Two-Stage Task Planning Based on Resource Interchange in Space Information Networks

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Abstract. The high computational complexity and the mismatch between the space-time distribution of tasks and resources raise great challenges on task planning in space information networks (SINs). This paper studies the task planning problem in SINs by exploiting resource interchange to handle the bottleneck resources. First of all, we use time-varying resource graph to capture the dynamic coordination relationship among resources in SIN. Then, we explore resource interchange and derive its quantitative condition. On this basis, an optimization model for task planning based on resource interchange is formulated. Furthermore, we decompose the task planning problem into two stages for global optimization and local adjustment, and develop the algorithms respectively. Finally, simulation results show that compared with existing works the proposed algorithm strikes a better balance between the number of completed tasks and computational complexity.

Keywords: Space information networks · Resource interchange · Task planning · Resource representation

1 Introduction

Space information network is a network system which could acquire, deliver and process spatial information in real time [1]. Due to the prominent features such as wide coverage and flexible networking free from geographical restrictions [2,3], SINs have played important roles in both military and civilian fields in recent years. There are many types of resources (e.g., communication, computation, storage, observation resources, etc.) in SINs, and complex tasks always require coordination of multiple types of resources [4]. Moreover, due to the high-speed movement of space nodes, the distribution of resources in the network is dynamic

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and non-uniform in both space and time dimension. Similarly, the space-time distribution of task arrivals is also of great randomness [5]. With the increasing task demands, the temporal shortage of some kinds of resources in certain region becomes more and more obvious, which brings great challenges to the timely completion of tasks.

Faced up with this problem, some intrinsic properties of SIN such as resource mobility [6] and emerging technologies such as software defined payloads [7] are utilized to compensate the bottleneck resources timely. Literature [6] and [8] study the mode of utilizing resource mobility such as resource interchange and resource aggregation, and show that the utilization of resource mobility can effectively improve the service capability of SINs. On this basis, [9] proposes a task planning strategy that considers the interchange of storage and communication resources of SINs. By designing a time-space dimensional resource representation model of software defined satellite networks, literature [10] characterizes the transformation among network resource functions, and thus proposes a resource management method.

Although the above methods [9,10] have good performance in terms of compensating the bottleneck resources, there still exists a lot room for improvement. Firstly, these methods only exploit resource mobility qualitatively, while the quantitative study of conditions for its utilizations such as resource interchange is still lacking. Secondly, in spite of enhancing the flexibility of the matching between resource combinations and tasks, the utilization of resource interchange also increases the space of feasible solution. As task planning of SIN is a complex combinatorial optimization problem, this significantly increases the computational complexity of solving problem. Most of the existing works either consider a network with limited size or design heuristic algorithm which decomposes the large scale task planning problem into multiple sub-problems according to time or scheduled resources, but ignores the correlation between resources [10,11].

To this end, this paper proposes a two-stage task planning strategy based on resource interchange. Specifically, we first use time-varying resource graph model to capture the dynamic coordination relationship among resources in SIN. Then, we explore the mechanism of resource interchange and propose its quantitative condition. On this basis, an optimization model for task planning based on resource interchange is formulated. Furthermore, we decompose the task planning problem into two stages, named coarse grained global optimization and fine-grained local adjustment, and design algorithms for them, respectively. Finally, simulation results show the effectiveness of the proposed algorithms in terms of task completion rate and computational complexity.

2 System Model

2.1 Network Scenario

We consider a space information network (as shown in Fig. 1), which consists:

- A set of earth observation satellites distributed on low earth orbits, denoted by $OS = \{os_1, os_2, ..., os_n, ...\}$. Each earth observation satellite is equipped with an imager, a solid state mass storage and two transceivers (to communicate with ground stations and data relay satellites respectively).
- A set of data relay satellites on the geostationary earth orbit, denoted by $RS = \{rs_1, rs_2, ..., rs_n, ...\}$.
- A set of ground stations $GS = \{gs_1, gs_2, ..., gs_n, ...\}$.
- A data processing center, denoted by dc.
- A set of observation targets distributed randomly on earth, denoted by $OB = \{ob_1, ob_2, ..., ob_n, ...\}$.

The set of nodes in SIN is denoted as $Nd = OS \cup RS \cup GS \cup OB \cup \{dc\}$.

