https://doi.org/10.1590/jatm.v17.1362 ORIGINAL PAPER

Multi-Objective Task Scheduling for Earth Observation InSAR Satellites via Non-Dominated Sorting Student Psychology Based Optimization Algorithm

Qingxian Jia[1], Weicheng Lian[1,2], Dan Yu[1,*], Qi Sun[1]

1. Nanjing University of Aeronautics and Astronautics – College of Astronautics – Nanjing – China.
2. Nanjing Research Institute of Electronics Engineering – Nanjing – China.

*Corresponding author: yudan@nuaa.edu.cn

ABSTRACT

This paper investigates the task scheduling problem for the Earth observation Interferometric Synthetic Aperture Radar (InSAR) satellite system. The mission time window generation method is introduced, and the constraint satisfaction model for task scheduling in the InSAR satellite system is constructed. To address the mission allocation issue between the chief satellite and deputy satellites, a mission conflict detection and resolution mechanism is developed. Moreover, based on the single-objective student psychology-based optimization (SPBO) algorithm, a modified non-dominated sorting SPBO (NSSPBO) algorithm is proposed to tackle the multi-objective task scheduling problem for the InSAR satellite system. Numerical simulations are presented to demonstrate the effectiveness and superiority of the proposed NSSPBO algorithm.

Keywords: InSAR satellite; Task scheduling; Student psychology based optimization algorithm; Non-dominated sorting algorithm.

INTRODUCTION

Earth observation satellites, equipped with onboard imaging instruments, have been employed in various tasks, including land resource distribution monitoring, natural disaster prevention and control, and military operations (Kim and Chang 2015; Zhao *et al.* 2023). In recent years, with advancements in spacecraft formation technology and increasing demand of Earth observation tasks, Interferometric Synthetic Aperture Radar (InSAR) satellite formation-based high-precision Earth observation has emerged as an area of significant concern (Chen *et al.* 2020; Li *et al.* 2023). The observation range is expanded by multiple satellites and multiple playload capacities. However, in order to achieve global observation and make full use of satellite resources, an effective satellite management and control strategy must be implemented to meet the needs of all users while maximizing satellite performance. Additionally, constraints for the InSAR satellite-based Earth observation missions, such as system configuration requirements, make these missions more challenging.

One critical issue in satellite resource management and control is the reasonable deployment of resources. The process of matching resources with missions is referred to as the satellite task scheduling. The number and timing of each satellite passing over ground observation targets are severely limited due to orbital and energy constraints. Furthermore, the functional capacity of the satellite payload and mission execution requirements are restricted and must be considered throughout the task scheduling

Received: Oct.12, 2024 | **Accepted:** Nov. 9, 2024
Section editor: Luiz Martins-Filho
Peer Review History: Single Blind Peer Review.

procedure (Jiang *et al.* 2022). It has been shown that the satellite task scheduling problem is NP-hard (Wolfe and Sorensen 2000), and therefore solving the problem using deterministic algorithms, such as the branch and bound algorithm (Chu *et al.* 2017), cannot guarantee a feasible solution in real-time when the dimension of the scheduling problem is large.

As a result, heuristic algorithms, such as tabu search (Sarkheyli *et al.* 2013), simulated annealing (Wu *et al.* 2017), and genetic algorithms (Zhang and Xing 2022), have been widely used in satellite task scheduling problems. For example, a standard genetic algorithm is employed for the satellite imaging and data transmission scheduling problem, using an encoding and decoding strategy to match specific requests (Zhang and Xing 2022), and the method is tested on large-scale optimization instances. In Wu *et al.* (2022), the large-scale scheduling problem is decomposed into multiple sub-problems, and a meta-heuristic algorithm based on the ant colony optimization and tabu search is proposed. However, these methods consider only the optimization of a single objective function.

A priority-based algorithm for agile Earth observation satellite scheduling, with total priority maximization, is proposed in Xu *et al.* (2016). A satellite task scheduling model based on the graph structures is constructed, and a node mid-degree ranking strategy is utilized to obtain the mission execution plan in Wang *et al.* (2016). A periodic task scheduling model with constraint satisfaction is established (Chen *et al.* 2017), and a decomposition-based multi-objective evolutionary algorithm with Pareto adaptive approximation is applied to minimize energy consumption. Non-dominated sorting and decomposition-based multi-objective optimization algorithms are used to solve the satellite management and control scheduling problem with various optimization objectives in Song *et al.* (2019) and Du *et al.* (2019), respectively. However, few studies have focused on scenarios in which missions conflict.

Motivated by the above-mentioned discussions, this paper investigates task scheduling for Earth observation using InSAR satellites. The student psychology-based optimization (SPBO) algorithm is a heuristic approach that has been shown to have potential in satellite task scheduling (Das *et al.* 2020). In this paper, a novel modified non-dominated sorting SPBO (NSSPBO) algorithm, with a conflict detection and elimination strategy, is proposed to address the task scheduling problem of InSAR satellites for Earth observation missions. The main contributions are summarized as follows:

- A construct a constraint satisfaction model is constructed to maximize the objective function of the observation mission sequence, while considering constraints such as resource capacity, mission demand, and the data transmission.
- Based on the single-objective SPBO algorithm and the non-dominated sorting algorithm, a novel NSSPBO algorithm-based multi-objective task scheduling technique for InSAR satellite systems is proposed. Additionally, a heuristic conflict detection and elimination strategy is employed to effectively resolve mission conflicts.

This paper is organized as follows. Firstly, the task scheduling problem for the InSAR satellite formation and the mission window generation method are introduced. Secondly, various constraints are analyzed and a constraint satisfaction model is proposed. Then, the NSSPBO-based task scheduling strategy with conflict detection and elimination is presented. In addition, simulation experiments and comparisons are provided. Finally, the concluding remark is given.

Preliminaries

Introduction to the InSAR satellite Earth observation system

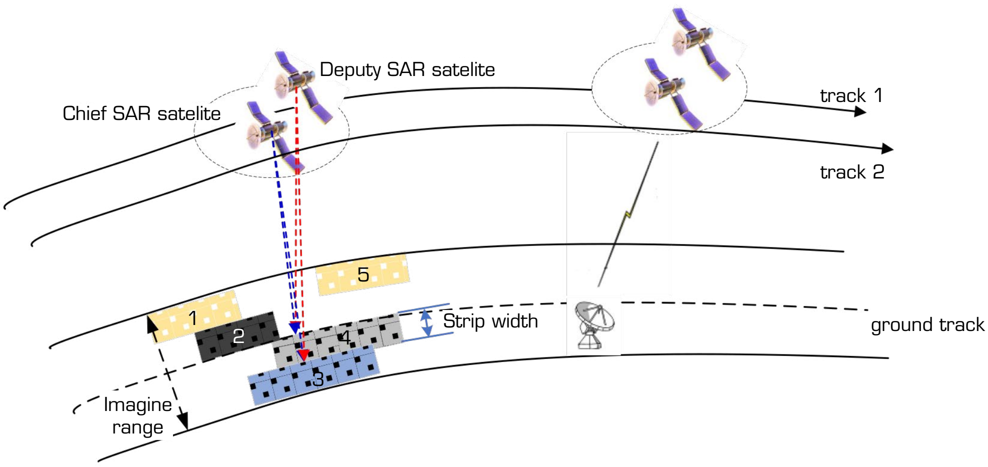
As depicted in Fig. 1, the InSAR satellite system consists of a chief satellite and a deputy satellite. The satellite formation's observation range is composed of multiple observation strips. The length of each observation strip is determined by the observation time, while the amplitude width is governed by the internal and external angles of the imaging.

