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Multi-Objective Mission Planning for Multi-Payload Satellite Constellation via Non-Dominated Sorting Carnivorous Plant Algorithm

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ABSTRACT

This study investigates the issue of multi-objective mission planning for multi-payload satellite constellations via the non-dominated sorting carnivorous plant algorithm (NSCPA). Observation time windows are generated, and a constraint satisfaction model is established based on multiple regional targets, satellite orbits, and characteristics of the synthetic aperture radar (SAR) payload and optical payload. A task conflict detection and resolution method is proposed to handle the task assignment among multiple satellites. Based on the existing single objective-based CPAs, a modified multi-objective NSCPA is first developed for multi-objective planning optimization using the non-dominated sorting algorithm. The effectiveness and superiority of the NSCPA are verified by a series of simulation experiments and comparisons with the traditional non-dominated sorting genetic algorithms-II (NSGA-II) and particle swarm optimization (PSO).

Keywords: Satellite constellation; Earth observatory satellite; Mission planning; Non-dominated sorting algorithm; Carnivorous plant algorithm.

INTRODUCTION

The Earth-observation satellite constellation is a crucial component of spacecraft systems in space information applications, and plays an increasingly vital role in meeting the surging demand and scale of satellite constellations. As a result, planning multi-satellite Earth observation tasks has become an urgent problem in the current satellite application field (Bunkheila and Circe 2018; Kim and Chang 2020). A traditional single-payload satellite constellation is no longer sufficient to handle the escalating task demands for data services. To overcome this challenge, multiple satellite systems carrying different payloads are utilized to complement and connect with each other, enabling them to cover a wider area and improve the coverage characteristics of specific areas. Such a constellation design ensures that the target area is covered by the satellite at the required time interval, or coverage time (Sun *et al.* 2017). For instance, a combination of two satellite constellations with distinct functions can be employed for cross-coverage: one for quick revisit coverage of the target area, and the other for high-precision imaging.

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Previous satellite mission planning and planning systems were primarily designed for single payloads. Whenever new satellite resources become available, the planning model must be adjusted or redesigned (She *et al.* 2018; Song *et al.* 2019). As a result, it is a challenge to adapt them to the growing scale and heterogeneity of constellations (Chen *et al.* 2019; Xhafa *et al.* 2012). The quality of the mission planning results for multi-payload satellite constellations is directly affected by the planning model. To optimize the utilization of space resources and meet user needs, a more efficient and scalable approach is required for planning multi-payload satellite constellations. However, the Earth observation satellite mission planning problem is an nondeterministic polynomial time (NP)-hard combinatorial optimization problem, making it difficult to obtain a global optimal solution using mathematical functions (Bonnet *et al.* 2015; Wang *et al.* 2016). Chen *et al.* (2019) propose a mixed integer linear model-based multi-satellite task planning approach, but simple constraints are only taken into consideration. Wei *et al.* (2021) construct a task planning model for multiple objectives, considering the planning model for changing objectives over time and solving the NP-hard problem and time change characteristics. Berger *et al.* (2020) extend the problem modeling to successfully handle virtual constellations, avoiding the inappropriate use of traditional regional coverage decomposition schemes. Lan and Shengping (2021) study the observation task planning of mobile satellites facing multi-region targets, simplifying the target area division into point observation problems and using genetic algorithms (GAs) for optimization, but the repeated coverage issue is inevitable. Tianyang *et al.* (2022) propose a distributed constellation collaborative iterative optimization strategy, allowing multiple subpopulations distributed on different satellites to interact and evolve in parallel with information and continuously optimizing the plan combination of each satellite. However, this method requires significant resource consumption.

Moreover, the conflict resolution algorithm used in the mission planning process of multi-payload satellite constellations determines the extent to which the final planning result is excellent. Marinelli *et al.* (2011) use an improved Lagrangian relaxation algorithm to enhance the efficiency of the planning model. However, it cannot perform dynamic task planning and has limited capabilities. Wang *et al.* (2022) propose a method for on-orbit autonomous mission planning based on reinforcement learning theory, but it relies on the decision network provided by the ground and is not convenient. Wu *et al.* (2022) propose a multi-satellite mission planning algorithm based on a particle swarm optimization (PSO), which has good scalability but low result accuracy. Qianzhou *et al.* (2021) propose a hyper-heuristic-based multi-satellite collaborative task planning algorithm, but it has a long runtime. Cui and Zhang (2019) propose a task planning method based on priority ranking, which improves the speed and accuracy of optimization iterations. However, it cannot be applied to task planning with multiple objective functions. Xhafa *et al.* (2012) propose a collaborative GA that can simultaneously obtain effective execution strategies and attitude paths. However, it falls into the category of local optimal solutions. Yi *et al.* (2020) propose an efficient algorithm combining an improved GA and local search method. The improved GAs rapidly improves the quality of the planning scheme, and the neighborhood search is used for subsequent small-scale optimization. Kim and Young-Keun (2020) study the crossover mutation operator when a non-dominated sorting GAs-II (NSGA-II) is applied to large-scale task planning, which improves the ability of the GA to apply to multi-objective iterative optimization to a certain extent. Zhou *et al.* (2015) use the GA to adjust the weighting factor of each target to optimize the mission plan, ensuring that the target in the optimal area can be imaged multiple times and quickly. However, this method is only applicable to the single-target optimization process and single-payload satellite constellations. It is worth noting that, the above algorithms have no focus on the mission planning issue of multi-payload satellite constellations.

