(u, v), \\ & \text{C3: } \tau \geq 1, \tau \in R^*, S \geq 1, Q \geq 1, \\ & \text{C4: } l_{s,s'}^{\min} \leq f_s^r(t) \leq l_{s,s'}^{\max}, \end{aligned} \quad (1)$$

As shown in Formula (1), S represents the satellites that have a visible time window with the ground base station during the period of $t, t \text{ in } \tau$. The task queue on the satellite $s, s \in S$ is denoted as Q , where the time required for the task $q, q \in Q$ to be executed is denoted as $f_s(g_q(t))$. The execution time consumption of task q varies depending on the merit of the resource scheduling policy. The model (1) describes the minimum time cost to be consumed in discrete-time τ to execute the tasks on the satellite according to the resource scheduling scheme. Therefore, we need to calculate the minimum value of the function $f_s(g_q(t))$, where the constraint C1 indicates that each satellite can communicate with at most one object in a slot. The object includes satellites or observation targets, which is the constraint C2 of the inter-satellite link. The amount of data that needs to be transmitted is less than the maximum capacity of the transmission link established between the satellites. C3 indicates the lower limit of the time range, the number of satellites, and the number of resource requests in the satellite queue. C4 shows the link bandwidth constraint, $l_{s,s'}^{\min}$ represents the lower bandwidth limit, and $l_{s,s'}^{\max}$ denotes the upper limit of the link bandwidth.

The paper considers the global resource scheduling optimization problem with a new idea, studies the global optimization problem of the satellite resource request queue, and proposes a dynamic reconstruction method of the multi-satellite coordination global resource request queue.

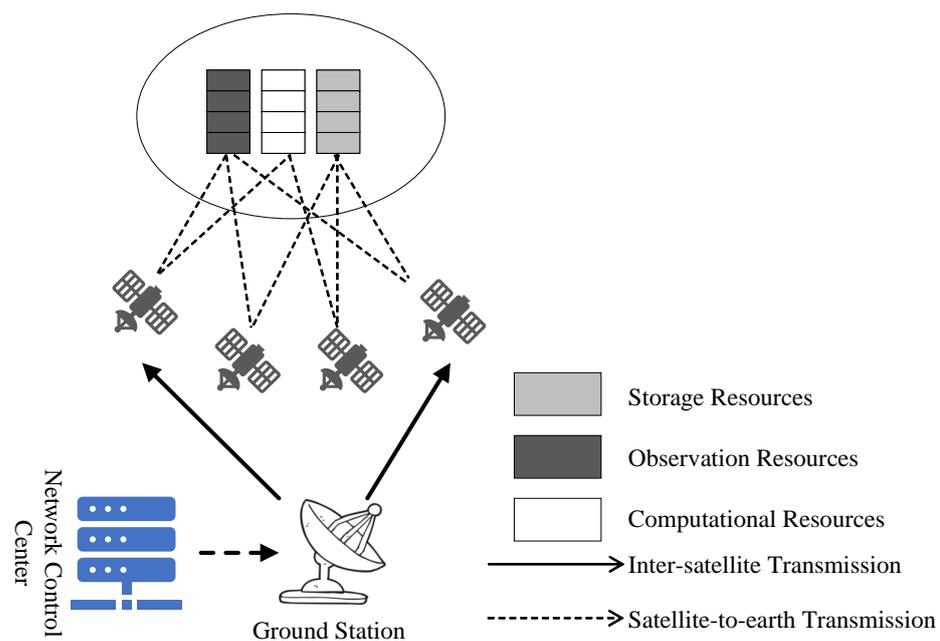


Figure 1. Schematic diagram of the existing spatial information network resource scheduling process.

4. Resource Request Queue Reconstruction and Collaborative Scheduling Method

For multi-satellite and multi-mission high time and high load resource scheduling problems, the single-satellite resource scheduling method can no longer meet the multi-resource and high time requirements. In an onboard autonomous resource allocation environment with multiple missions and resource requests, local LEO and medium orbit satellites may face many resource requests, resulting in long resource request queues for local satellites and multiple types of resource requests that are idle resources for the remaining satellites. Therefore, the pressure of high-load resource requests is relieved based on idle satellite and link resources, effectively reducing the resource request response time and improving resource utilization. In this research direction, we propose an online dynamic scheduling and queue reconfiguration method for multi-satellite resource request queues which solves the problems of excessive resource request pressure on a single satellite and waste of idle satellite resources and achieves the purpose of autonomous redistribution and dynamic scheduling of resource request queues on satellites.

This paper aims to solve the problem of collaborative scheduling of multi-satellite resources in space information networks. As shown in Figure 2, we use the block diagram [44,45] to describe the construct of the initialized network according to the resource state, then calculate the inter-satellite link selection and satellite resource allocation strategy based on the theory of multicommodity network flow. Finally, we update the resource quantity data of the network and complete the collaborative resource scheduling among multiple satellites.

As shown in Figure 3a shows that there are three satellites that have received the resource request sent by the ground station or other satellites at a slot t , where $S = \{s_1, s_2, s_3\}$ represents the set of satellites that have received resource requests in the spatial information network. The gray squares in the queue represent the number of storage resources requested, the white squares represent the number of observation resources required, and the black squares represent the number of computing resources needed. Figure 3b shows the state in which the satellite set S redistributes all received resource requests at a time $T = t + \delta$ and cooperates with neighboring satellites to share the resource request pressure, where the time interval δ satisfies $\forall \delta \in N_+$ at this time $\delta > 0$. The satellite set $S' = \{s_1, s_2, s_3, s_4, s_5, s_6\}$ includes the original satellite set S and other satellite sets $\{s_4, s_5\}$ that are coordinated. Each satellite in the satellite set S' is allocated a certain amount of resource request operations according to the number and status of satellite resources. From

the satellite state figure at the time $T = t + \delta$, it can be seen that the number of resource request operations on the original satellite set S has been reduced, and the resource type has become more singular. In contrast, the idle satellite set $\{s_4, s_5\}$ has obtained a certain number of resource request operations.