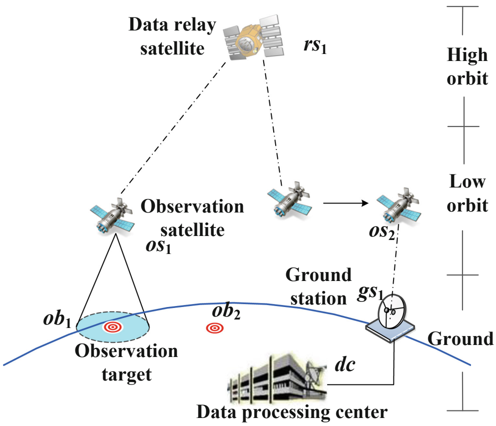

Fig. 1. Network scenario.

2.2 Resource Model

Owing to the high-speed movement of satellite nodes, the topology and coordination relationship among different resources in SINs is of great dynamic. With the advantage of characterizing the resources of dynamic networks in time-space dimensional, the time-extended graph model proposed by Fulkerson [12] and its varieties have been widely used in SINs in recent years [13]. In order to utilize resource interchange, we consider the time-varying resource graph (TVRG) model, which can not only jointly represent multiple kinds of resources of SINs, but also take resource mobility into account.

To construct the TVRG of SIN, we first divide the planning horizon into K equal-length time slots, each with duration τ. As shown in Fig. 2, time-varying resource graph $G_K(V, A)$ is a K-layered directed graph, wherein each layer represent to the topology of SIN of corresponding time slot. V and A represent the set of vertices and arcs in TVRG, respectively.

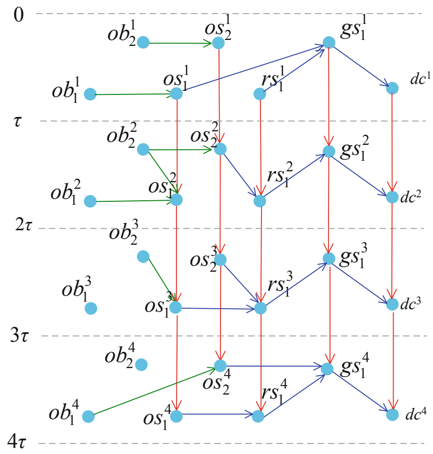

Fig. 2. The time-varying resource graph.

The vertex set V in TVRG is composed of the temporal replicas of the nodes in SIN for every time slots, which can be expressed as $V = V_{OB} \cup V_{OS} \cup V_{RS} \cup V_{GS} \cup V_{DC}$, wherein $V_{OB}, V_{OS}, V_{RS}, V_{GS}$ and V_{DC} are the sets of the temporal replicas of observation targets, observation satellites, relay satellites, ground stations and data processing center, respectively. Specifically, the set of the temporal replicas of observation targets is expressed as

$$V_{OB} = \{ob_i^k | 1 \leq k \leq K, 1 \leq i \leq |OB|\}, \tag{1}$$

wherein ob_i^k represents the observation target ob_i in the kth time slot. Similarly, we have $V_{OS} = \{os_i^k | 1 \leq i \leq |OS|, 1 \leq k \leq K\}$, $V_{RS} = \{rs_i^k | 1 \leq i \leq |RS|, 1 \leq k \leq K\}$, $V_{GS} = \{gs_i^k | 1 \leq i \leq |GS|, 1 \leq k \leq K\}$ and $V_{DC} = \{dc^k | 1 \leq k \leq K\}$, wherein os_i^k, rs_i^k, gs_i^k and dc^k represent observation satellite os_i, data relay satellite rs_i, ground station gs_i and data processing center dc in the kth time slot, respectively.

The arcs in TVRG represent different types of resources in the network, of which the set is defined as $A = A_O \cup A_L \cup A_S$, wherein A_O, A_L and A_S are the set of observation, transmission and storage arcs, respectively. The observation arcs model the opportunities for earth observation satellites to acquire data from observation targets, i.e.,

$$A_O = \{(ob_i^k, os_j^k) | lc(ob_i) \in R(os_j, k), 1 \leq i \leq |OB|, 1 \leq j \leq |OS|, 1 \leq k \leq K\}, \tag{2}$$

where $lc(ob_i)$ represents the location of observation target ob_i, and $R(os_j, k)$ represents the visible range of observation satellite os_j in the kth time slot. The capacity of observation arc $(ob_i^k, os_j^k) \in A_O$ is the maximum amount of data that observation satellite os_j can acquire from observation target ob_i in the kth slot, i.e., $C(ob_i^k, os_j^k) = ro_j \cdot \tau$, where ro_j represents the data acquisition rate of the imager in os_j. The set of transmission arcs is expressed as $A_L = A_{ol} \cup A_{fl}$, wherein A_{ol} represents the set of opportunities for earth observation satellites communicates with data relay satellites or ground stations, and A_{fl} represents the set of fixed links from data relay satellites to their specific ground stations and from ground stations to data processing center, i.e.,