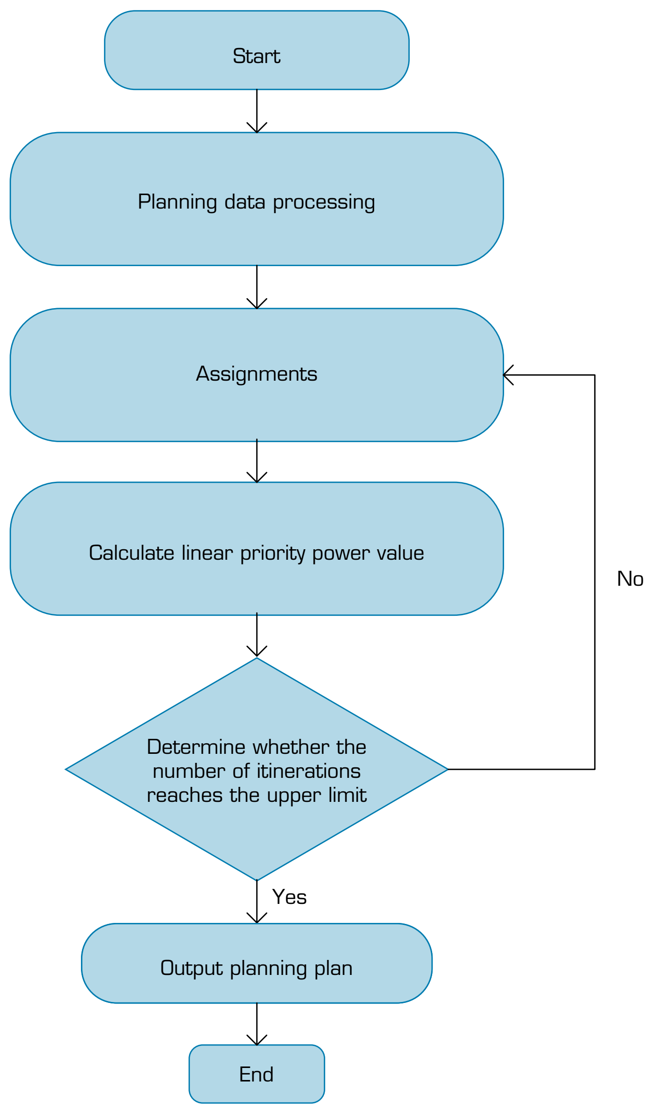
In Ong *et al.* (2021), the carnivorous plant algorithm (CPA) was first proposed for an optimization problem. Compared with traditional optimization methods (Hongrae and Young-Keun 2020; Wu *et al.* 2022; Zhou *et al.* 2015), the CPA has a fast convergence speed and strong constraint processing, and much progress has been conducted (Ma and Gu 2023; Sheng and Du 2023). However, the existing achievements on the CPAs have focused on a single-objective optimization problem. To solve the mission planning issue of multi-payload satellite constellations with strong constraints and multiple objectives, this paper proposes the non-dominated sorting CPA (NSCPA) to address these issues. NSCPA allows satellites to perform iterative optimization independently, and it overcomes the weaknesses of GAs and taboo search, as well as the low precision problem of PSO algorithms. Additionally, NSCPA has the advantages of flexibility and resource savings. This paper achieves three objectives for the task planning problem of multi-payload satellite constellations in Earth observation missions:

- Maximize the objective function of the observation task sequence by analyzing constraints such as task priority weight and coverage imaging time and building a constraint satisfaction model.
- Propose a carnivorous plant multi-objective optimization algorithm based on the non-dominated sorting algorithm, which introduces a classification strategy in the solution space.
- Utilize a heuristic conflict detection and resolution algorithm to effectively handle conflicts among planning tasks.

The rest of this paper is organized as follows: the multi-payload satellite constellation task planning process, the time window generation method, the task planning model and target function will be illustrated. The iterative optimization process of the NSCPA will be provided. Three algorithms – NSCPA, NSGA-II, and PSO – will be compared and analyzed through simulation experiments. Some concluding statements are provided in the last section.

Mission planning analysis

For the mission planning of the multi-payload satellite constellation, it is necessary to consider mission objectives and various constraints (Kilic and Ozhan 2017). The mission planning flow chart (Wang *et al.* 2019) is described in Fig. 1.

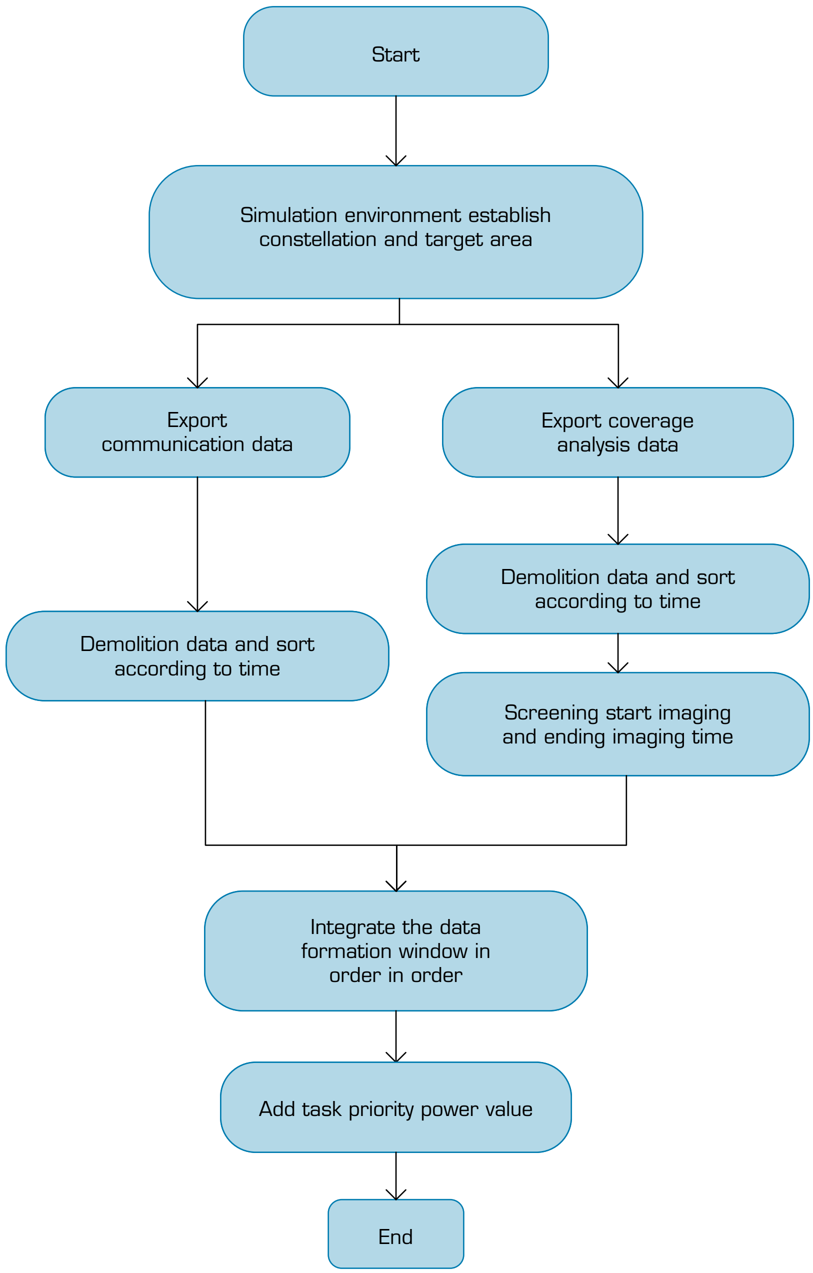


Source: Elaborated by the authors.