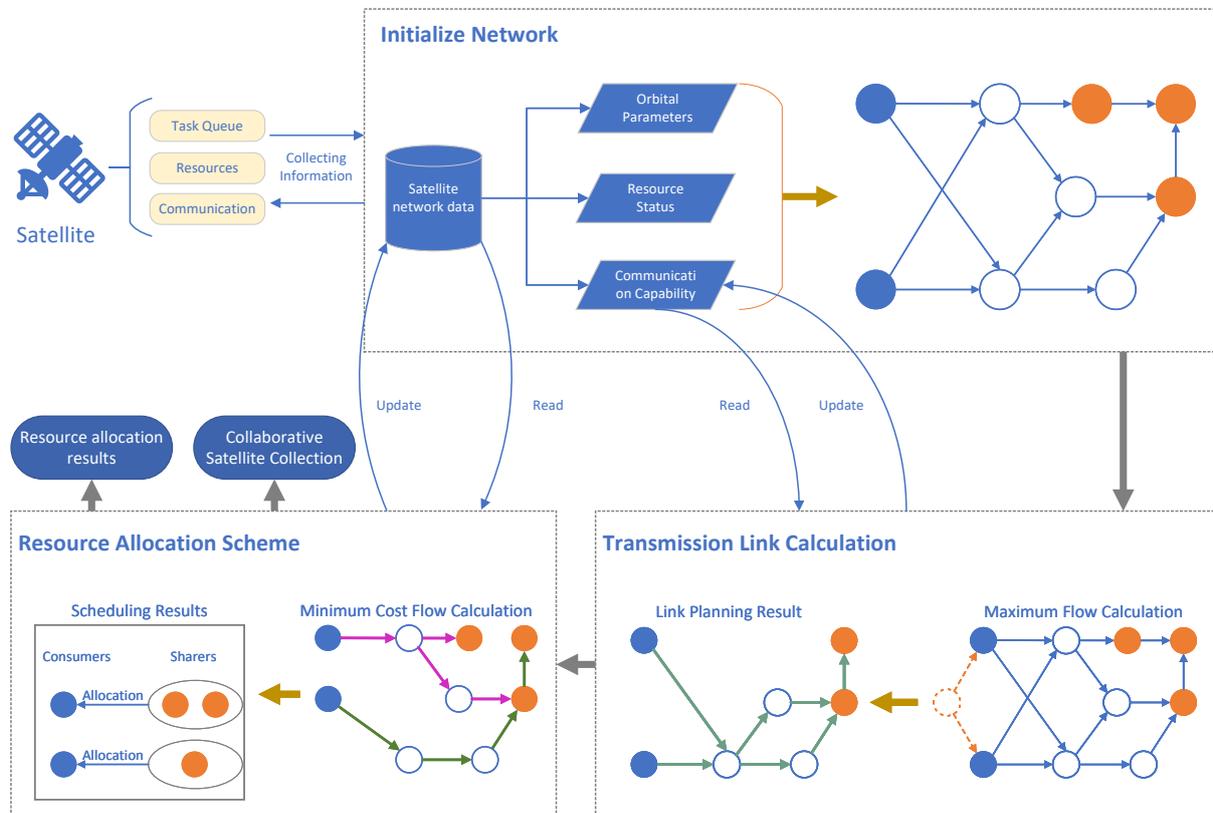


Figure 2. The multi-satellite resource collaborative scheduling method in spatial information networks.

When faced with many resource request jobs, the single-satellite resource scheduling method is challenging in terms of meeting the high timeliness and real-time requirements. We propose a method of synergizing the resources of the current satellite and its surrounding satellites to improve the overall resource utilization of the space information network. As shown in Figure 3, the state subgraph (a) to the state subgraph (b) is the process of reducing the satellite service load.

In order to clearly describe the specific process of resource request queue reconstruction and unified planning, we use spatio-temporal axes to represent the satellite spatio-temporal variation [26]. Figure 4 is an example of the data transmission process of multi-satellite resource request queue reallocation. The satellite set $sours = \{s_1, s_2, s_3\}$ is the resource request sent by the ground base station or surrounding satellites, and the satellite set $nei = \{s_4, s_5\}$ is the surrounding satellite set $sours$.

In order to describe the state after the satellite receives the resource request and the state after the resource request queue is reconstructed, we divide the satellite into two conditions, namely the resource request receiving state s_i and the queue reconstruction state s'_i . $s_{i,j}$ denotes the state of the i -th satellite in the j -th time.

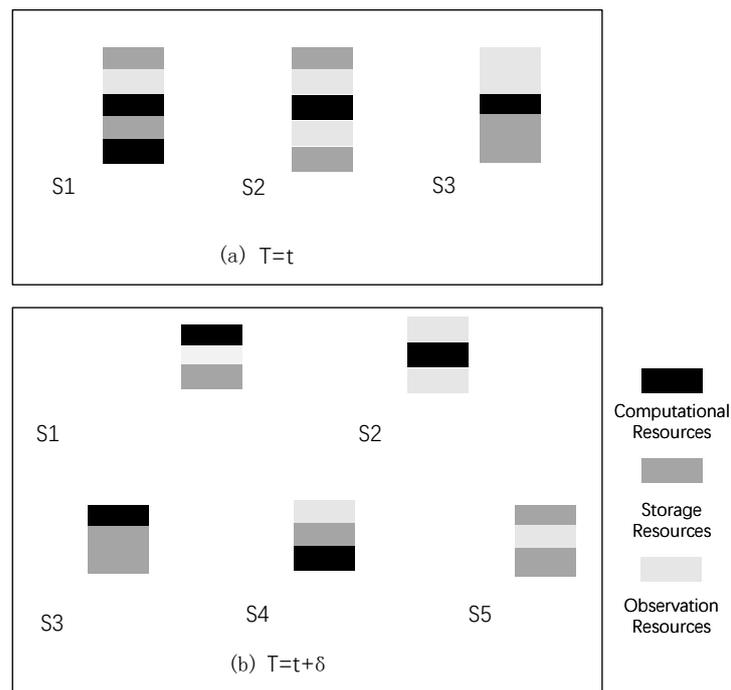


Figure 3. Schematic figure of autonomous reconstruction of resource request queue on a spatial information network.