The InSAR satellite observation mission scenario is illustrated in Fig. 2. The observation strip is observed by different beam positions of the InSAR satellites. As the satellite can only select one load beam position for observation at a time and its total energy is restricted, a suitable beam position for observation should be selected when the satellite passes over the observation strip.

Once passing over the ground target, the InSAR satellite images the target within the observation range, and stores the acquired imaging data information in the onboard storage unit. The InSAR satellite formation can only observe one strip at a time, and the satellite can only perceive the ground target if it passes through the sub-satellite point and the ground target is within the rectangular strip region. When the InSAR satellite approaches the communication range of the ground station, it communicates with the ground station and transmits the stored data information to the ground station. Therefore, when the InSAR satellite executes an imaging mission on the target, the time period is referred to as the "observation mission time window," while the time period for satellite data transmission is referred to as the "data transmission mission time window."

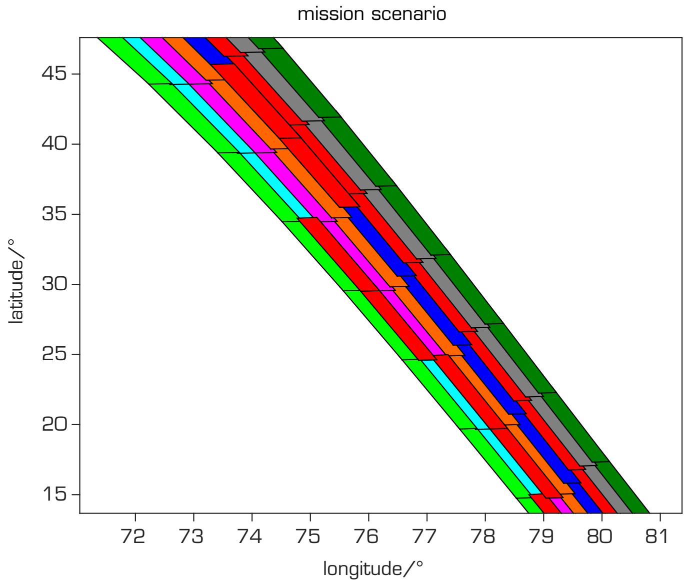
The fundamental problem with InSAR satellite task scheduling involves generating the mission time window, in which the global land attributes must be processed while planning constraints are taken into account. The mission preprocessing operation is shown in Fig. 3.

Considering the strict regression orbit of the InSAR satellite, the global grid matrix of the SAR beam position can be established using the following steps:



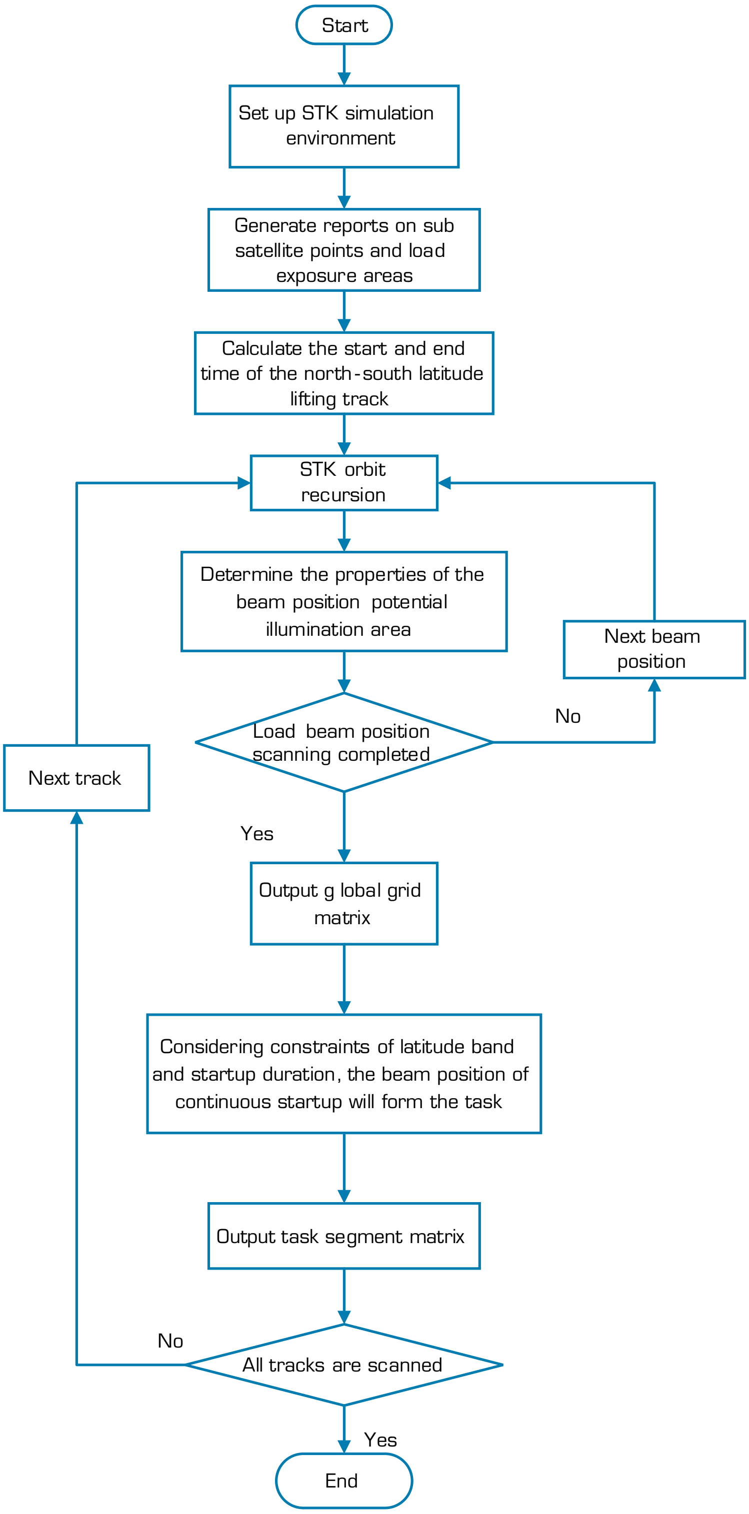
Source: Elaborated by the authors.

Figure 1. Schematic diagram of the formation satellite mapping.



Source: Elaborated by the authors.

Figure 2. Example of mission scenario.



Source: Elaborated by the authors.

Figure 3. Mission preprocessing operation flow chart.