Figure 1. Mission planning flow chart.

Time window generation

Typical constraints for mission planning encompass mission target area priority, satellite priority, payload priority, imaging task priority, etc. (Liu *et al.* 2021a). To facilitate multi-payload satellite constellation task planning, the time window data are extracted from the Satellite Tool Kit (STK) software and preprocessed (Sun and Cao 2020). The process flowchart for generating time windows is illustrated in Fig. 2.



Source: Elaborated by the authors.

Figure 2. Process flowchart of time window generation.

Based on the process flowchart of time window generation, the following steps are taken to design the time window:

Step 1: Establish the satellite constellation simulation environment, which includes range constraint definition on SAR payloads, lighting constraints for optical payloads, and imaging range constraints. Set up target areas, add ground stations, and input communication data for ground stations. Set the simulation's start and end times.

Step 2: Establish communication links between satellites and target areas, and generate communication reports.

Step 3: Conduct coverage analysis between satellites and target areas and generate coverage analysis reports.

Step 4: Sort the communication reports and coverage analysis reports in chronological order. For coverage analysis reports, keep the start and end times when the satellite completes full coverage of the target area.

Step 5: Determine whether full coverage is achieved during the task execution. If the communication end time is greater than the coverage end time, full coverage is achieved. If not, the task's imaging start time is set to -1, and the end time is set to 0.

Step 6: Calculate the priority weight value for the task by adding up the priority weight values for the executing satellite number and target area number according to the priority weight definition.

Step 7: Combine the task table from Step 5 with the task priority weight table from Step 6 to obtain the time window.

Parameter definition

Based on the above discussion, this paper establishes a multi-objective constraint model for multi-payload satellite constellations and time observation windows required for mission planning. Firstly, the following assumptions have been made (Greco *et al*. 2019):

Assumption 1: Task objectives for SAR payload satellites and optical payload satellites for Earth observation are all selected as regional targets.

Assumption 2: When imaging data are received by the ground station, the imaging data are sent to the ground station.

Assumption 3: This paper considers only satellite communication rates and ground data transmission under ideal conditions, without being affected by other factors.

Assumption 4: Meteorological factors are random events in satellite-ground observation events that have a certain impact on the imaging of the optical payload, but the imaging process of the SAR payload is not affected. For SAR payload satellites, once the observation begins, it cannot be interrupted.

Assumption 5: The task planning problem of a multi-payload satellite constellation is decomposed into a linear task planning problem, according to the characteristics of data-based task planning for SAR payload satellites and optical payload satellites.

Before constructing the model for task planning in a multi-payload satellite constellation, some parameter symbols are defined as follow: M : mission set, $\{M_1, M_2,\ldots, M_{N_i}\}$, where N_i represents the number of tasks; R: executive task collection, $R = \{R_1, R_2,\ldots, R_{S_N}\}$, where S_N represents the number of tasks for execution; G: ground station resources, $G = \{g_1, g_2,\ldots, g_{N_d}\}$, where N_d represents the number of ground stations; TG: cyber communication time with the ground station with satellite $TG = \{d_{S_1}, d_{S_2},\ldots, d_{N_{dt}}\}$, where N_{dt} represents the number of ground stations communicating with satellite; TO_{SN}: satellite observation time; A_i: satellite scanning area; A_m: task target table area; T_m: imaging task execution time; V_m: task priority weight.

Mission planning model construction

Decision variables

C_i: Cover indicator, i represent target area number.

W_{Ni}: Climate constraints (for optical load), W_{Ni} represents optical payload in the work state, $W_{Ni} = 0$ represents that the optical-payload satellites are shut down.

Z_{dwt}: Represents satellite S whether the data is performed under the data window at the ith ground station time window, if the satellite execute the mission, then $Z^S_{dwt} = 1$, otherwise $Z^S_{dwt} = 0$.

Constraint conditions

$$C_i = \frac{A_s}{A_m} \leq 1 \tag{1}$$

The Eq. 1 represents the task completion index, which defines the coverage rate. If $R^{off}_{N_i} - R^{start}_{N_i} \geq TO^{off}_{N_i} - TO^{start}_{N_i}$, which indicates that the task can achieve complete coverage imaging of the target area within the communication time, while $C_i = 1$, otherwise $C_i = 0$.

$$TO_{SN} \leq R^{off}_{N_i} - R^{start}_{N_i} \tag{2}$$

The Eq. 2 represents that the observation time must fall within the designated on-off time period for the satellite.

$$M_{N_i} \leq 1 \tag{3}$$

The Eq. 3 represents that each task can only be executed once.

$$T_{tNi} \subseteq TG \tag{4}$$

The Eq. 4 represents that satellite data transmission must occur within the satellite communication time period.

$$T_{tNi} \cap M_{N_i} = \varnothing \tag{5}$$

The Eq. 5 represents that in the event of a conflict in the task window, a task plan must be selected.

Satellite task planning is a combinatorial optimization problem with multiple constraints and objectives. This paper aims to obtain a solution that can prioritize the observation of high-value targets while improving the task completion rate. Based on this consideration, the following objectives have been set:

- The Eq. 6 represents that the number of tasks executed cannot be less than 50% of the total number of tasks generated within the time window.

$$\frac{R}{M} \times 100\% \geq 50\% \tag{6}$$

- The Eq. 7 represents that the tasks executed within the scene setting time should have the highest priority weight and be able to achieve complete coverage of the target area within the communication time.

$$C_i = 1 \tag{7}$$

Optimization objectives

- Maximize the time for executing full-coverage tasks for the target area to enhance task timeliness.

$$f_1 = \max \sum_{n=1}^{m} T_m \tag{8}$$

- The task priority weight should be maximized.

$$f_2 = \max \sum_{n=1}^{m} V_m \tag{9}$$

NSCPA-based multi-objective mission planning design

CPA review

Firstly, the sample pool is initialized by sorting the samples in descending order of fitness value, where the top samples are classified as carnivorous plants and the remaining samples are classified as prey. Subsequently, the samples are further differentiated into different categories, such as first-class carnivorous plants, second-class carnivorous plants, first-class prey, second-class prey, and so on. The groups are then sorted by fitness level, and during the grouping process, the prey with the best fitness value is assigned to the top-ranked carnivorous plant. Similarly, the second-best prey is assigned to the second-class carnivorous plant, and so on, until all assignments are completed. Generally, the number of samples should satisfy that m ≥ 3n, with the sample number m and each group contains n individuals. This grouping method effectively reduces the possibility of assigning poor prey to excellent carnivorous plants, which is crucial for improving the survival ability of carnivorous plants (Ong *et al.* 2021).