$$\begin{aligned} A_{ol} = &\{(os_i^k, rs_j^k) | lc(os_i) \in R(rs_j, k), os_i^k \in V_{OS}, rs_j^k \in V_{RS}\} \\ &\cup \{(os_i^k, gs_j^k) | lc(os_i) \in R(gs_j, k), os_i^k \in V_{OS}, gs_j^k \in V_{GS}\} \end{aligned} \tag{3}$$

$$\begin{aligned} A_{fl} = &\{(rs_i^k, gs_{rg(i)}^k) | rs_i^k \in V_{RS}, gs_{rg(i)}^k \in V_{RS}\} \\ &\cup \{(gs_i^k, dc^k) | 1 \le i \le |GS|, 1 \le k \le K\}, \end{aligned} \tag{4}$$

wherein $rg(i)$ denotes the index of the specific ground station for data relay satellite rs_i. The capacity of a transmission arc is the maximum of data that the corresponding link can transmit in a time slot, which is given by $c(v_i^k, v_j^k) = rd(v_i, v_j)$, where $rd(v_i, v_j)$ is the transmission rate of the link (v_i, v_j). The storage arc represents the ability of storage resources to store data, the set of storage arcs is expressed as

$$A_S = \{(v_i^k, v_i^{k+1}) | v_i^k \in V_{OS} \cup V_{RS} \cup V_{GS} \cup V_{DC}, 1 \le k \le K-1\} \tag{5}$$

The storage arc capacity is the volume of the storage of corresponding nodes.

The capacity of the arcs in TVRG represents the size of the ability of corresponding resources, which are measured by uniform unit bit. Moreover, the flows in TVRG represent the task execution process in SIN. Specifically, the set of arcs passed by a flow represents the combination of resources required to complete the corresponding task, and the value of the flow represents the volume of the data acquired, stored, and transmitted by the task.

Definition 1 (Resource Combination). *A set of consecutively connected arcs from vertex v_s^k to v_d^l in TVRG, denoted by $rc(v_s^k, v_d^l) = \{a_1, a_2, ..., a_m\}$, which satisfies*

$$\begin{aligned} &start(a_1) = v_s^k, end(a_m) = v_d^l, \\ &start(a_{i+1}) = end(a_i), \forall 1 \le i \le m-1, \end{aligned} \tag{6}$$

is referred to as a resources combination from node v_s to node v_d in SIN, where $start(a_i)$ and $end(a_i)$ represent the start and end point of arc a_i, respectively.

2.3 Quantitative Condition for Resource Interchange in SINs

In SINs the bottleneck resources can be compensated by the transformation or replacement with non-scarce resources, which is referred to as resource interchange [6,8]. More specifically, the resource mobility improves the freedom of coordination relationship between different resources in SINs. It provides additional opportunities for different resources to replace each other to complete of tasks, so that the shortage of certain types of resources can be supplemented by other types of resources that are relatively surplus at the same time. For example, on account of the mobility of satellites, data can be carried long distance through network in their storage, therefore some communication links can be replaced by mobile storage resources to a certain extent.

Note that the same service capability is the essential condition for different resources or resource combinations to interchange with each other to complete tasks. In order to uniformly quantify the service capability of resource combination in SINs, we define two metrics: 1) spatial displacement, 2) transferred data volume. More specifically, the spatial displacement of resource is a vector representing the position difference of resources, which may be caused by resources mobility or the difference of the locations of different resources. Let $llv_i^k = (lov_i^k, lav_i^k)$ denote the location of node v_i in the kth slot of SIN, where lov_i^k and lav_i^k represent the longitude and latitude of v_i in the kth slot, respectively. The spatial displacement from vertex v_i^k to v_j^m, denoted by llv_{ij}^{km}, is defined as

$$llv_{ij}^{km} = (lov_j^m - lov_i^k, lav_j^m - lav_i^k). \tag{7}$$

The transferred data volume of a resource is the amount of data that the resource can handle in a unit time, which equals to the capacity of the arc corresponding to the resource. For example, the transferred data volume of communication resource (v_i^k, v_j^k) is number of bits transmitted by the link (v_i, v_j) in the kth time slot (i.e., $c(v_i, v_j)$). Similarly, the transferred data volume of storage resource (v_i^k, v_j^{k+1}) is $c(v_i^k, v_j^{k+1})$.