Step 1: calculate the use of different beam positions of the satellite load in each latitude zone according to the available load beam positions in different latitude zones;

Step 2: traverse the global grid matrix and read the latitude zone where the sub-satellite point is located at the current time;

Step 3: set the attribute of the unavailable load beam position in the latitude zone at the current time in the grid matrix to zero;

Step 4: traverse the number of satellite load beam positions, search for all the observation times in the global grid matrix that use the current load beam position number, and collect all the observation times into the observation time set;

Step 5: consider the maximum working time constraint of the satellite load. The mission segment composed of the continuous observation time is saved into the mission time window set;

Step 6: calculate the priority of the observation mission after generating the mission time window set. Traverse the mission segment in the mission set, check the number of key observation areas in the global grid matrix, and calculate the priority of the corresponding mission segment.

Step 7: generate the observation mission matrix to be planned.

The observation mission matrix is shown in Table 1.

Table 1. Observation mission matrix.

Number	1	2	3	4	5	6	7
Properties	Observation start time	Observation end time	Satellite resource	Load wave position	Revenue	Priority	Orbit

Source: Elaborated by the authors.

InSAR satellite task scheduling modelling

In this paper, a multi-objective constraint satisfaction model for satellite formation task scheduling, which includes objective functions and operational constraints, is proposed. The following assumptions are made:

- The observation missions obtained after preprocessing are all regional targets.
- Data transmission in the ideal situation is considered, i.e., the time required to establish a link between the satellite and the ground station is neglected, and the satellite-to-ground data transmission rate is only determined by the imaging time and the size of the imaging region.
- Once an observation mission is started, it cannot be interrupted.

Mathematics notations

S: satellite resource set;

N: number of satellite resources;

Task: observation mission set;

M: number of observation missions;

Sta: ground satellite station resource set;

B: beam position set;

D: data transmission mission set;

tws_i: start time of observation mission i;

twe_i: end time of observation mission i;

dws_i: start time of data transmission mission i;

dwe_i: end time of data transmission mission i;

$benfit_i$: benefits when executing observation mission i;

$priority_i$: priority of observation mission i;

$Times^{max}_{start}$: maximum satellite imaging times per orbit;

$time^{max}_{on}$: maximum satellite imaging duration per orbit;

$times^{max}_{on}$: maximum switching times of beam position per orbit;

sat_{start}: satellite restart interval;

sat_{on}: maximum imaging duration of a single satellite;

$sensor_{restart}$: sensor restart interval;

$Beam_{trans}$: beam position switching time interval of sensor.

Decision variables

Define the following decision variables that are used for the multi-objective optimization problem:

$^{b}_{is}$, $i \in Task$, $s \in S$, $b \in B$: $x^{b}_{is} = 1$, if the satellite S will observe the mission i through the beam position b, and $x^{b}_{is} = 0$ indicates that the mission i is not observed through the beam position b;

$y_{i,j}$, $i,j \in Task$: $y_{i,j} = 1$ indicates that mission i and mission j are executed using the same satellite, where mission i is executed before mission j, and $y_{i,j} = 0$ indicates that mission i and j are executed using different satellites;

z_{ista}, $i \in D$, $sta \in Sta$: the data transmission mission i from ground satellite station sta is executed if $z_{ista} = 1$, and otherwise, $z_{ista} = 0$.

The decision variables x^{b}_{is} and $y_{i,j}$ are used to determine whether the satellite observes a specific mission and whether it continuously observes a certain two missions, respectively.

Objective functions

The total benefits of satellite observation mission f_1 and total priority of satellite observation mission f_2 are defined as follows, respectively:

$$f_1 = max \sum_{i=1}^{M} \sum_{s=1}^{N} x^{b}_{i,s} \cdot benefit_i \tag{1}$$

$$f_2 = max \sum_{i=1}^{M} \sum_{s=1}^{N} x^{b}_{i,s} \cdot priority_i \tag{2}$$

The priority of the mission is determined by the key areas included in the observation zone. The mission benefits as well as the importance of observation missions, are taken into account, and the objective of satellite task scheduling is to design an observation sequence that maximizes the above multi-objective functions.

Operational constraints

To accommodate real-world application requirements, the following constraints are considered in this paper:

- Mission uniqueness constraints:

$$\sum_{i=1}^{M} \sum_{s=1}^{N} x^{b}_{i,s} \leq 1 \tag{3}$$

According to Eq. 3, each imaging mission can only be executed at most once throughout the planning period, ensuring that each mission's imaging time window $[tws_i, twe_i]$ is unique.

- Mission time window constraints:

$$if\ y_{i,j} = 0, \text{then } twe_i \leq tws_j \tag{4}$$

Equation 4 indicates that when two missions are observed by different satellites, time windows of two missions cannot conflict.

From Eq. 5, when beam positions of two missions are inconsistent and observed by the same satellite, the time interval between two missions must satisfy the beam position switching requirement:

$$if\ y_{i,j} = 1\ \&\ b_i \neq b_j, \text{then } twe_i + beam_{trans} \leq tws_j \tag{5}$$

Equation 6 indicates that when beam positions of two missions are consistent and observed by the same satellite, the time interval between two missions must meet the sensor restart time requirement:

$$if\ y_{i,j} = 1\ \&\ b_i = b_j, \text{then } twe_i + sensor_{restart} \leq tws_j \tag{6}$$

- Satellite resource constraints:

$$\sum_{i=1}^{M} x_{i,s}^{b} \leq times_{start}^{max} \tag{7}$$

Equation 7 indicates the total number of satellite imaging times cannot exceed the maximum number of satellite imaging times allocated for each orbit. Moreover,

$$\sum_{i=1}^{M} x_{i,s}^{b} \cdot (twe_i - tws_i) \leq time_{on}^{max} \tag{8}$$

which implies that the imaging time of satellite per orbit shall not exceed the maximum imaging duration of each orbit.

- Data transmission constraints:

$$if\ [tws_i,\ \ twe_i] \cap \left[dws_j,\ \ dwe_j\right] \neq \emptyset, \text{then } x_{i,s}^{b} \cdot z_{i,sta} = 0 \tag{9}$$

Equation 9 indicates that the imaging mission and the data transmission mission cannot be executed at the same time, and only one of the imaging missions or data transmission missions can be selected for execution.

NSSPBO algorithm-based satellite task scheduling

The satellite task scheduling problem is a multi-objective multi-constraint optimization problem and has been shown to be NP-hard. In this section, first, the SPBO algorithm is first briefly reviewed, as it can be used for solving the single-objective optimization problems, and then a modified NSSPBO algorithm for satellite task scheduling is proposed.

Student psychology-based optimization algorithm

The SPBO algorithm was inspired by the students' psychology to improve their academic performance and evolve into top students (Das *et al.* 2020). The algorithm classifies students into four categories based on their performance in class: best students, good students, ordinary students, and students who try to improve their grades randomly.

The four types of students in SPBO are updated as follows:

- Best student. The student with the highest total score in the test is considered the best student in the class. The improvement of the best student is given as:

$$X_{bestnew} = X_{best} + (-1)^k \times rand \times \left(X_{best} - X_j\right) \tag{10}$$

where X_{best} is the score obtained by the best student, X_j denotes the score obtained by a randomly selected student *j*, *rand* is a random number between 0 and 1, and *k* is a parameter which is designed as either 1 or 2.