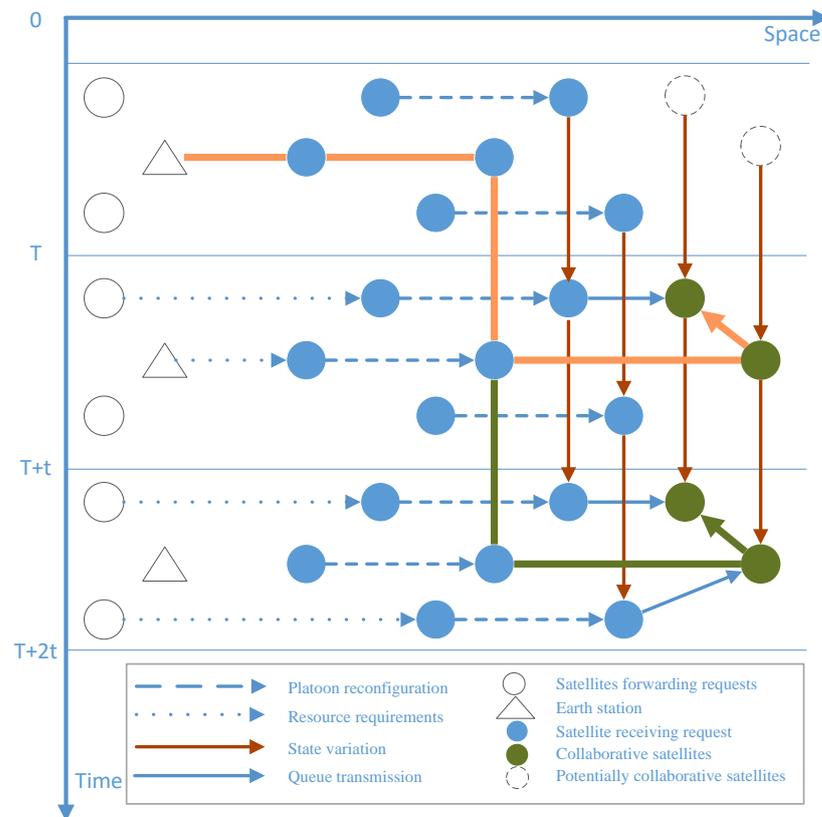


Figure 4. Multi-satellite resource request queue redistribution data transmission process.

We consider the changes and interrelationships of the satellite states in three-time intervals. The satellite set *sours* receives resource requests from the ground base station or other surrounding satellites in the first-time interval to form a resource request queue.

Meanwhile, the satellite communicates with the surrounding satellites and senses the resource status information and resource request queue information. The satellites that received the resource request in the first-time interval perceive two nearby satellites $s_{4,1}$ and $s_{5,1}$ coordinate the resource request. As shown in the Figure 4, the satellite autonomously plans the resource request queue of itself and the surrounding available satellites according to its own resource status and the resource demand information of the mission.

Resource request tasks generally have the characteristics of a specific execution order. The resources required for the task are related to each other, which means that the resources we provide should also be in order. In addition, different types of resource requests usually have different priorities, and the same resource type belonging to various tasks also has different execution priorities. In order to satisfy the resource requirements of the resource request queue, the satellite resource scheduling problem is mainly divided into two aspects: optimizing the maximum profit of the network and the task minimum execution time. The process of discovering a visible time window and establishing links between satellites is usually slow. Suppose the processing time of the resource request operation is longer. In that case, it will inevitably cause the loss of available resources, not guaranteeing the timeliness requirements of multi-task and multi-resource requests. The existing resource scheduling method mainly relies on the central control method of the ground station, and the limitation of the visible time window from the satellite to the ground causes the scheduling time to increase.

4.1. Problem Conversion

In order to compensate for the space-time limitation and improve the timeliness of satellite resource scheduling, we propose a dynamic reconfiguration and collaborative allocation model. The model considers the dynamic changes of inter-satellite links and the cooperative allocation of multi-satellite resources in dynamic networks and aims to solve the high timeliness of multi-satellite resource scheduling on spatial information networks. In the process of spatial information network resource scheduling, we mainly consider the time consumed by satellite resources and inter-satellite link resource scheduling operations. As shown in Formula (2), the model describes the process of minimizing the time consumption incurred by allocating resources to tasks according to the resource scheduling matrix when visible links exist between satellites or between satellites and the ground station. Where $U_s^r(t)$ represents the time cost consumption for the resource request r of satellite s to transmit unit data. $f_s^r(t)$ denotes the resource data amount to be transmitted for a time slot t in the spatial information network for task r . $B_s^r(t)$ shows the scheduling matrix of source request task on satellite s at time t , and the value range of the element $b_s^r(t)$ in the matrix is $\{0, 1\}$. $L_{s,s'}(t)$ indicates the state of establishing a communication link between satellite and satellite s at time t . If it is successfully established, then $L_{s,s'}(t) = 1$, otherwise $L_{s,s'}(t) = 0$. $\Phi_s^r(t)$ denotes the time consumption of the task latency, payload device transition, and the start of task execution to the end of execution during different tasks operations. We need to calculate the minimum time spent in the resource scheduling process within a period. In addition, the time calculation function should be incremental, continuously differentiable, and strictly concave. Therefore, we define the time calculation function as $\log((U_s^r(t)f_s^r(t) + E(r))B_s^r(t)L_{s,s'}(t) + \Phi_s^r(t))$, where $E(r)$ denotes the time consumed by task r from the start execution time to the end execution time. The incrementality of the time calculation function is manifested in that the time required for calculation should be increased with the passage of time. The concavity is that the total number of resource request operations is constant and gradually decreases with time. We can transform the original model (2) as the following model.

$$\begin{aligned}
 & \min \sum_{t=1}^{\tau} \sum_{s=1}^S \sum_{r=1}^R \log \left((U_s^r(t) f_s^r(t) + E(r)) B_s^r(t) L_{s,s'}^r(t) + \Phi_s^r(t) \right) \\
 & \text{s.t.} \\
 & \text{C1 : } B_s^r(t) = 1, \forall t \in \{begin, end\}, \\
 & \text{C2 : } L_{s,s'}^r(t) = 1, \forall t \in \{W_{s,s'}^{start}, W_{s,s'}^{end}\}, \\
 & \text{C3 : } l_{s,s'}^{\min} \leq f_s^r(t) \leq l_{s,s'}^{\max}, \\
 & \text{C4 : } 0 < u_s^r(t) \leq \zeta, \\
 & \text{C5 : } b_s^r(t) \in \{0, 1\}, \\
 & \text{C6 : } \theta_s(r) - \theta_s(r') = \gamma, \gamma > 0, \\
 & \text{C7 : } s^{ant} \in N^*, \\
 & \text{C8 : } L_s^{ant} \in N^*, \\
 & \text{C9 : } \sum_{v \in s} f(u, v) = 0, u \neq s_{source}, s_{target}, \\
 & \text{C10 : } L_{s,s'}^r(t) \in \{0, 1\},
 \end{aligned} \tag{2}$$