Once a prey is captured, the CPA algorithm incorporates an attraction rate variable to reduce the likelihood of pairing failures. For each pair, a prey is randomly selected and compared to a randomly generated number. If the prey's attraction rate is higher than the generated number, the carnivorous plant will capture and digest the prey to continue growing. The growth model for the new carnivorous plant is given by

$$NewCP_{i,j} = growth * CP_{i,j} + (1 - growth) * \mathrm{Prey}_{v,j} \tag{10}$$

$$growth = growth\_rate * rand_{i,j} \tag{11}$$

where $CP_{i,j}$ represents level i prey, $Prey_{v,j}$ represents randomly selected prey, $growth\_rate$ is a predefined value, and rand is a randomly selected value from the range (0,1). The attraction rate in CPA is typically specified as 0.8.

On the other hand, if the attraction rate is lower than the randomly generated value, the prey successfully escapes the trap and continues to grow, mathematically expressed as

$$NewPrey_{i,j} = growth * Prey_{u,j} + (1 - growth) * \mathrm{Prey}_{v,j}, \ u \neq v \tag{12}$$

$$growth = \begin{cases} growth\_rate*rand_{i,j} f(prey_v)>f(prey_{\mathrm{u}}) \\ 1 - growth\_rate*rand_{i,j} f(prey_v)<f(prey_{\mathrm{u}}) \end{cases} \tag{13}$$

where $Prey_{u,j}$ represents another randomly selected prey in the third population. Repeat the growth process of carnivorous plants and prey until the predetermined number of iterations is completed.

The breeding process of only the best solution in the population, i.e., the one ranked first is carried out to avoid unnecessary utilization of other solutions and save computational cost. The breeding process of the top-ranked carnivorous plant is represented as follows:

$$NewCP_{i,j} = CP_{i,j} + Reprodution\_rate * rand_{i,j} * mate_{i,j} \tag{14}$$

$$mate_{i,j} = \begin{cases} CP_{v,j} - CP_{i,j} \int(CP_i) > \int(CP_v) \\ CP_{i,j} - CP_{v,j} \int(CP_i) > \int(CP_v) \end{cases}, \ i \neq v \neq 1 \tag{15}$$

The newly generated carnivorous plants and prey are combined with the previous population to form a new population. Then, this group of new individuals is sorted in ascending order according to their fitness values. After that, the top N individuals in the ranking are selected from this group as the new candidate solutions.