- Good student. This category of students may be considered as subject-wise good students, who try to exert more effort in a specific subject so that their overall performance can improve. The performance of this type of student may be defined as:

$$X_{new_i} = X_{best} + [rand \times (X_{best} - X_i)] \tag{11}$$

$$X_{new_i} = X_i + [rand \times (X_{best} - X_i)] + [rand \times (X_i - X_{mean})] \tag{12}$$

where X_i and X_{mean} are the scores obtained by the *i*th good student and the average scores of the class in that specific subject, respectively. The performance of the good student is updated as follows: randomly generate r_1, r_2 between (0, 1), if $r_1 < r_2$, then choose Eq. 11, otherwise, choose Eq. 12.

- Ordinary student. These students are considered as students with ordinary grades. The performance of these students may be represented by:

$$X_{new_i} = X_i + rand \times (X_{mean} - X_i) \tag{13}$$

where X_i is the score obtained by the ith student in this category.

- Student who tries to improve their grades randomly. Some students try to improve their overall performance by giving efforts randomly to different subjects. The performance of this category of student may be represented by:

$$X_{new_i} = X_{min} + rand \times (X_{max} - X_{min}) \tag{14}$$

where X_{max} and X_{min} are the subject's maximum and minimum score limits, respectively.

The SPBO algorithm starts by initializing the population and selecting the convergence criterion. The algorithm then evaluates the initial performance of the class, and at each iteration, the algorithm checks the category of students, updates the performance of each student, and evaluates the performance of the class. If the new performance is better than the old performance, then the old performance is replaced, otherwise, the old performance is preserved. After convergence, the performance of the best student is regarded as the optimum solution.

Remark

The performance of the SPBO algorithm has been demonstrated in Das *et al.* (2020), where it was compared to ten other state-of-the-art optimization algorithms on two benchmark problems. However, the standard SPBO algorithm is designed to solve continuous optimization problems, whereas satellite task scheduling is a discrete problem with multiple constraints. Furthermore, the proportions of students in each of the four categories are not specified in the original algorithm. Moreover, only Eq. 12 and Eq. 14 are global searching strategies, whereas the other strategies are local searching strategies, which may lead to the convergence to a local optimum.

NSSPBO algorithm for satellite task scheduling

To tackle the problems with the SPBO algorithm, this paper proposes an NSSPBO algorithm for solving the InSAR satellite task scheduling problem with multiple optimization objectives and various constraints. The integer coding strategy is proposed, and the performance improvement strategies for the four categories are modified. The conflict mission detection and correction strategy is designed to address the constraints in the task scheduling problem.

Coding

According to the sequence information of satellites and observation targets, the coding method of multi-satellite observation mission sequence is designed as follows. Denote the number of observation missions as M, and the number of satellite resources as N. Denote an integer sequence Seq = $\{T_1, T_2, \dots , T_M\}$ with a length of M as the observation sequence, where $T_i = 0$ represents that observation mission T_i is not executed, and $T_i = s$ represents that observation mission T_i is executed by satellite s.

Without loss of generality, assume that the number of observation missions $M = 10$ and the number of satellites $N = 4$. One example of the initial mission sequence code is shown in Fig. 4. The mission sequence is related to the benefit of the observation mission and the priority of the mission execution. T_i is a random integer in the range $[0,N]$. For example, in Fig. 4, $T_1 = 2$ indicates that mission T_1 is observed by satellite 2, while $T_8 = 0$ indicates that mission T_8 is not executed. The above encoding method is utilized to generate ST integer sequences as the initialization population Seq in NSSPBO algorithm, where ST is the number of students in the class.

Seq	2	4	1	3	0	1	2	0	3	1
	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}

Source: Elaborated by the authors.

Figure 4. Initial mission sequence code.

NSSPBO performance improvement strategy

Since students' current achievements will have an impact on their future learning attitudes and efforts, which will affect the learning strategy that they will adopt, it is proposed to group students into four types based on their grade ranking in the class, and to redefine the psychological characteristics and grade updating strategies for each type of student.

Suppose the mission sequence of student i is Seq_i, and the corresponding rank of the sequence is $rank_i$. According to the psychological characteristics of the four categories, the following performance improvement strategies are defined.

- If $rank_i \leq ST \cdot 10\%$, sequence Seq_i is the best student.

To characterize the self-adjustment behavior of best students, the mutation operator is introduced as:

$$Seq_{best}^{1} = Seq_{best} \otimes (m * Seq_{best}) \tag{15}$$

where Seq^1_{best} represents the sequence of the best student Seq_{best} after self-adjustment, ⊗ denotes the mutation operation of students, and m is a random integer between $[0,M]$. The process is illustrated in Fig. 5, which is summarized in Algorithm 1.

Algorithm 1. Mutation operation.
1. Randomly generate an integer m from 1 to M (total number of missions);
2. Randomly generate an integer s from 0 to N (total number of satellite resources);
3. Reassign the code at location m to s to get a new mission sequence. If $s \neq 0$, then satellite s is the new execution satellite of mission m, and if $s = 0$, it indicates that mission m is not executed.

						m			
Seq_{best}	2	4	1	3	0	1	2	0	3	1
Seq^1_{best}	2	4	1	3	0	1	4	0	3	1

Source: Elaborated by the authors.

Figure 5. Mutation operator operation.

The crossover operator is introduced to characterize the behavior of best students when influenced by other students:

$$Seq_{bestnew} = Seq_{best}^{1} \oplus Seq_j \tag{16}$$

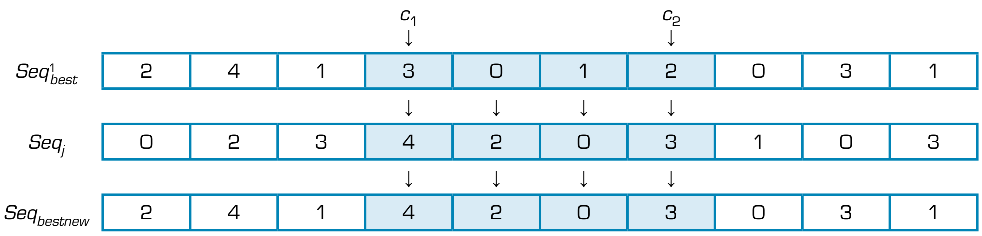
where Seq_i represents the sequence of the jth randomly selected student, and ⊗ represents the crossover operation when the student's performance is affected by other students. The process is illustrated in Fig. 6, and is summarized in Algorithm 2.

Algorithm 2. Crossover operation.
1. Randomly generate two integers C_1 and C_2 from 1 to M (total number of missions);
2. Select the sequence between c_1 and c_2 from Seq^1_{best} and Seq_i;
3. Exchange the sequence between c_1 and c_2 from Seq^1_{best} and Seq_i to obtain a new sequence.

Therefore, the best student's sequence adjustment is completed and a new sequence is obtained as:

$$Seq_{bestnew} = (Seq_{best} \otimes (m * Seq_{best})) \oplus Seq_j \tag{17}$$

- If $ST \cdot 10\% < rank_i \leq ST \cdot 50\%$, then Seq_i is a good student.



Source: Elaborated by the authors.

Figure 6. Crossover operator operation.