Based on the definition of spatial displacement and transferred data volume resources, the service capability measurement of a resource can be defined. The service capability of resource (v_i^k, v_j^m) is defined as the product of its spatial displacement and transferred data volume resources, i.e.,

$$sc_{ij}^{km} = c(v_i^k, v_j^m) \cdot llv_{ij}^{km}. \tag{8}$$

As the amount of data can be processed by resource combination $rc(v_s^p, v_d^q)$ is the minimum capacity of the arcs therein, i.e., $min\{c(v_i^k, v_j^m)|(v_i^k, v_j^m) \in rc(v_s^p, v_d^q)\}$, the service capability of resource combination $rc(v_s^p, v_d^q)$ is defined as

$$min\{c(v_i^k, v_j^m)|(v_i^k, v_j^m) \in rc(v_s^p, v_d^q)\} \cdot llv_{sd}^{pq}. \tag{9}$$

With the uniform "transferred data volume spatial displacement" measurement for the service capability of resource combination, we can decide whether different resource combinations can be interchange or not, thereby providing a premise for effective utilization of resource interchange in SINs.

3 Problem Formulation and Decomposition

3.1 Problem Description

There are a set of observation tasks $OM = \{om_1, om_2, ...\}$ to be planned within the plan horizon Th. The requirement for each task can be represented by a four-dimensional tuple, i.e., $om_i = [ob_i, da_i, ts_i, te_i]$, where ob_i is the observation target of task om_i, da_i represents the amount of data required to be acquired by task om_i, and $[ts_i, te_i]$ represents the effective execution window of task om_i, i.e., ts_i is the earliest start time of the task, and te_i is the latest end time.

SIN completes the tasks according to the plans that are made off-line by the operation control center in advance. A task plan indicates whether a task requirement is successfully planned or rejected, and specifies the detailed data acquisition, storage and transmission process of tasks (e.g., the observation satellites, observation the ground station or data relay satellite receive data, and transmission windows allocated to each task). The goal of task planning is to maximize the number of successful planed tasks, of which all the requirements are satisfied.

3.2 Problem Formulation

As we have discussed in Sect. 2.2, the flows in TVRG represent the task execution processes in SIN. Therefore, the task planning problem in SIN can be modeled into the multi-community flow problem in TVRG. To represent the SIN task requirements into flow constraints in TVRG, task om_i is modeled as flow $ob_i^k \rightarrow dc^l$, which is originated from vertex ob_i^k and destined to vertex dc^l in TVRG, where l and k satisfy $\lceil ts_i/\tau \rceil \leq k \leq l \leq \lfloor te_i/\tau \rfloor$. The set of flows corresponding to the feasible execution processes of task om_i is given by

$$F_i = \{ob_i^k \rightarrow dc^l | \lceil ts_i/\tau \rceil \leq k \leq l \leq \lfloor te_i/\tau \rfloor\}. \tag{10}$$

The set of flows for all the tasks in SIN is expressed as $\mathcal{F} = \bigcup_{1 \leq i \leq |OM|} F_i$. Let $w(f)$ denote the value of flow f in TVRG, and $w(v_i^k, v_j^l, f)$ represent the value of f on the arc (v_i^k, v_j^l). Furthermore, boolean variable δ_i denote whether task om_i is successfully planned. The task planning problem maximizing the number of successfully planned tasks can be modeled as follows.

$$\mathbf{P1}: \qquad \max \sum\nolimits_{1 \leq i \leq |OM|} \delta_i$$

subject to

$$\text{C1}: \sum\nolimits_{f \in F_i} w(f) = \delta_i \cdot da_i, \ \forall 1 \leq i \leq |OM|$$

$$\text{C2}: \sum\nolimits_{(v_i^k, v_j^l) \in A} w(v_i^k, v_j^l, f) - \sum\nolimits_{(v_j^l, v_i^k) \in A} w(v_j^l, v_i^k, f)$$

$$= \begin{cases} -w(f) \ v_i^k = s(f), f \in F \\ \quad 0 \ v_i^k \in V - \{s(f), d(f)\}, f \in F \\ \ w(f) \ v_i^k = d(f), f \in F \end{cases}$$

$$\text{C3}: \sum_{f \in F} w(v_i^k, v_j^l, f) \leq C(v_i^k, v_j^l), \ \forall (v_i^k, v_j^l) \in A_S \cup A_{fl}$$

$$\text{C4}: \sum_{f \in F} w(v_i^k, v_j^l, f) \leq C(v_i^k, v_j^l) \cdot y(v_i^k, v_j^l), \forall (v_i^k, v_j^l) \in A_O \cup A_{ol}$$

$$C5 : \sum_{(os_i^k, rs_j^k) \in A_{ol}} y(os_i^k, rs_j^k) \leq 1, \forall os_i^k \in V_{OS}$$

$$C6 : \sum_{(os_i^k, gs_j^k) \in A_{ol}} y(os_i^k, gs_j^k) \leq 1, \forall os_i^k \in V_{OS}$$

$$C7 : \sum_{(os_i^k, v_j^k) \in A_{ol}} y(os_i^k, v_j^k) \leq 1, \forall v_j^k \in V_{RS} \cup V_{GS}$$

$$C8 : \sum_{(ob_i^k, os_j^k) \in A_{O}} y(ob_i^k, os_j^k) \leq 1, \forall os_j^k \in V_{OS}$$