where τ denotes the discrete-time period and $t, t \in \tau$ denotes the time gap. S denotes the set of satellites available within some time gap t as $S, s, s \in S$ denotes the satellites for which some visible time window exists. R denotes the queue of missions on satellite s , and $r, r \in R$ denotes a particular mission on satellite s . $U_s^r(t) f_s^r(t) B_s^r(t) L_{s,s'}^r(t)$ denotes the time consumption of a mission r in satellite s on some time gap t transmit to the target satellite or ground base station in the presence of a visible time window. If there is no visible time window, the time consumption is zero. $B_s^r(t) L_{s,s'}^r(t) E(r)$ denotes the execution time consumed by the task from the beginning to the end of execution if there is a visible time window for the satellite and the number of resources required by the task can be satisfied. C1 indicates that if the resource request operation is executable, the data transmission related to resource scheduling should be completed within the specified time. C2 indicates that the related data transmission of the resource request operation should be executed within the visible time window. C3 indicates that the amount of data transmitted after a successful inter-satellite link is established must be greater than the unit data and the bandwidth occupied by the currently transmitted data must not be greater than the link bandwidth threshold. C4 indicates that the time consumed for unit data transmission must be more significant than 0 and less than the specified threshold ζ . C5 represents the value range of the resource scheduling state of the inter-satellite link. C6 indicates that multiple resource request operations use the same satellite resources, and there should be enough conversion time. C7 manifests that the satellite antennas number should be a positive number. C8 means that the number of links that any satellite antenna can use should be positive. C9 represents the flow conservation constraint. C10 represents the link connectivity state matrix.

In fact, the constraints of the above conditions are far from sufficient in solving the actual problem, such as the influence of power constraints and space radiation on satellites. However, it is necessary to ignore the constraints that have minimal impact on the problem to illustrate the main problem of resource scheduling more clearly. Therefore, we consider the main constraints and propose a simplified model to minimize the resource scheduling time consumption. The model proposed in this paper is also applicable to more complex application scenarios by adding constraints related to specific application scenarios. To solve the minimum time consumption problem of resource scheduling, we investigate the method of collaborative idle satellites to share the pressure of global resource requests and achieve the goal of optimal resource scheduling in the global context. Suppose a satellite network $G(V, E)$ is given, where the edge $(U, V) \in E$ represents the inter-satellite connection link and V represents the satellite node. Suppose there are K requesting jobs $K = [k_1 \ k_2 \ \dots \ k_n]$ with different resources. s_{source} indicates the source satellites in the

network G . We need to reconstruct the task queue and send tasks to s_{target} . The target satellites s_{target} are responsible for completing the resource scheduling requirements of the allocated resource request operations. $K_i = (s_{source}^i, s_{target}^i, d_i)$ denotes the resource demand d_i of the i -th resource request operation from satellite s_{source}^i to satellite s_{target}^i . The flow caused by the task r along the edge (u, v) at a slot t is $f_{u,v}^r(t)$. From the above definition, the global reallocation of resource request queues can be transformed into an inter-satellite link resource contention problem and a multi-satellite resource coordinated allocation optimization problem. Furthermore, the optimization of inter-satellite link resource contention can maximize data transmission in resource request queue redistribution. The solution of the multi-satellite resource coordination optimization problem can minimize time consumption in the resource scheduling process. Therefore, model (2) can be decomposed into two models: the contention model for inter-satellite link resources and the multi-satellite resource collaborative allocation optimization model.

4.2. Link Resource Competition Optimization

As mentioned above, the spatial information network resource scheduling problem can be decomposed into the network link optimization and the network resource cooperative allocation. In this section, we focus on modeling and algorithm design for the network model link optimization problem, aiming to solve the high delay of data transmission and incomplete data caused by dynamic link changes in the process of time-varying network resource scheduling. In addition, it is commonly recognized that inter-satellite links in space information networks are dynamically changing, and the maximum amount of data that can be accommodated on the network changes continuously over time t . Therefore, we need to calculate the maximum amount of data that can be accommodated on the current network before allocating satellite resources. Without exceeding the maximum capacity, we transmit the tasks r on each satellite to the satellite with free resources, thus reducing the resource request load on the original satellite. The Formula (3) can be constructed for the contention of inter-satellite link resources. It shows the time consumption of calculation, storage, or antenna switching delay within the satellite.

As shown in Formula (3), the model describes the minimum time cost of interstellar link data transmission. Where $U_s^r(t)f_s^r(t)L_{s,s'}(t)\bar{c}_s^r(t)$ denotes the time cost consumed for data transmission on the satellite link, Φ denotes the waiting delay for data transmission over the inter-satellite link and the corner time sum of the antenna equipment. C1 indicates that once the link resource is occupied, it is not allowed by other jobs until the job transfer is finished or the visible time window disappears. The constraint is defined because the link resources between satellites are relatively precious, and we are only concerned with the contention of link resources. Therefore, if we want the task execution time to become shorter, link resource utilization needs to be maximized. Thus, frequent switching operations consume link resources while causing more severe time loss. C2 – C10 are the same with the Formula (2), C11 in $\sum_{w \in V} f_{u,w}^r(t) < f_{u,v}^r(t)$ shows that the actual flow transmitted between satellites is less than the inter-satellite link capacity. $I_{s,s'}^{\min} \leq f_{u,v}^r(t) \leq I_{s,s'}^{\max}$ exhibits that the total flow to be transmitted between the satellites $f_{u,v}^r(t)$ is greater than the minimum flow allowed to be transmitted $I_{s,s'}^{\min}$ and less than the maximum flow $I_{s,s'}^{\max}$ allowed to be transmitted on the inter-satellite, C12 denotes that the flow sent by the original satellite needs to be transmitted to the target satellite in its entirety. C13 indicates that the total flow transmitted on the space information network is less than what the satellite network is allowed to send.

$$\begin{aligned}
 & \min \sum_{t=1}^{\tau} \sum_{s \in S_{new}} \sum_{r \in R_{new}} \log \left(U_s^r(t) f_s^r(t) L_{s,s'}(t) \zeta_s^r(t) + \Phi \right) \\
 & \text{s.t.} \\
 & \text{C1: } \sum_{r \in R_{new}} \zeta_s^r(t) = 1, \zeta_s^r(t) \in \{0, 1\}, r \in R_{new}, s \in S_{new}, t \in \tau. \\
 & \text{C2: } L_{s,s'}(t) = 1, \forall t \in \{W_{s,s'}^{start}, W_{s,s'}^{end}\}, \\
 & \text{C3: } l_{s,s'}^{\min} \leq f_s^r(t) \leq l_{s,s'}^{\max}, \\
 & \text{C4: } 0 < u_s^r(t) \leq \zeta, \\
 & \text{C5: } b_s^r(t) \in \{0, 1\}, \\
 & \text{C6: } \theta_s(r) - \theta_s(r') = \gamma, \gamma > 0, \\
 & \text{C7: } s^{ant} \in N^*, \\
 & \text{C8: } L_s^{ant} \in N^*, \\
 & \text{C9: } \sum_{v \in s} f(u, v) = 0, u \neq s_{source}, s_{target}, \\
 & \text{C10: } L_{s,s'}(t) \in \{0, 1\}, \\
 & \text{C11: } \sum_{w \in V} f_{u,w}^r(t) < f_{u,v}^r(t), l_{s,s'}^{\min} \leq f_{u,v}^r(t) \leq l_{s,s'}^{\max}, \\
 & \text{C12: } \sum_{w \in V} f_{s_{source},w}^r(t) \Leftrightarrow \sum_{w \in V} f_{w,s_{target}}^r(t), \\
 & \text{C13: } \sum_{t=1}^{\tau} \sum_{s \in S_{new}} \sum_{r \in R_{new}} f_s^r(t) \leq \max(V_S^R(t)).
 \end{aligned} \tag{3}$$