The self-adjustment operation of the good student is:

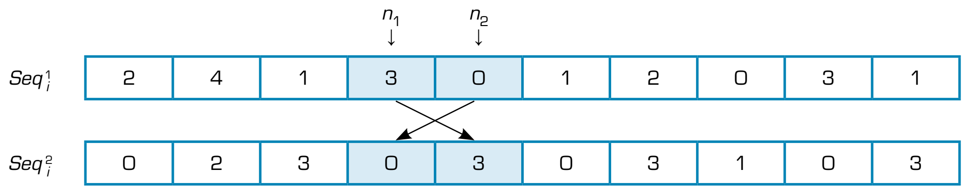
$$Seq_i^1 = Seq_i \otimes (m * Seq_i) \tag{18}$$

where m is a random integer between $[0,M]$.

Good students make further self-adjustment in order to catch up with the best students, and the behavior is characterized via the permutation operation:

$$Seq_i^2 = (n_1 * Seq_i^1) \otimes (n_2 * Seq_i) \tag{19}$$

where n_1, n_2 are random integers between $[0,M]$. The process is illustrated in Fig. 7 and is summarized in Algorithm 3.



Source: Elaborated by the authors.

Figure 7. Permutation operator operation.

Due to the mutation and permutation operations in the self-adjustment strategy for good students, the local searching ability has been improved to avoid falling into local optimal solutions.

Algorithm 3. Permutation operation.
1. Find all positions where the element from sequence Seq_i^1 is nonzero to construct the planned mission set T_1;
2. Randomly select the position n_1 to be replaced from the mission set T_1;
3. Determine whether the adjacent position of n_1 exists. If there are two adjacent locations, randomly select one location as n_2; if there is only one adjacent location, then the location is n_2;
4. Replace the elements at positions n_1 and n_2 to obtain a new sequence.

Further, to characterize the behavior of good students that learning from the best students, the crossover operator operation is modified. Different from Eq. 16, the crossover operator operation consists of the sequence of good students Seq_i and the sequence of a randomly selected best students Seq_{best}, and is given as:

$$Seq_{new_i} = Seq_i^2 \oplus Seq_{best} \tag{20}$$

Therefore, Eqs. 11 and 12 for updating the performance of good students are modified as:

$$Seq_{new_i} = [n_1 * (Seq_i \otimes (m * Seq_i))] \otimes (n_2 * Seq_i) \tag{21}$$

$$Seq_{new_i} = [(n_1 * Seq_i \otimes (m * Seq_i)) \otimes (n_2 * Seq_i)] \oplus Seq_{best} \tag{22}$$

and the performance of the good student is updated by randomly generating r_1 and r_2 between (0, 1), and if $r_1 < r_2$, then choose Eq. 21, otherwise, choose Eq. 22.

- If $ST \cdot 50\% < rank_i < ST \cdot 80\%$, then Seq_i is an ordinary student.

The permutation operator operation is used to represent the self-adjustment of ordinary students, and the crossover operator operation is used to represent the behavior of ordinary students affected by other students:

$$Seq_{new_i} = [(n_1 * Seq_i) \otimes (n_2 * Seq_i)] \oplus Seq_j \tag{23}$$

where Seq_j is the sequence of randomly selected student j.

- If $ST \cdot 80\% < rank_i \leq ST$, then Seq_i is the student who try to improve their grades randomly.

The mutation operator operation is used to indicate the self-adjustment of students trying to improve randomly, and the crossover operator operation is used to indicate the operation that students trying to improve randomly learning from the best students:

$$Seq_{new_i} = [Seq_i \otimes (w * Seq_i)] \oplus Seq_{best} \tag{24}$$

where Seq_{best} represents the sequence of the best students and w is a random integer in the range $[0,M]$.

Conflict detection and correction strategy

Missions in the mission sequence coding Seq_i are subject to time window constraints and satellite resource constraints. There must be no time window conflicts between observation missions executed in Seq_i. Furthermore, the accumulated working time of all observation missions carried out in Seq_i must not exceed the maximum working time constraint. The executing satellites of some observation missions may have been changed when the mission sequence Seq_i is updated via the NSSPBO algorithm, and hence, conflict mission detection is required to determine whether Seq_i violates the above constraints. A solution that violates the constraints is referred to as an infeasible solution, and a correction strategy is proposed to address the infeasible solution. The conflict detection and correction strategy steps are given in Algorithm 4.

Algorithm 4. Conflict detection and correction strategy.

Step 1. Collect all executed observation missions $T = \{t_1, \ldots t_n\}$ in the mission sequence Seq_i, where n is the number of missions in the set. If $n < 2$, no conflict detection is required, skip to **Step 5**; otherwise, go to **Step 2**.
Step 2. Check if the next mission adjacent $t_i + 1$ to the current mission t_i exists. If $t_i + 1$ exists, choose missions t_i and $t_i + 1$ from the mission set T, and go to **Step 3**; otherwise, skip to **Step 5**.
Step 3. Check if the satellite resources of missions t_i and t_i+1 are the same. If the coded numbers of t_i and t_i+1 in the Seq_i are different, check if t_i and t_i+1 meet constraints of Eq. 4; if the coded numbers are the same, check if the beam positions of mission t_i and t_i+1 are the same; if the beam positions of t_i and t_i+1 are different, check if t_i and t_i+1 meet the constraints of Eq. 5; if the beam positions are the same, check if t_i and t_i+1 meet the constraints of Eq. 6; if missions t_i and t_i+1 meet the constraint conditions, let $i = i + 1$, and go to **Step 2**; otherwise, go to **Step 4**.
Step 4. Compare the priority of mission t_i and t_i+1 and correct the sequence Seq_i as follows: if $priority_i \leq priority_{i+1}$, assign the coded number in the corresponding position of mission t_i to zero; if $priority_i > priority_{i+1}$ assign the coded number in the corresponding position of mission $t_i + 1$ to zero; return to **Step 1**.
Step 5. Classify the observation missions in set T according to satellite resources, generate the observation sequence S_{eq_i} set of each satellite, and check the sequence of each satellite in turn. If the observation sequence of satellite S_i is not empty, calculate the imaging times and imaging duration of satellite S_i in the current orbit, and check whether the constraints of Eqs. 7 and 8 are met. If the constraint conditions are not met, go to **Step 6**; otherwise, go to **Step 7**.
Step 6. Compare the priority of all missions in the observation sequence of satellite*s* and reserve the high-priority missions first. Assign the value of the mission with the lowest priority to 0 and return to **Step 5**.
Step 7. The conflict detection and correction of the current sequence Seq_i are completed.

Simulation analysis

To evaluate the effectiveness of the NSSPBO algorithm-based satellite task scheduling technique, numerical simulations are performed and compared to the NSGA-II (Wu *et al.* 2019) and SPEA2 (Zitzler *et al.* 2001) algorithms. MATLAB 2018b is used on a desktop computer running Windows 10 × 64, with a Core R7-9700H 2.4GHz CPU, and 16GB of memory. All algorithms are executed using the same system configuration. The orbit of the TerraSAR satellite is used, and the orbit parameters of the main satellite are shown in Table 2. The satellite system has 167 orbital periods in a return period, and the return period is 11 days. The planned start time is 2021/7/1 00:00:00 UTCG and the end time is 2021/7/12 00:00:00 UTCG.