In P1, constraint C1 specifies the amount of data should be delivered for each successfully planned task. C2 is the flow conservation constraint, which ensures that in each time slot, the amount of data sent out plus the amount of data stored in a node is equal to the amount of remaining data in the storage at the end of the previous time slot plus the amount of newly arrived data, and $s(f)$ and $d(f)$ respectively represent the source and destination of flow f in TVRG. C3 is the capacity constraint for the storage arcs and fixed transmission arcs, which models the impact of the limited amount of storage and communication resources on the task execution process in SIN. C4 is the capacity constraint for the observation arcs and opportunity transmission arcs, wherein boolean variable $y(v_i^k, v_j^k)$ ($\forall (v_i^k, v_j^k) \in A_O \cup A_{ol}$) represents whether resource (v_i^k, v_j^k) is scheduled or not. C5–C8 are resource scheduling conflict constraints, which are imposed by the limited service capability of onboard antenna/imagers. For example, because the onboard single access antenna can point to only one satellite/ground station at the same time, the schedules of a antenna communicating with different nodes in the same slot conflict with each other, even if all these nodes are in its coverage range. Similarly, the schedules of an imager observing different targets in one slot conflict with each other, too. Specifically, C5 and C6 restrict that each observation satellite only communicates with one data relay satellite and ground station in one slot, respectively. C7 ensures that each data relay satellite or ground station can only receive the data from one observation satellite in one slot. C8 imposes that each imager can only observe one targets in one slot.

By solving problem P1, the optimization task plan can be obtained through the optimized value of variables. More specifically, the value of δ_i determines whether the task is planned successfully, and $w(v_i^k, v_j^l, f)$ indicates which resource is occupied by the task corresponding to flow f in each time slot.

3.3 Problem Decomposition

As we can see from problem P1, variables $w(f)$ and $w(v_i^k, v_j^l, f)$ are continuous variables, and the variables δ_i and $y_{ov}(v_i^k, v_j^l)$ are integer variables, and the optimization subjective and constraints are linear. Therefore, P1 is a mixed integer linear programming problem [14], which is a NP-hard problem in general [15]. With the growth of the size of SIN, the number of feasible resource combinations for each task request increases exponentially, which leads to an explosive increase of the feasible solution space and thus raises great difficulties to find the global optimization of the problem. Moreover, due to the conflicting relationship among resources, it is inefficient to solve P1 by simply decomposing it into small-scale sub-problems according to time or type of resources.

With the consideration that the complexity of solving problem P1 mainly comes from the combinational relationship of feasible resource combinations, this paper aims to reduce the computational complexity by exploring the relationship among resource combinations. It can be observed that the conflict relationship among resources has correlation in time dimension. For example, if communication resources (os_1^k, gs_1^k) and (os_2^k, gs_1^k) conflict with each other in the kth slot, they would will also conflict with each other in $k+1$th slot with a high probability. In order to quantify the correlation between resource combinations, we employ the concept of independent degree of resource combination proposed in [8].

Definition 2 (Resource Combination Independence). *The independence between resource combinations* p_1 *and* p_2 *is defined as the minimum time distance* $d(a_1, a_2)$ *between the arcs* a_1 *and* a_2 *which respectively belong to* p_1 *and* p_2 *and correspond to the same imager or link, i.e.,*

$$Z(p_1, p_2) = \min\{d(a_1, a_2) | \forall a_1 \in p_1, \forall a_2 \in p_2\}, \tag{11}$$

wherein the time distance of resources $a_1 = (v_{i1}^k, v_{j1}^k)$ *and* $a_1 = (v_{i2}^t, v_{j2}^t)$ *is expressed as follows:*

$$d(a_1, a_2) = \begin{cases} \infty, v_{i1} \neq v_{i2} \ or \ v_{j1} \neq v_{j2} \\ |k-t|, v_{i1} = v_{i2} \ and \ v_{j1} = v_{j2} \end{cases}. \tag{12}$$