Therefore, we mainly consider the problem of link utilization in the model (3). In the task execution process, the resource utilization rate of the inter-satellite link directly affects the overall resource scheduling time. Ideally, we can consider that the resource utilization reaches the maximum, then the time consumed by resource scheduling is the minimum when all resource requests are satisfied. Therefore, we designed the following algorithm to improve the utilization of link resources.

According to Algorithm 1, we first create virtual source nodes and sink nodes according to the resource amount that needs to transmit on the full link at a particular time t in the spatial information network (lines 1–5), converting the multi-commodity network flow problem into a single source and single sink problem. Then, we use the Ford-Fulkerson algorithm to find the maximum flow in the network and the flow value that can circulate on each edge (line 6). Based on the time consumed by the unit data on the link, we calculate the maximum time consumed by the entire network at the current moment t . Finally, we obtain the minimum data transmission time (lines 8–9).

4.3. Resource Cooperative Allocation Optimization

The multi-satellite resource coordination and allocation optimization problem requires multiple satellites to provide various resources for mission execution. Multi-satellite and multi-mission scenarios usually have multiple sources and multiple sink satellites. Due to time variation and communication latency issues, it is difficult to assign tasks based on satellite resource status. This may result in an imbalance of mission requests processed by satellites, with some satellites being overstressed and others being relatively underloaded. Meanwhile, the satellite resources cannot handle the tasks in time. Therefore, the multi-satellite resource coordination problem can be solved based on the minimum cost multimodal network flow theory. The model is constructed as follows,

$$\begin{aligned}
 & \min \sum_{t=1}^{\tau} \sum_{(u,v) \in E} \left(U_{u,v}(t) \sum_{r=1}^R f_{u,v}^r(t) \right) \\
 & \text{s.t.} \\
 & \text{C1: } \sum_{v \in s} f_{u,v}^r(t) = 0, u \neq s_{source}, s_{target}, \\
 & \text{C2: } \sum_{w \in V} f_{u,w}^r(t) < f_{u,v}^r(t), l_{s,s'}^{\min} \leq f_{u,v}^r(t) \leq l_{s,s'}^{\max}, \\
 & \text{C3: } \sum_{w \in V} f_{s_{source},w}^r(t) \Leftrightarrow \sum_{w \in V} f_{w,s_{target}}^r(t).
 \end{aligned} \tag{4}$$

As shown in Formula (4), it describes the least cost incurred by the multi-satellite resource allocation scheme within the discrete time-period τ . The nodes in the network are represented as satellites, and the edges on the network are represented as visible links between satellites. (u, v) denotes the visible links from satellite u to v , E denotes all links on the network at the slot t . $U_{u,v}(t)$ denotes the time consumption per unit of the flow on the visible link (u, v) , and $\sum_{r=1}^R f_{u,v}^r(t)$ denotes the flow of the task r over the link (u, v) . In addition, C1 is the inter-satellite link capacity constraint. C2 is the inter-satellite transmission flow storage constraint, which indicates that no data is stored on the satellite during the data transmission. C3 denotes the resource requirement satisfaction constraint. Meanwhile, we identify the traffic scheme when we have solved for the minimum value. We assume that the satellite whose mission exceeds the load is a source node in the satellite networks. Then, we assign resources to the target satellite based on the flow from the source node to other nodes. Therefore, we can obtain the multi-satellite resource allocation scheme by calculating the minimum cost flow of the network, while we can ensure the minimum cost consumption of the resource allocation scheme.

Algorithm 1 Maximum traffic allocation of inter-satellite link resources

Input: Given network $G(V, E, s_{source}, s_{target}, U, l)$. Initialize the number of transmissions d_i , the time $U_{u,v}^r$ consumed per unit of data transmission, link bandwidth $l_{s,s'}^{\max}$, source point s_{source} , and sink point s_{target} ,

Output: Network flow allocation time *Time*

```

1 if  $s_{source} \neq \emptyset$  &  $s_{target} \neq \emptyset$  then
2   superSourceNode.next() =  $s_{source}$  ;
3   superTartgetNode.next() =  $s_{target}$  ;
4   G.add(superSourceNode);
5   G.add(superTargetNode);
6 MF=FordFulkerson( $d, l_{s,s'}^{\max}$ ); // Use the algorithm Ford-Fulkerson to
   calculate the maximum flow value MF allowed in the network G
7 ; for each  $(u, v) \in E$  do
8   Time = Time +  $U_{u,v}^r \times MF(u, v)$ ;
9 Time = time +  $\Phi$ ; // The sum time consumed is the sum of link data
   transmission time, antenna switching, satellite internal
   calculations, and other operations.
10 return Time

```

As shown in Figure 5, we can observe the inter-satellite links and the satellites' initial state in the spatial information network. Our purpose is to find all paths that consume the shortest time.

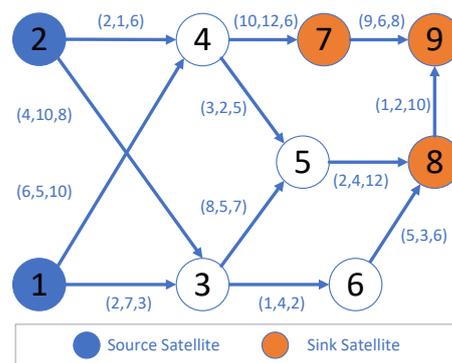


Figure 5. The initial state of spatial information network resource allocation schematic diagram.

As shown in Table 2, we give a simple resource type and predefined value of the demand quantity on the network G . The network G includes two resources, two source nodes, three sinks, and the resource demand quantity on each node. On a given network G , we design the following algorithm based on the spatial information network environment characteristics to solve the minimum time consumption problem for resource allocation.