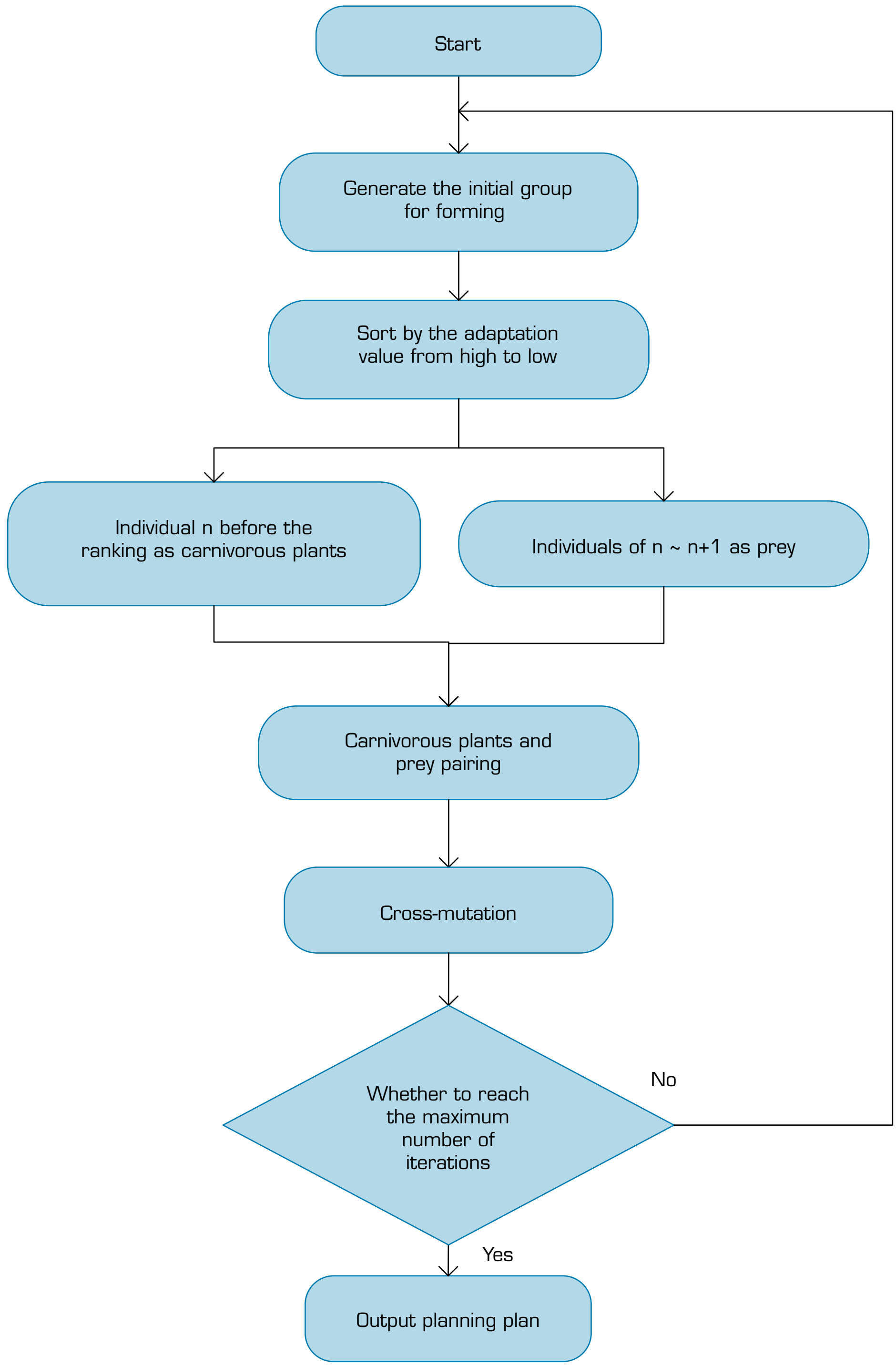
Novel multi-objective NSCPA design

As mentioned before, NSCPA will perform iterative optimization steps based on the proposed time window. The NSCPA flow chart is given in Fig. 3.

According to the NSCPA flow chart, the procedure for designing the multi-payload satellite constellation task planning is as follows:

Step 1: Obtain satellite orbit information and payload information as well as communication information between the satellite constellation and target area, generate a satellite payload task sequence matrix $W=\{w_1,w_2,\dots w_{N_{task}}\}$, where w_i represents task i of the satellite constellation and the target area during the task time, N_{task}; N_{task} represents all constraint conditions in a task, including the start time of satellite communication T_{ts}, the end time of communication T_{ts}, the start time of task imaging T_{es}, the end time of imaging T_{ce}, the imaging task number C_i, etc. Next, preprocessing on the satellite payload task sequence matrix is executed.

Step 2: Each task in the preprocessed time window task sequence is randomly assigned Z_i, if $Z_i = 0$, indicates that the task is not executed in this task sequence, if $Z_i = 1$, then perform the task N_{task}. Use the assigned satellite payload task sequence matrix W_i as an individual of the initial population.



Source: Elaborated by the authors.

Figure 3. NSCPA flow chart.

Step 3: Refine the initial population by resolving conflicts to obtain an updated population and satellite task sequence. The updated population is then utilized as the previous generation, and a conflict resolution operator is applied to transform infeasible solutions into feasible ones.

Step 4: Step 4 involves constructing the multi-objective function by calculating the weighted sum of the priority values of executed tasks in the task sequence and the imaging time of the target area. Non-dominated sorting is then used to rank individuals in the population based on their objective function values.

Step 5: Involves applying the division standard of carnivores and prey in NSCPA to divide and match the ranked population from Step 4, and performing crossover and mutation using NSCPA to generate a new population NewCP. The NewCP is then merged with the original population, and non-dominated sorting is performed on the merged population to select the top m individuals as the new population.

In the previous steps, conflict resolution in step 3 is based on step 2, where all mission assignments are deleted when $Z_i = 0$. In this step, the execution satellite numbers of the first task and the second task in the time window will be compared. If they are the same, the start times of the first two tasks in the sequence are used to determine if a conflict will arise. If no conflict occurs, the task sequence will be retained, and the execution satellite number of the first task will be compared with that of the third task. If a conflict occurs, the complete coverage of the task sequence will be evaluated during the communication in the time window, and the task that has completed the complete coverage will be retained. If both tasks achieve complete coverage, the task with a higher priority weight will be retained. This process was repeated until all task sequences in the individual had no task conflicts.

Once conflict resolution is completed for all individuals in the population, the new population is used as the object for iterative optimization in NSCPA. In step 5, NSCPA iteratively optimized the preprocessed population using the following steps:

- Perform non-dominated sorting based on the sum of priority weights for executing tasks and the time required for complete coverage imaging of the target area. After sorting, select the top n individuals as carnivorous plants, the next $n + 1 \sim 2n$ individuals as the first type of prey, and the remaining individuals as the second type of prey. If the population size is less than required, discard the data. Otherwise, generate a third type of prey, and so on.
- Pair the sorted carnivorous plants and prey in order.
- After pairing, randomly select a segment of the task sequence $M_i \sim M_{i+j}$ from a carnivorous plant individual and a corresponding task sequence from the first type of prey for crossover, mutation, conflict resolution, and calculate the total sum of priority weights for the carnivorous plant.
- The priority weight sum of the newly obtained carnivorous plants is processed as follows:
  - If the sum is less than the original sum, replace the segment $M_i \sim M_{i+j}$ with the same position task sequence of the second type of prey for crossover, mutation, and conflict resolution, and then calculate the sum of priority weights.
  - If the total priority weight of the replaced carnivorous plant task sequence is greater than the original total, continue to select a task sequence $M_a \sim M_{a\text{-}b}$ from a different position to replace the same position task sequence in the second type of prey. Then, perform conflict resolution and calculate the sum of priority weights for the replaced task sequence. Keep the task sequence with the higher sum of priority weights.
- For the new population after crossover and mutation, use the iterative method of adjacent replacement. Randomly select a segment of the task sequence from adjacent individuals, replace the segment with a random position task sequence from the adjacent individual, and then calculate the sum of priority weights.
- Order all individuals according to the sum of priority weights and complete coverage of consumption time using non-dominant ordering. Identify new carnivorous plants, first-class prey, and second-class prey. The ordered population will continue to update and iterate as a new population.

SIMULATION RESULTS AND ANALYSIS

In this section, a numerical simulations and comparisons are provided to demonstrate the applicability and superiority of the NSCPA-based mission planning method for the SAR-optical payload satellite constellation. The simulation experiments are conducted on a desktop computer with a Windows 10*64 operating system, a Core R7-9700H 2.4GHz CPU, and 16GB of memory capacity. The MATLAB 2018b software is used as the coding environment, and calls the modules in the STK software.

Simulation environment setup

The simulation considers a SAR-optical payload satellite constellation including three SAR-payload satellites and three optical-payload satellites. The six orbital elements of SAR-payload satellites and optical-payload satellites are respectively provided in Tables 1 (Cheng *et al.* 2012) and 2 (Wu *et al.* 2013).

Table 1. Orbital elements of SAR-payload satellites.