Table 2. Six elements of satellite orbit (D'Amico *et al.* 2004).

Parameter	Symbol	Value
Semimajor axis·km	a	6883.510
Eccentricity	e	0
Inclination/°	i	97.4220
Right ascension/°	Ω	104.2750
Argument of perigee/°	ω	-
Mean anomaly/°	M_0	360

Source: Adapted from D'Amico (2004).

The satellite has a total of nine imaging beam positions, with minimum and maximum field angles of 27.402° and 45.520°, respectively. Table 3 shows the minimum and maximum field angles of view for each beam position. The specific constraints during the task planning process are shown in Table 4. Mission windows are generated for each orbit, with various mission sizes chosen for the experiment. The specific number of missions in each test scenario is shown in Table 5.

Table 3. Angle of view of imaging beam position (Fiedler *et al.* 2008).

ID	1	2	3	4	5	6	7	8	9
θ_{min}(°)	27,402	29,652	31,850	33,956	35,931	37,808	39,522	41,115	42,520
θ_{max}(°)	29,975	32,157	34,426	36,205	38,965	39,764	41,344	42,737	43,880

Source: Adapted from Fiedler (2008).

Table 4. Constraint conditions.

Variable	Description	Value
$Time_{on}^{max}$	Maximum satellite imaging duration per orbit	960 s
$Time_{start}^{max}$	Maximum satellite imaging times per orbit	10
sat_{on}	Maximum imaging duration of a single satellite	80 s
$sat_{restart}$	Satellite restart interval	15 s
$beam_{trans}$	Beam position switching time interval of sensor	15 s

Source: Elaborated by the authors.

Table 5. Mission test cases of different sizes.

Test case	1	2	3	4
Number of missions	39	113	173	243

Source: Elaborated by the authors.

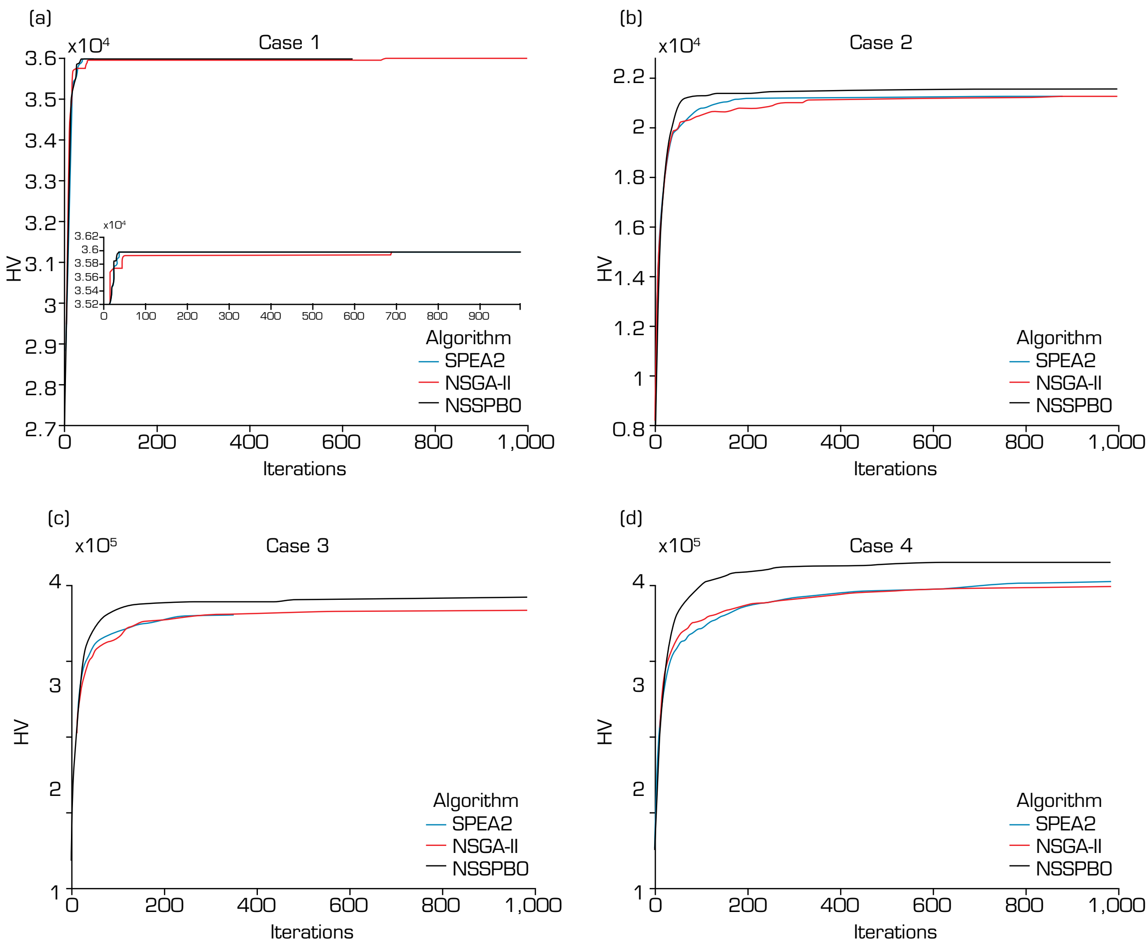
The performance of satellite task scheduling algorithms based on NSSPBO, NSGA-II, and SPEA2 are compared in various test situations, and the hypervolume index (HV) (Zitzler and Thiele 1999) is used to evaluate the performance of the three methods. HV is a commonly used metric for evaluating multi-objective solution sets, describing the volume of the algorithm's non-dominated solution set and reference points. Higher HV indexes indicate that the convergence and diversity performance of the population are better for minimization problems. The reference point for calculating HV is set to (1,1,1), which is dominated by the entire population. The parameters of each algorithm are shown in Table 6, where *No.* represents the number of populations, and *T* represents the maximum number of iterations.

Table 6. Algorithm parameter setting.

Algorithm	No.	T	Parameter
NSSPBO	200	1,000	-
NSGA-II	200	1,000	$pro_c = 0.9$, $pro_m = 0.1$
SPEA2	200	1,000	$pro_c = 0.9$, $pro_m = 0.1$

Source: Elaborated by the authors.

The HV index of three multi-objective optimization algorithms with different mission sizes is shown in Fig. 8a-d, respectively. When the mission size is small, the final HV index of the three algorithms can converge to the same value, as shown in Fig. 8a, but the NSSPBO-based task scheduling technique converges faster than the other algorithms. This demonstrates that when the mission size is modest, all three algorithms produce the same solution set, but task scheduling based on the NSSPBO algorithm offers a faster convergence rate. It can be seen from Fig. 8c, d that when the mission scale is massive, NSSPBO achieves a much higher HV index than other algorithms, while SPEA2 and NSGA-II have slightly different HV indexes. This also demonstrates that NSSPBO achieves faster convergence speed and higher convergence accuracy with large mission sizes. As a result, using the NSSPBO algorithm for task scheduling results in the best overall performance across a range of test sizes.