Table 2. Resource scheduling initial data sample.

Resources Type	Sources Number	Sinks Number
1	1	2
1	2	4
1	7	−4
1	8	−1
1	9	−1
2	1	3
2	2	3
2	7	−1
2	8	−4
2	9	−1

As shown in Algorithm 2, we use Algorithm 1 to calculate the maximum traffic value that the current satellite network can accommodate (lines 1–7). If a resource request operation is added to the source satellite set, all resource request queues of the current satellite set are updated (line 10). Meanwhile, the total resource demand of the network at the current moment is obtained. Suppose the total demand is within the accommodating range of the entire network. In that case, the gurobi solver (a widely used solver, we have obtained a license) is used to solve the optimal resource allocation route, and then the current unallocated resources are updated (lines 11–13). If no new resource requests are added, the optimal resource allocation plan is resolved using gurobi, then the currently unallocated resources are updated and returned to the current minimum time resource allocation plan (lines 18–20).

As shown in Figure 6, the computational results of the above simple example depict the reconstruction of the satellite resource request queue and satellite resource coordination scheme as well as the final route planning for resource coordination. The example shows resource cooperation among satellites, where satellites accomplish resource request tasks through resource sharing.

Algorithm 2 Satellite resource allocation in dynamic network

```

Input: Given network  $G(V, E, s_{source}, s_{target}, U, l)$ . Initialize the number of
resource requirements  $d_i$ , unit data transmission time  $U_{u,v}^t$ , link bandwidth
 $l_{s,s'}$ , source  $s_{source}$  and sink  $s_{target}$ ,
Output: Network flow allocation time Time
1 if  $s_{source} \neq \emptyset \& s_{target} \neq \emptyset$  then
2   superSourceNode.next() =  $s_{source}$  ;
3   superTartgetNode.next() =  $s_{target}$  ;
4    $G^*.add(\text{superSourceNode})$ ;
5    $G^*.add(\text{superTargetNode})$ ;
6 MF=FordFulkerson( $d, l_{s,s'}^{\max}$ ); // Use the algorithm Ford-Fulkerson to
   calculate the maximum flow value MF allowed in the network  $G^*$ 
7 ; for each  $t < \tau$  do
8   if a new resource request queue is added then
9     UpdateQueue( $d(s_{source})$ );
10    if the resource demand at the current moment  $d < MF$  then
11      Route=gurobi.optimize(); // Use the gurobi solver to calculate
   the minimum time-consuming planning scheme.
12       $d - d_{Allocated} = d_{new}$ ; // Update unallocated resources.
13    else
14      MF=FordFulkerson(); // Update the maximum flow capacity.
15    else
16      Route=gurobi.optimize();
17       $d - d_{Allocated} = d_{new}$ ; // Update unallocated resources.
18 return Route

```

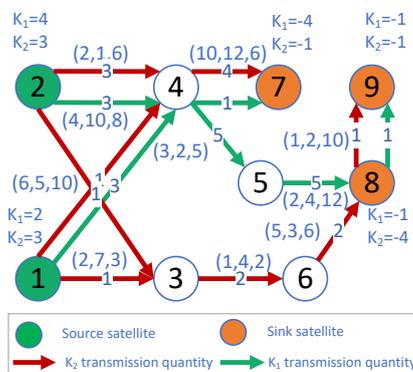


Figure 6. Satellite resource request queue reconstruction and inter-satellite resource coordination.

In summary, the optimization process of spatial information network resource scheduling is the process of source request queue redistribution and inter-satellite coordination, which ultimately minimizes the time consumed by the satellite resource scheduling process.

5. Numerical Experiment

5.1. Algorithm Complexity Analysis

The resource coordination scheduling method of a spatial information network is mainly divided into two parts: the dynamic allocation of network resources and the maximum flow allocation of inter-satellite link resources. The time complexity of adding super source nodes and super sink nodes in the process of network resource dynamic allocation is $O(s_{source} + s_{target})$, and the time complexity of the Ford-Fulkerson algorithm is $O(Ef)$. We use approximate algorithms to solve the minimum cost calculation results

of multiple resource types under multiple sinks and multiple source conditions. The time complexity is only related to the scale n of the input example, and it varies with the parameters ε . Therefore, the time complexity of PTAS ranges from $O(n^{1/\varepsilon})$ to $O(n^{\exp(1/\varepsilon)})$. According to the above analysis, the time complexity of Algorithm 1 is $O(s_{source} + s_{target} + Ef + n^{1/\varepsilon})$ or $O(s_{source} + s_{target} + VE^2 + n^{\exp(1/\varepsilon)})$, and the final time complexity is $O(Ef + n^{1/\varepsilon})$ or $O(Ef + n^{\exp(1/\varepsilon)})$. As with Algorithm 1, Algorithm 2 first adds virtual nodes for the source and sink points with the time complexity of $O(s_{source} + s_{target})$ and then solves the maximum flow of the network. The time complexity of the algorithm Ford-Fulkerson is $O(Ef)$. Finally, satellite resources are allocated according to the traffic on each edge. We call the algorithm proposed in this paper RQRCS, then the best time complexity of RQRCS is $O(Ef)$, and the worst-case time complexity is $O(Ef + n^{\exp(1/\varepsilon)})$.

RQRCS proposes the algorithm with the smallest time-complexity among all algorithms when the maximum flow f is small in the paper. When the maximum flow value f is relatively large, then the advantages of this method will be significantly reduced. However, influenced by the spatial information network, the number of satellites that can establish a network with adjacent satellites at a specific moment is small, and the amount of data transmitted by the inter-satellite link is also minimal. Therefore, we do not need to consider the high time complexity caused by the large scale of the spatial information network. We address the problem of the local small satellite network in resource request queue reconstruction and satellite coordinated allocation.