Satellite serial number	Track height/km	Eccentricity	Inclination/deg	RAAN/deg	Mean anomaly/deg	Argument of perigee/deg
1	7,043.14	0	68	0	0	0
2	6,928.14	0	41	0	0	0
3	6,878.14	0	90	0	0	0

Source: Adapted from Cheng *et al.* 2012.

Table 2. Orbital elements of optical-payload satellites.

Satellite serial number	Orbit height/km	Eccentricity	Inclination/deg	RAAN/deg	Mean anomaly/deg	Argument of perigee/deg
1	7,378.14	0	90	0	0	0
2	7,578.14	0	55	0	0	0
3	7,378.14	0	90	0	60	0

Source: Adapted from Wu *et al.* 2013.

The parameters of SAR payload and optical payload (Wu *et al.* 2019) are set in Table 3.

Table 3. Satellite payload parameter setting.

Factor load	Sensor type	FOV	Swing range	Imaging conditions	Min Elevation-angle	Max Elevation-angle
SAR	SAR	5°	-40~40°	Azimuth > 15°	15.2°	51.9°
Optical	Rectangular	5°	-40~40°	Sun elevation angle > 30°	15.2°	51.9°

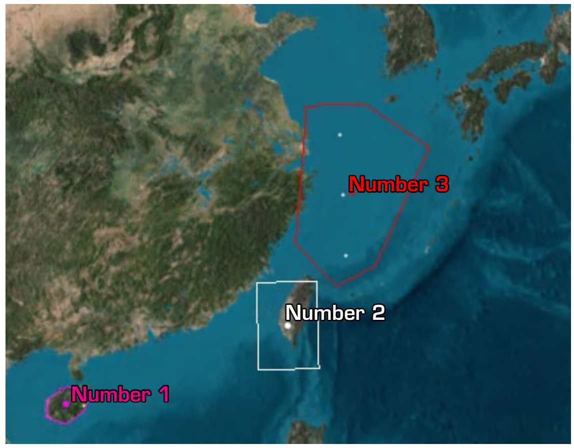
Source: Adapted from Wu *et al.* 2019.

The three observed regional targets are assumed and their locations (longitude, latitude) are given in Table 4. The target area generated based on the longitude and latitude data in Table 4 is shown in Fig. 4.

Table 4. Observation area.

Area number	Area	Boundary longitude and latitude
1	Target area 1	(20.03,109.69), (19.29,108.65), (18.51,108.79), (18.24,109.7), (18.83,110.6), (19.76,111.04)
2	Target area 2	(24,115), (24,125), (30,115), (30,125)
	Target area 3	(33.11,121.8), (26.72,120.94), (24.77,122.99), (25.63,125.01), (31,128.32), (33.18,125.04)

Source: Elaborated by the authors.



Source: Elaborated by the authors.

Figure 4. STK target area demo.

The observation time windows are generated using the proposed algorithm, and intercept some time window sequences with task conflicts for display. The results are shown in Table 5.

Table 5. Example of a task planning time window.

Task serial number	Start time (unit/s)	End time (unit/s)	Imaging start time (unit/s)	Imaging end time (unit/s)	Full coverage of the target	Area number	Execute the task satellite serial number	Task priority weight
1	13,288	13,594	13,289	13,398	1	2	2	21
2	15,193	15,869	-1	0	0	17	5	19
3	19,216	19,571	19,216	19,258	1	8	2	16
4	19,257	19,700	-1	0	0	14	2	12

Source: Elaborated by the authors.

Performance comparison and evaluation

To demonstrate the effectiveness and superiority of the NSCPA, a comparison between the NSCPA, NSGA-II, and PSO (Sun *et al.* 2017) is provided in the detail. The parameters designed in the NSCPA, NSGA-II, and PSO algorithms are provided in Table 6.

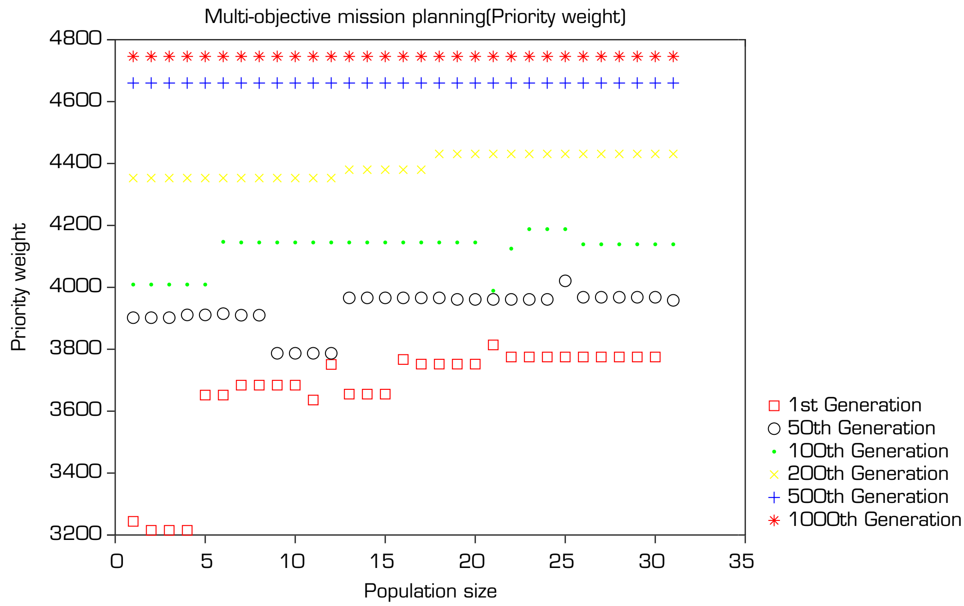
Table 6. Parameter settings of three optimization algorithms.

Algorithm	Group number	Generation	Parameter
NSCPA	30	1,000	Rand = 0.8 nCP = 5 nPrey = 25 Croprob = 0.9
NSGA-II	30	1,000	Cro = 0.9 Mut = 0.1
PSO	30	1,000	Cro = 0.9 Mut = 0.1

Source: Adapted from Liu *et al.* 2021b.