The value of $Z(p_1, p_2)$ reflects the degree of independence between resource combination p_1 and p_2. The larger $Z(p_1, p_2)$ is, the less temporal correlation between the two resource combinations. That is to say, for the feasible resource combinations of a task with weak independence, if one resource combination conflict with a resource combination of other tasks, the other resource combinations would conflict with the same resource combination with a high probability. Therefore, it is inefficient to directly search the optimization task plan from all the feasible resource combinations with the same weight. To reduce the complexity of solving problem P1, we explore the correlation among resource combinations, and divide the solving process into two stages:

1. **Coarse grained global planning:** For each task, sample the feasible resource combinations to obtain a candidate resource combination set of which the independence between any two resource combinations is no less than n. Then, search for the optimal task plan from the candidate resource combination set, thereby reducing the complexity of global optimization.
2. **Fine-grained local adjustment:** Adjust the global planning results locally by utilizing resource interchange, so that more tasks can be successfully planned.

4 Two-Stage Task Planning Based on Resource Interchange

4.1 Coarse Grained Global Planning Algorithm

In the coarse grained global planning stage, we first sample the feasible resource combinations for each task and obtain a candidate resource combination set of which the independence of any two resource combination is no less than n. Let P_{se} denotes the set of candidate resource combinations of SIN, which is expressed as

$$P_{se} = \bigcup_{1 \le i \le |OM|} P_i, \tag{13}$$

where P_i is the candidate resource combination set of task om_i. Then, problem P1 is transferred into a problem P2, which aims at matching the task requests in OM with a set of conflict-free resource combinations in P_{se} to maximize the number of successful planned tasks.

$$\mathbf{P2} : \max \sum_{1 \le i \le |OM|} \delta_i$$

$$\begin{aligned} s.t.\ \ & \text{C1} : \delta_i = \sum\nolimits_{1 \le k \le |P_i|} \phi_{i,k},\ \forall 1 \le i \le |OM| \\ & \text{C2} : \sum\nolimits_{1 \le k \le |P_i|} \phi_{i,k} \le 1,\ \forall 1 \le i \le |OM| \\ & \text{C3} : \phi_{i,k} + \sum\nolimits_{p_{j,l} \in O(p_{i,k})} \phi_{j,l} \le 1,\ \forall p_{i,k} \in P_{se} \end{aligned}$$

$p_{i,k}$ represents the kth candidate resource combination of task om_i, and boolean variable $\phi_{i,k}$ represents whether $p_{i,k}$ is scheduled. Constraint C1 and C2 impose that there is at most one resource combination is allocated to each task. Constraint C3 ensures that the scheduled resource combinations are not conflict with each other. $O(p_{i,k})$ represents the set of all resource combinations that conflict with the resource combination $p_{i,k}$, and the conflict relationship between resource combinations is defined as follows.

Definition 3 (Conflict of Resource Combinations). *Two resource combination $p_{i,k}$ and $p_{j,l}$ are referred to as conflict with each other, if one of the following conditions is satisfied*

1. *there exist $(v^r_{m1}, v^r_{n1}) \in p_{i,k}$ and $(v^t_{m2}, v^t_{n2}) \in p_{j,l}$, which satisfy $v^r_{m1} = v^t_{m2}$ and $v^r_{m1} \in V_{OS}$;*
2. *there exist $(v^r_{m1}, v^r_{n1}) \in p_{i,k}$ and $(v^t_{m2}, v^t_{n2}) \in p_{j,l}$, which satisfy $v^r_{n1} = v^t_{n2}$ and $v^r_{n1} \in V_{OS} \cup V_{RS} \cup V_{GS}$.*

In order to solve P2, we construct a resource combination conflict graph $RCG(V_C, E_C)$, as shown in Fig. 3. Each of the vertices in RCG represents a candidate resource combination, i.e., $V_C = P_{se}$. The edges of RCG represent the

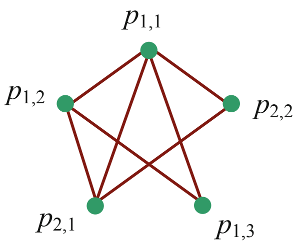

Fig. 3. The resource combination conflict graph.

conflicting relationship among the resource combinations. Specifically, for two resource combinations $p_{i,k}$ and $p_{j,l}$, if one of the following conditions is satisfied, there is an edge between the vertices they corresponding to in RCG:

1. Resource combinations $p_{i,k}$ and $p_{j,l}$ conflict with each other;
2. $i = j$ and $k \neq l$.

With the resource combination conflict graph, problem P2 can be modeled into an maximum independent set problem. Based on the largest degree first rule for the maximum independent set problem [16], a global optimization algorithm based on candidate resource combinations is designed, of which the details is shown in Algorithm 1.