5.2. Simulation Scenario

In order to study the critical problems of mission scheduling, link optimization, collaborative computing, and network topology discovery of spatial information networks, we developed a Chinese version of the Space-based information network satellite ToolKit (CSTK) independently based on the actual satellite and common mission data in spatial information networks. In this system, we simulated satellite data, including satellite load data, satellite orbit data, inter-satellite visible time window and satellite ground visible time window data, satellite resource capacity, and satellite resource quantity. In addition, we simulated data of common Earth observation application scenarios, including Earth observation area, mission execution time demand, mission resource type, mission resource demand, etc. Moreover, we have developed various computational libraries required for the CSTK system. The experiments in this paper were finished based on the CSTK experimental simulation platform and coded in Python. Eventually, the system created a multi-satellite and multi-task earth observation scene. The scene start time is "13 June 2021 04:00:00.000 UTCC", and the end time is "14 June 2021 04:00:00.000 UTCC". The Earth observation scene contains 10 practical satellites, of which five satellites are used in the Earth observation scene, and the remaining five are communications satellites. The three-dimensional and two-dimensional views of the satellite and the earth in the Earth observation simulation scene are shown in Figures 7 and 8. As shown in Figure 8, we depict the track of the subsatellite point in the two-dimensional plane. CSTK uses the satellite orbit parameter data provided by celestrak (<https://celestrak.com/>, accessed on 27 October 2021) to calculate the track of subsatellite point in the two-dimensional plane. We denote the satellite coordinates in its orbital plane as $cr=(x_0, y_0, z_0)$. The calculation Formula (5) is as follows,

$$cr = \begin{cases} x_0 = -a(1 - e^2) \times \frac{\cos(\theta)}{1 + e \cos(\theta)} \\ y_0 = -a(1 - e^2) \times \frac{\sin(\theta)}{1 + e \cos(\theta)} \\ z_0 = 0 \end{cases} \quad (5)$$

where a denotes semi major axis, θ indicates true anomaly, e represents eccentricity. We obtain basic satellite information and satellite orbit information from celestrak and third-party satellite simulation calculation packages. The parameters of satellites in the simulation scenario are shown in Table 3.

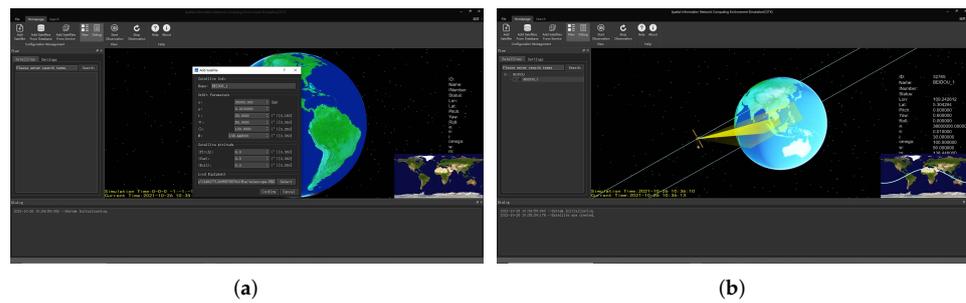


Figure 7. Spatial information network computing environment simulation platforms. (a) Satellite management. (b) Observation scene.

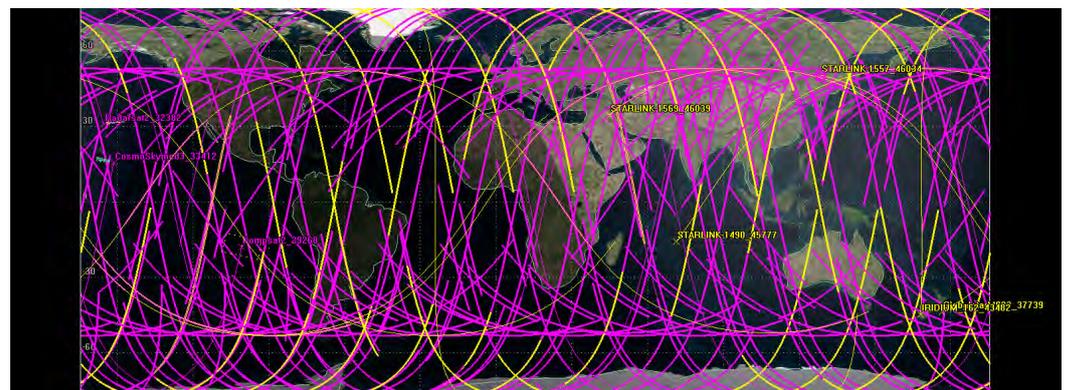


Figure 8. Two-dimensional trajectory of satellite.

Table 3. Satellites parameters in the simulation scenario.

Id	Satellite	Mission Class	Mean	Eccentricity	Inclination	Argument of Perigee	RAAN	Mean Anomaly
1	COSMO-SkyMed 3	Earth Observation	0.0617566 deg/s	0.0001561	97.8893 deg	93.4363 deg	348.021 deg	266.704 deg
2	ZiYuan 2C	Earth Observation	0.0626305 deg/s	0.004758	97.2866 deg	62.7732 deg	35.4333 deg	297.833 deg
3	IRIDIUM_162	Communications	0.0601366 deg/s	0.0002317	86.4485 deg	96.0452 deg	133.275 deg	264.101 deg
4	STARLINK-1490	Communications	0.0627664 deg/s	0.0001502	53.0558 deg	82.9425 deg	45.8273 deg	277.173 deg
5	STARLINK-1557	Communications	0.0627666 deg/s	0.0001709	53.0575 deg	117.008 deg	336.223 deg	243.109 deg
6	STARLINK-1569	Communications	0.0627667 deg/s	0.0001654	53.0574 deg	108.432 deg	336.473 deg	251.684 deg
7	KOMPSAT-2	Earth Observation	0.060932 deg/s	0.0018448	97.9422 deg	95.7576 deg	43.5438 deg	264.572 deg
8	Proba-V	Earth Observation	0.0592918 deg/s	0.0005443	98.4077 deg	91.3034 deg	212.541 deg	268.877 deg
9	RADARSAT-2	Earth Observation	0.0595828 deg/s	0.0001296	98.5743 deg	92.0516 deg	171.152 deg	30.1928 deg
10	Globalstar M083	Communications	0.0525945 deg/s	0.0000275	51.9838 deg	225.309 deg	186.696 deg	305.39 deg

To facilitate experimental verification, only the observation and storage resources required by the resource request queue are considered in this experiment.

5.3. Parameter Setting

We take a particular instantaneous network structure and assume that the number of task queues at that moment is 12. If a new task is added to the queue at the next moment, then the resource scheduling result needs to be recalculated. According to the numbering of the satellites in Table 3, we assume that satellite 1 and satellite 2 have already met the amount of mission resources requests. However, there are still tasks waiting to be executed with observing resource requirements of six photographs and storage resources of six GB. Next, we can schedule idle satellite resources to perform tasks currently waiting due to resource shortages. This experiment compares the resource scheduling algorithm *RQRCS* proposed in this paper with benchmark algorithms to verify its effectiveness. These algorithms include Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Both PSO and GA are provided by the Python 3.6 supported toolkits

'sko.GA' and 'sko.PSO'. The parameter settings for the PSO and GA algorithms are shown in the following Table 4, where ID denotes the parameter number, *size_pop* indicates size of population, and *max_iter* denotes max iteration.