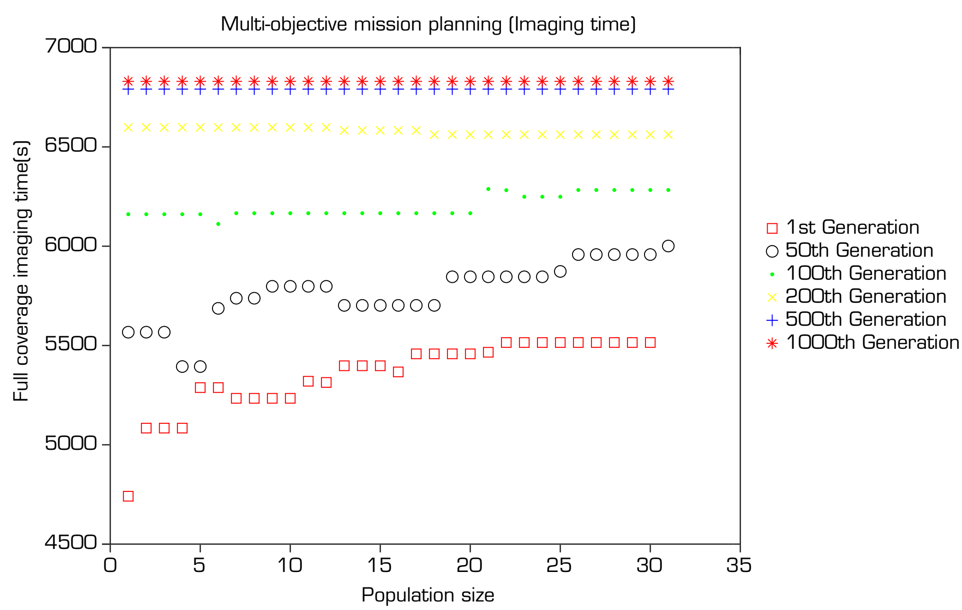
nCP represent the number of carnivorous plants in each population, *nPrey* represents the number of prey, and *Croprob* represents the probability of cross-mutation.

In this paper, the hypervolume (HV) method is used to evaluate the performance of the above three algorithms. The HV method measures the volume of the hypercube formed by the non-dominated set of solutions and the reference point. To optimize the accuracy of the algorithms, this paper ran each algorithm for 10 generations on our own platform and evaluated the best result obtained in these 10 generations. The convergence graphs of the task priority weight and the total time taken for full coverage imaging during communication in the multi-objective optimization are shown in Fig. 5 and 6.



Source: Elaborated by the authors.

Figure 5. Multi-objective mission optimization results (task priority weight).



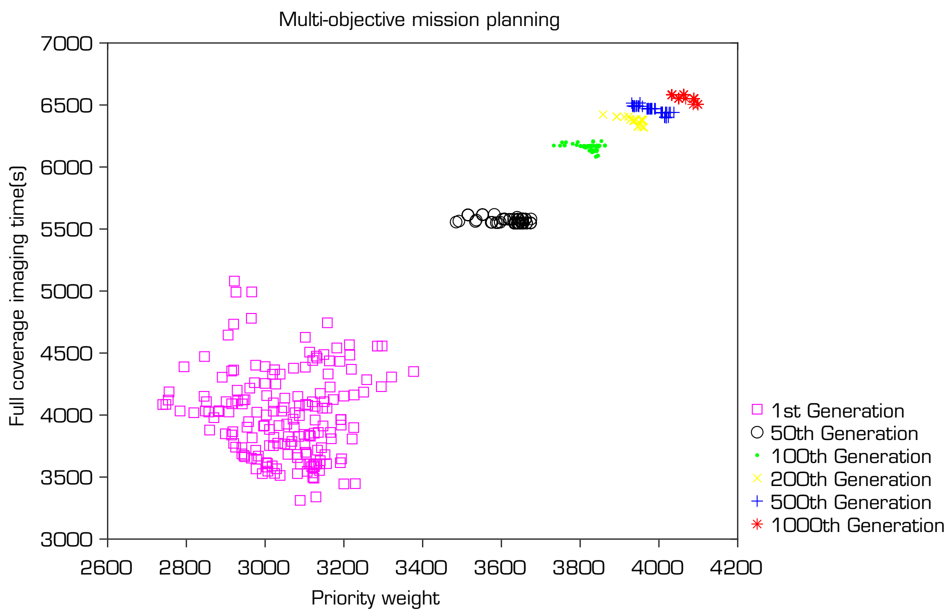
Source: Elaborated by the authors.

Figure 6. Multi-objective mission optimization results (imaging time).

For the task priority weight objective function, the final iteration result of the CPA is 4769. As can be seen from the Fig. 5, the convergence trend gradually slows down from the beginning of the 500th generation.

From Fig. 6, it can be seen that the final iteration result of the CPA is about 6,800 seconds for the target region to fully cover the imaging time target function. Meanwhile, the results of 500th and 1,000th generations show no significant difference, indicating that the CPA has good convergence.

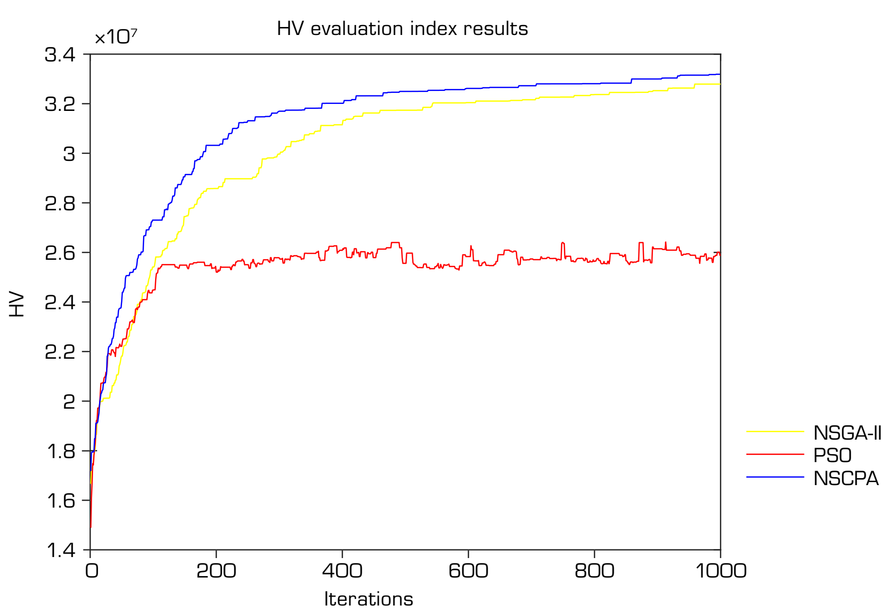
Figure 7 shows the convergence diagram of NSCPA over 1,000 iterations. Considering that the convergence after 200th generations cannot be seen when the population size is 30, in order to more intuitively display the optimization effect the CPA in the case of multiple objective functions, the population size is adjusted to 180 to obtain a clearer convergence trend. As can be seen from the Fig. 7, NSCPA began to converge after approximately 500 iterations.