Algorithm 1. Global optimization algorithm

Input: $RCG(V_C, E_C)$;
Output: P_{su};

```
Initialize P_su = ∅
while V_C ≠ ∅ do
    Select the vertex with largest degree in V_C denoted as p_0;
    P_su ← P_su ⋃ {p_0};
    Remove vertex p_0 and all adjacent vertices from V_C;
    Remove all the edges associated with the deleted vertices from set E_C;
end while
```

4.2 Local Adjustment Based on Resource Interchange

After the global planning stage, we adjust the resource allocation result locally through resource interchange to make more tasks successfully planned. The main idea is as follows. Firstly, the resource shortage degree of the unplanned tasks are quantified. Then, we adjust the local resource allocation to release the occupied resources for the unplanned tasks by resource interchange in the descending order of their resource shortage degree.

Algorithm 2. Local Adjustment algorithm

Input: $G_K(V, A), OM_w, G'_K(V', A')$;
Output: OM_y;
Initialize $n \leftarrow 1, OM_y \leftarrow OM - OM_w$
Calculate the source shortage degree of the tasks in OM_w and sort them in descending order;
while $n \leq |OM_w|$ **do**
  for each $a \in P_{Zn}$ **do**
    $om_0 \leftarrow fom(a)$;
    if Exist the path p_z from $ob_0^{\lceil ts_0/\tau \rceil}$ to $dc^{\lfloor te_0/\tau \rfloor}$ in $G'_K(V', A')$ **then**
      Replace the resource combination allocated to task om_0 with p_z;
      Update $G'_K(V', A')$;
      $P_{Zn} \leftarrow P_{Zn} - \{a\}$;
    end if
  end for
  if $P_{Zn} = \emptyset$ **then**
    Find the shortest path from $ob_n^{\lceil ts_n/\tau \rceil}$ to $dc^{\lfloor te_n/\tau \rfloor}$ in $G'_K(V', A')$ as the resource combination allocated to task om_n;
    $OM_y \leftarrow OM_y \bigcup \{om_n\}$;
    Update $G'_K(V', A')$;
  end if
  $n \leftarrow n + 1$
end while

The resource shortage degree of an unplanned task om_i is defined as the minimum shortage degree of its feasible resource combinations, i.e.,

$$\eta_i = \min_{p_{i,k} \in P_i} \eta_{i,k}, \tag{14}$$

where $\eta_{i,k}$ denotes the number of resources occupied by the planned task in the kth feasible resource combination of task om_i, which can be calculated by following steps:

1. Assign weights to the arcs in TVRG: If the resources corresponding to the arc have been occupied by planned tasks, the weight is assigned 1; otherwise, the weight is assigned 0.
2. For unplanned task om_i, find the shortest path between $ob_i^{\lceil ts_i/\tau \rceil}$ and $dc^{\lfloor te_i/\tau \rfloor}$ on the weighted TVRG, and the resource shortage degree η_i is defined as the sum weight of shortest path.

The local adjustment algorithm based on resource interchange is shown in Algorithm 2. OM_y and OM_w denote the successfully planned tasks and unplanned tasks, respectively. $G'_K(V', A')$ is the sub-graph of $G_K(V, A)$ which excludes the arcs representing the resources occupied by planned tasks. Pz_n represents the set of occupied resources in the feasible resource combination with the minimum shortage degree of unplanned tasks om_n. $fom(a)$ denotes the task that occupies resource a.

5 Simulation Results

We conduct a simulation scenario of SIN based on STK (Satellite Tool Kit), which includes 10 low-orbit earth observation satellites distributed in sun-synchronous orbits with altitude from 505 km to 645 km and inclination from 97.4° to 98.5°, 3 data relay satellites distributed in geosynchronous orbit, with longitudes of 16.65°, 76.95° and 176.76° respectively, 100 observation targets randomly distributed on the earth's surface, and three ground stations located in Beijing, Sanya, Kashi and one ground processing center. The planning horizon is 24 h, and 60–300 observation tasks are randomly generated.

In order to verify the performance of the proposed resource interchange based task planning algorithm (RITPA) in terms of task completion, resource utilization, and computational complexity, we employ the following two algorithms for comparison:

1. Time-oriented decomposition based task planning algorithm (TDTPA), which decomposes the task planning problem by dividing the plan horizon into multiple time intervals.
2. Resource-oriented decomposition based task planning algorithm (RDTPA), which decomposes the task planning problem into two stages for observation and data transmission to plan separately.