Table 4. Parameter settings for PSO and GA algorithms.

ID	PSO		GA	
	<i>size_pop</i>	<i>max_iter</i>	<i>size_pop</i>	<i>max_iter</i>
P1	200	400	200	400
P2	300	600	300	600
P3	400	800	400	800
P4	500	1000	500	1000

5.4. Results Analysis

In the experiment, the RQRCS algorithm simultaneously considers two types of resources: storage and observation. The resource scheduling scheme with minimum time consumption is found by optimizing the network transmission path of multiple resources. As shown in Tables 5 and 6, RQRCS finds the target satellites participating in the collaboration and the least time-consuming path to the target satellite. In addition, we can observe that satellite 7 has received five resource requests, including 4 GB of storage resources and one observation of the use of resources; Satellite 8 received resource requests from seven units, But satellite 8 requests two units of resource quantity from satellite 9. Therefore, satellite 8 participates in allocating five units of resources, respectively; the use of 1 GB storage resources and the use of four observation resources. Satellite 9 needs to allocate 1 GB of storage resources and the use of one observation resource.

Table 5. RQRCS scheduling observation resource calculation results.

Scheduling Route	Resource Transfers
1 → 4	3
2 → 4	3
4 → 5	5
4 → 7	1
5 → 8	5
8 → 9	1
Amount of time consumed per unit	62

Table 6. RQRCS scheduling storage resource calculation results.

Scheduling Route	Resource Transfers
1 → 4	1
1 → 3	1
2 → 4	3
2 → 3	1
3 → 6	2
4 → 7	4
6 → 8	2
8 → 9	1
Amount of time consumed per unit	71

Figures 9 and 10 shows the multiple optimization solution processes using PSO and GA algorithms based on different parameter settings for multi-satellite resource allocation. The minimum ordinal value in the figure is the minimum resource scheduling time

consumed by the algorithms. The minimum time consumption value for PSO and GA algorithms are 230 and 283 units of time, respectively. Table 7 shows that the algorithm RQRCS exhibits less time consumption in the multi-satellite resource coordination process compared to the baseline algorithms PSO and GA. Therefore, the experimental verification and analysis indicate that the RQRCS algorithm has certain advantages.

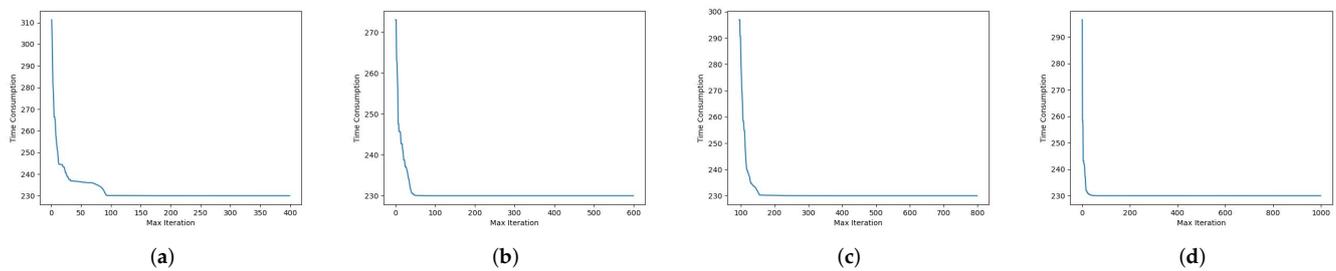


Figure 9. PSO solution process based on different parameter settings. (a) PSO process based on parameter P1, (b) PSO process based on parameter P2, (c) PSO process based on parameter P3, (d) PSO process based on parameter P4.

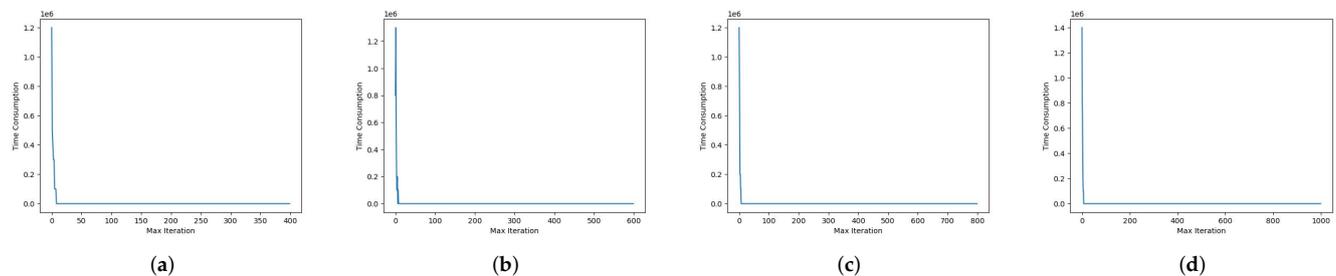


Figure 10. GA solution process based on different parameter settings. (a) GA process based on parameter P1, (b) GA process based on parameter P2, (c) GA process based on parameter P3, (d) GA process based on parameter P4.

Table 7. Comparison of the time consumption of the three algorithm scheduling resource processes.

Algorithm	Time Consumption				
	-	P1	P2	P3	P4
RQRCS	133	-	-	-	-
PSO	-	230	230	230	230
GA	-	291	302	288	283

6. Conclusions

This paper studies the cooperative scheduling problem of space information network resources. Aiming at the pain points of the strong dependence of resource scheduling on ground base stations, weak autonomous coordination of resources, and low resource utilization, we propose a low time complexity algorithm based on the related theory of graphs to achieve dynamic reconfiguration of satellite resource request queues and inter-satellite resource collaboration. We compare the time complexity of several baseline algorithms for resource scheduling, analyze the computation time of multiple algorithms in spatial information network scenarios, and compare the performance of the algorithms. In future research, there are still some issues to be addressed. First, the model constraints constructed are not perfect, such as power and radiation constraints. The time complexity of the maximum flow algorithm determines the time complexity of the algorithm designed in this paper. Optimization of the maximum traffic algorithm for dynamic networks can effectively improve the computational efficiency of the whole algorithm. In addition, the threshold setting of the number of coordinated satellites is not considered in this paper. If the coordinated satellite resources are abundant, it will generate much link resource

occupation and path optimization time consumption. If the coordinated satellite resources are too few, the resource request and pressure will not be significantly relieved. Therefore, how to select the number of peripheral satellites needs further study.

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