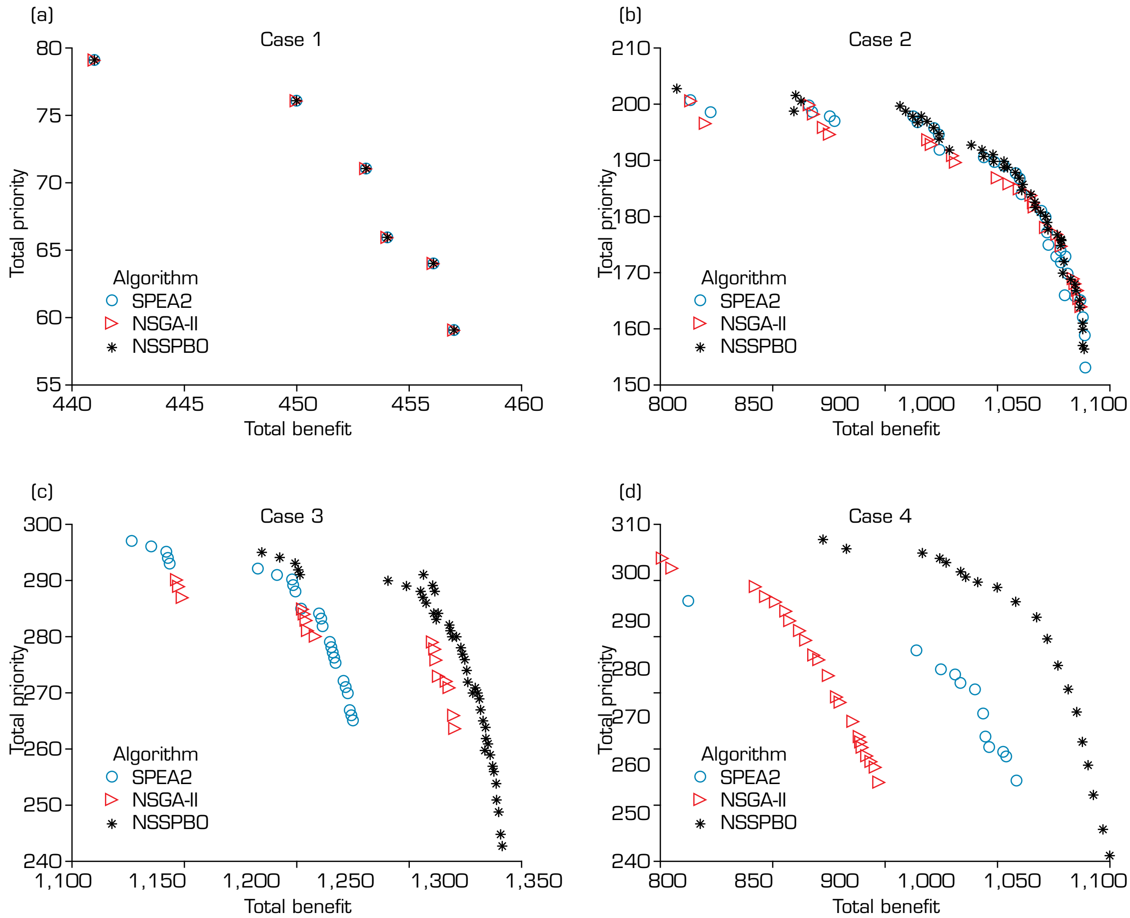
Source: Elaborated by the authors.

Figure 8. Iterative graph of algorithm HV index. (a) Case 1; (b) Case 2; (c) Case 3; (d) Case 4.

Comparisons of solution set distributions on four mission tests are shown in Fig. 9a-d, with the black asterisk representing the NSSPBO solution set, the triangle representing the NSGA-II solution set, and the circle representing the SPEA2 solution set.

The distribution of the solution set yields the same conclusions. The final solution set of the three algorithms remains the same when the mission size is small; however, as the mission size increases, the NSSPBO-based task scheduling algorithm improves both the convergence of the algorithm and the diversity of the solution set. The experimental results demonstrate that using the NSSPBO algorithm for task scheduling enhances the planning results.

To better test the performance of the three algorithms, a Monte Carlo simulation with 10 independent runs was performed. The maximum number of iterations was still set to 1,000. The average HV index for the three algorithms is compared in Table 7 for nine mission scenarios with different mission sizes. The best results are in bold and underlined. The table shows that when the mission size is modest, the convergence performance of the three algorithms in scenarios 1 and 2 is comparable (average HV index). Moreover, Fig. 8a demonstrates that the NSSPBO-based task scheduling algorithm converges faster. From the data in scenarios 3 through 9 in the table, it is clear that task scheduling using the NSSPBO algorithm outperforms that using NSGA-II and SPEA2, as compared to the mean HV index, the best HV index, and the worst HV index. Experimental results indicate that the NSSPBO algorithm has a faster convergence rate when solving the image scheduling problem with a small mission size and can improve the diversity of the solution set.



Source: Elaborated by the authors.

Figure 9. Solution set distribution of three algorithms on different cases. (a) Case 1; (b) Case 2; (c) Case 3; (d) Case .

Table 7. Average HV index of three algorithms under different mission scale scenarios.

Mission scenario	Mission number	Parameters	NSSPBO	NSGA-II	SPEA2
Scenario 1	21	MEAN	8067	8067	8067
		BEST	8067	8067	8067
		WORST	8067	8067	8067
Scenario 2	39	MEAN	35989	35989	35989
		BEST	35989	35989	35989
		WORST	35989	35989	35989
Scenario 3	69	MEAN	3.21E+05	3.06E+05	3.03E+05
		BEST	3.30E+05	3.24E+05	3.18E+05
		WORST	3.03E+05	2.95E+05	2.83E+05
Scenario 4	88	MEAN	1.54E+05	1.50E+05	1.52E+05
		BEST	1.82E+05	1.58E+05	1.58E+05
		WORST	1.46E+05	1.46E+05	1.43E+05
Scenario 5	113	MEAN	2.15E+05	2.11E+05	2.13E+05
		BEST	2.18E+05	2.15E+05	2.16E+05
		WORST	2.13E+05	2.12E+05	2.03E+05
Scenario 6	126	MEAN	2.11E+05	2.04E+05	2.06E+05
		BEST	2.12E+05	2.11E+05	2.10E+05
		WORST	2.09E+05	1.87E+05	1.86E+05
Scenario 7	142	MEAN	2.98E+05	2.84E+05	2.88E+05
		BEST	3.07E+05	2.95E+05	2.99E+05
		WORST	2.81E+05	2.63E+05	2.73E+05
Scenario 8	151	MEAN	3.21E+05	3.06E+05	3.03E+05
		BEST	3.30E+05	3.24E+05	3.18E+05
		WORST	3.03E+05	2.94E+05	2.83E+05
Scenario 9	173	MEAN	3.83E+05	3.70E+05	3.71E+05
		BEST	4.00E+05	3.91E+05	3.83E+05
		WORST	3.65E+05	3.51E+05	3.62E+05

Source: Elaborated by the authors.

From the above experiments, it can be seen that the task scheduling algorithm based on NSSPBO, proposed in this paper, can effectively address the multi-satellite observation planning problem. In terms of solution effectiveness, the NSSPBO algorithm outperforms various classical algorithms in terms of planning benefits. The proposed algorithm not only performs well in obtaining the optimal solution but it also outperforms other algorithms regarding the stability of results.