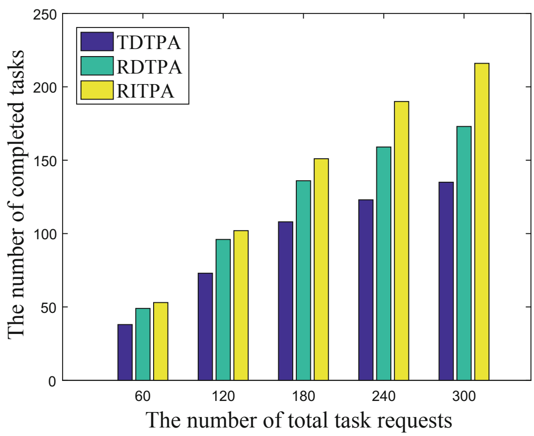

Fig. 4. The number of completed tasks v.s. task number.

Figure 4 depicts the number of completed tasks for the three algorithms with varying task requests. It can be observed that RITPA performs the best, while TDTPA has the worst performance. The reason is that under the temporal decomposition of TDTPA, each sub-planning only focus on the completion of the task requests in current interval and ignores their impact to the tasks in

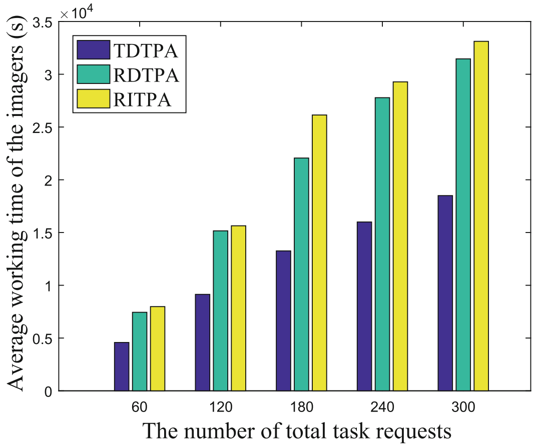

Fig. 5. Average working time of the imagers v.s. task number.

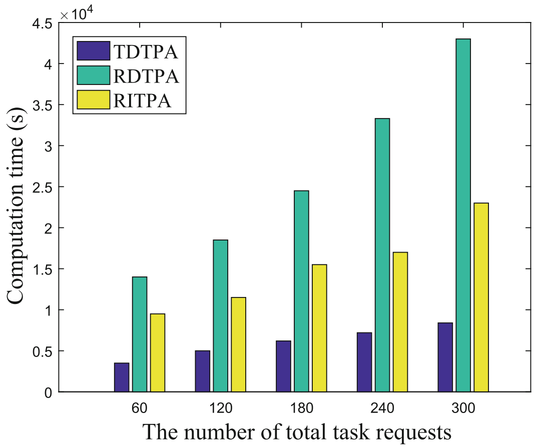

Fig. 6. Computation time v.s. task number.

subsequent intervals. Since the both planning stages of RDTPA are based on the whole planning horizon, it has better performance than TDTPA. However, because the coordination relationship between the observation and communication resources are omitted in RDTPA, some tasks which have been successful planed in the observation stage may be failed in the second stage due to lacking feasible communication resources. RITPA plans globally in both time and the resource dimension in the first stage, and adjust the plans locally in the second stage, which is the main reason why it is superior to TDTPA and RDTPA.

In order to compare the utilization of resources for the three algorithms, Fig. 5 illustrates the average working time of the imagers with varying number of task requests. It can be observed that RITPA has the highest utilization of the observation resource, while that of TDTPA is the lowest. This is because that TDTPA plan least tasks successfully. Moreover, due to the separate planning observation and data transmission in RDTPA, some tasks cannot be delivered to DPC in time after successful observation. This is the main reason that the gap between the imaing time of RDTPA and RITPA is smaller than the gap between the completed task number of those algorithms.

Figure 6 compares the computation time of the three algorithms with varying task requests. It can be observed that TDTPA requires the least computational time, followed by RITPA, and RDTPA requires the most computational time. This is because that TDTPA divides the task requests into time intervals to be planned chronologically, thereby lead to small computational complexity of each sub-planning. Although RDTPA decomposes the planning into two stages, the optimization of both stages is based on the entire planning horizon, which leads to the highest computational complexity of the three algorithms. RITPA proposed in this paper samples feasible resource combinations in the global planning stage, thereby striking a good balance between the performance and computational complexity.

6 Conclusion

This paper proposes a two-stage task planning based on resource interchange in SINs. Specifically, we first we explore the mechanism of resource interchange through TVRG model, and then propose the quantitative condition of it. On this basis, an optimization model for task planning based on resource interchange is formulated. Furthermore, we decompose the task planning problem into two stages: coarse grained global optimization and fine-grained local adjustment, and develop the solving algorithms respectively. Simulation results show that compared with the existing works, the proposed algorithm strikes a better balance between task completion performance and computational complexity.

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