CONCLUSION

In this paper, the task scheduling problem of an InSAR satellite system was investigated. A task scheduling model was established based on actual observation constraints, and objective functions were designed to account for the observation benefits of satellites. The NSSPBO algorithm was proposed to tackle task scheduling problems with multiple constraints and multiple objective functions.

The effectiveness and superiority of the proposed NSSPBO-based task scheduling algorithm in solving multi-satellite and multi-mission scheduling problems were demonstrated through simulation experiments. Extending the proposed method to the global observation task scheduling method based on the re-planning strategy will be investigated in future work.

CONFLICT OF INTEREST

Nothing to declare.

AUTHORS'CONTRIBUTION

Conceptualization: Jia Q; **Methodology:** Jia Q; **Software:** Lian W and Sun Q; **Validation:** Lian W; **Formal analysis:** Lian W and Jia Q; **Investigation:** Yu D; **Resources:** Lian W; **Data Curation:** Lian W; **Writing - Original Draft:** Lian W and Jia Q; **Writing - Review & Editing:** Lian W and Sun Q; **Supervision:** Jia Q; **Project administration:** Yu D; **Funding acquisition:** Jia Q; **Final approval:** Jia Q.

DATA AVAILABILITY STATEMENT

All data sets were generated or analyzed in the current study.

FUNDING

State Key Laboratory of Micro-Spacecraft Rapid Design and Intelligent Cluster
Grant No. MS01240109

ACKNOWLEDGMENTS

Not applicable.

REFERENCES

Chen H, Du C, Li J (2017) An approach of satellite periodic continuous observation task scheduling based on evolutionary computation. Paper presented 2017 Genetic and Evolutionary Computation Conference Companion. SIGEVO; Berlin, Germany.

Chen Z, Dong X, Li Y, Hu C (2020) Formation design for single-pass geo InSAR considering earth rotation based on coordinate rotational transformation. Remote Sens 12(3), 573. https://doi.org/10.3390/rs12030573

Chu X, Chen Y, Tan Y (2017) An anytime branch and bound algorithm for agile earth observation satellite onboard scheduling. Adv Space Res 60, 2077-2090. https://doi.org/10.1016/j.asr.2017.07.026

D'Amico S, Arbinger C, Kirschner M, Campagnola S (2004) Generation of an optimum target trajectory for the TerraSAR-X repeat observation satellite. Paper presented 2004 18th International Symposium on Space Flight Dynamics. German Space Operations Center of DLR; Munich, Germany.

Das B, Mukherjee V, Das D (2020) Student psychology based optimization algorithm: a new population based optimization algorithm for solving optimization problems. Adv Eng Softw 146:102804. https://doi.org/10.1016/j.advengsoft.2020.102804

Du Y, Xing L, Zhang J, Chen Y, He Y (2019) MOEA based memetic algorithms for multi-objective satellite range scheduling problem. Swarm Evol Comput 50:100576. https://doi.org/10.1016/j.swevo.2019.100576

Fiedler H, Krieger G, Zink M, Geyer M, Jäger J (2008) The TanDEM-X acquisition timeline and mission plan. Paper presented 7th European Conference on Synthetic Aperture Radar. Institute of Electrical and Electronics Engineers; Friedrichshafen, Germany.

Jiang X, Song Y, Xing L (2022) Dual-population artificial bee colony algorithm for joint observation satellite mission planning problem. IEEE Access 10:28911-28921. https://doi.org/10.1109/ACCESS.2022.3157286

Kim H, Chang YK (2015) Mission scheduling optimization of SAR satellite constellation for minimizing system response time. Aerosp Sci Technol 40:17-32. https://doi.org/10.1016/j.ast.2014.10.006

Li Y, Zhang Y, Chen Z, Fu T, Zhao X, Hu C, Monti-Guarnieri A-V (2023) A novel PF-based method for height reconstruction in distributed geosynchronous repeat-pass InSAR. IEEE Trans Geosci Remote Sens 61:5214715. https://doi.org/10.1109/TGRS.2023.3308171

Sarkheyli A, Bagheri A, Ghorbani-Vaghei B, Askari-Moghadam R (2013) Using an effective tabu search in interactive resources scheduling problem for LEO satellites missions. Aerosp Sci Technol 29(1):287-295. https://doi.org/10.1016/j.ast.2013.04.001

Song Y-J, Ma X, Li X-J, Xing L-N, Wang P (2019) Learning-guided nondominated sorting genetic algorithm ii for multi-objective satellite range scheduling problem. Swarm Evol Comput 49:194-205. https://doi.org/10.1016/j.swevo.2019.06.008

Wang X-W, Chen Z, Han C (2016) Scheduling for single agile satellite, redundant targets problem using complex networks theory. Chaos Solit Fractals 83:125-132. https://doi.org/10.1016/j.chaos.2015.12.003

Wolfe W, Sorensen S (2000) Three scheduling algorithms applied to the earth observing systems domain. Manage Sci 46(1):148-166. https://doi.org/10.1287/mnsc.46.1.148.15134

Wu G, Luo Q, Du X, Chen Y, Suganthan PN, Wang X (2022) Ensemble of metaheuristic and exact algorithm based on the divid-and-conquer framework for multisatellite observation scheduling. IEEE Trans Aerosp Electron Syst 58(5):4396-4408. https://doi.org/10.1109/TAES.2022.3160993

Wu G, Wang H, Pedrycz W, Li H, Wang L (2017) Satellite observation scheduling with a novel adaptive simulated annealing algorithm and a dynamic task clustering strategy. Comput Ind Eng 113:576-588. https://doi.org/10.1016/j.cie.2017.09.050

Wu K, Zhang D, Chen Z, Chen J, Shao X (2019) Multi-type multi-objective imaging scheduling method based on improved NSGA-III for satellite formation system. Adv Space Res 63(8):2551-2565. https://doi.org/10.1016/j.asr.2019.01.006

Xu R, Chen H, Liang X, Wang H (2016) Priority-based constructive algorithms for scheduling agile earth observation satellites with total priority maximization. Expert Syst Appl 51:195-206. https://doi.org/10.1016/j.eswa.2015.12.039

Zhang J, Xing L (2022) An improved genetic algorithm for the integrated satellite imaging and data transmission scheduling problem. Comput Oper Res 139:105626. https://doi.org/10.1016/j.cor.2021.105626

Zhao Q, Pepe A, Zamparelli V, Mastro P, Falabella F, Abdikan S, Calò F (2023) Innovative remote sensing methodologies and applications in coastal and marine environments. Geo-Spat Inf Sci 27(3):1-18. https://doi.org/10.1080/10095020.2023.2244006

Zitzler E, Laumanns M, Thiele L (2001) SPEA2: Improving the strength Pareto evolutionary algorithm. TIK-Report 103. https://doi.org/10.3929/ethz-a-004284029

Zitzler E, Thiele L (1999) Multi-objective evolutionary algorithms: a comparative case study and the strength Pareto approach. IEEE Trans Evol Comput 3(4):257-271. https://doi.org/10.1109/4235.797969