Source: Elaborated by the authors.

Figure 7. NSCPA-based multi-objective mission optimization and convergence.

The comparison of HV values indicates the best results obtained at different iterations in bold. The average value represents the average of the 10 convergences obtained by the algorithm, taking into account the diversity caused by the non-dominated solution set. The graph shows the value obtained by the algorithm after 10 runs. NSCPA exhibits better stability than NSGA-II and PSO. The comparison of HV values is presented in Fig. 8.



Source: Elaborated by the authors.

Figure 8. HV algorithm evaluation index map.

It is evident that NSCPA outperforms both NSGA-II and PSO in terms of faster convergence and higher accuracy, as measured by the HV index evaluation. As the HV index evaluation graph is evaluated based on area, it clearly shows that NSCPA has a larger area and is superior to both NSGA-II and PSO in the HV evaluation. This indicates that NSCPA is better at finding solutions that are both diverse and optimal, thus providing a higher-quality solution set. The graph also shows that NSCPA has better stability compared to NSGA-II and PSO, as it has a smaller variance in the HV values obtained. Overall, the HV evaluation provides strong evidence for the superiority of the NSCPA in solving the multi-objective task planning problem.

CONCLUSION

This study investigates the issue of NSCPA-based multi-objective mission planning for the SAR-optical payload satellite constellation. Based on the single-objective CPA and non-dominated sorting algorithm, an improved NSCPA is first developed to solve mission planning optimization with multiple constraints and objectives. Compared with the traditional NSGA-II algorithm and PSO algorithm, the proposed NSCPA is superior in both convergence speed and optimization accuracy in mission planning for the SAR-optical payload satellite constellation. The simulation experiment demonstrates the effectiveness and superiority of NSCPA.

AUTHORS' CONTRIBUTION

Conceptualization: Jia Q; **Methodology:** Jia Q; **Software:** Zhang Y; **Validation:** Zhang Y; **Formal analysis:** Zhang Y, Jia Q; **Investigation:** Wu Y, Liao H; **Resources:** Zhang Y; **Data Curation:** Zhang Y; **Writing - Original Draft:** Zhang Y, Jia Q; **Writing - Review & Editing:** Y Zhang Y, Jia Q; **Supervision:** Jia Q; **Project administration:** Wu Y, H Liao H; **Funding acquisition:** Jia Q; **Final approval:** Jia Q.

CONFLICT OF INTEREST

Nothing to declare.

DATA AVAILABILITY STATEMENT

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

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REFERENCES

Berger J, Lo N, Barkaoui M (2020) QUEST – A new quadratic decision model for the multi-satellite scheduling problem. Comput Oper Res 115:104822. https://doi.org/10.1016/j.cor.2019.104822

Bonnet J, Gleizes M-P, Kaddoum E, Rainjonneau S, Flandin G (2015) Multi-satellite mission planning using a self-adaptive multi-agent system. Paper presented 2015 9th International Conference on Self-Adaptive and Self-Organizing Systems. IEEE; Cambridge, USA. https://doi.org/10.1109/SASO.2015.9

Bunkheila F, Circi C, inventors; Telespazio SpA, assignee. 2018 May 23. Innovative satellite scheduling method based on genetic algorithms and simulated annealing and related mission planner. United State patent US 10726368B2.

Chen X, Reinelt G, Dai G, Spitz A (2019) A mixed integer linear programming model for multi-satellite scheduling. Eur J Oper Res 275(2):694-707. https://doi.org/10.1016/j.ejor.2018.11.058

Chen Y, Zhang D, Zhou M, Zhou H (2022) Multi-satellite observation scheduling algorithm based on hybrid genetic particle swarm optimization. In: Zeng D, editor. Advances in information technology and industry applications. Vol 136. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-26001-8_58

Cui J, Zhang X (2019) Application of a multi-satellite dynamic mission scheduling model based on mission priority in emergency response. Sensors 19(6):1430. https://doi.org/10.3390/s19061430

Greco C, Gentile L, Filippi G, Minisci E, Vasile M, Bartz-Beielstein T (2019) Autonomous generation of observation schedules for tracking satellites with structured chromosome GA optimization. Paper presented 2019 Congress on Evolutionary Computation. IEEE; Wellington, New Zealand. https://doi.org/10.1109/CEC.2019.8790101

Hongrae K, Young-Keun C (2020) Optimal mission scheduling for hybrid synthetic aperture radar satellite constellation based on weighting factors. Aerosp Sci Technol 107:106287. https://doi.org/10.1016/j.ast.2020.106287

Kilic S, Ozkan O (2017) Ant colony optimization approach for satellite broadcast scheduling problem. Paper presented 2017 8th International Conference on Recent Advances in Space Technologies. IEEE; Istanbul, Turkey. https://doi.org/10.1109/RAST.2017.8002936

Lan G, Shengping G (2021) Observation mission planning for maneuverable satellite constellation towards multiple area targets. J Astronaut 42(2):185-191.

Liu L, Dong Z, Su H, Yu D, Lin Y (2021a) Research on a heterogeneous multi-satellite mission scheduling model for earth observation based on adaptive genetic-tabu hybrid search algorithm. Paper presented *2021 5th Advanced Information Technology, Electronic and Automation Control Conference* Chongqing, China.

Liu Y, Wan Z, Dai Y, Zhao Y, Liu Q, Ji C (2021b) Emergency constellation design based on micro SAR satellites. Paper presented *2021 Global Reliability and Prognostics and Health Management* Nanjing, China.

Ma Y, Gu L (2023) The carrier-based optimization algorithm based on reverse learning and neighborhood mutations. Software Guide 22(7):44-50. https://doi.org/10.11907/rjdk.221877

Marinelli F, Nocella S, Rossi F, Smriglio S (2011) A Lagrangian heuristic for satellite range scheduling with resource constraints. Comput Oper Res 38(11):1572-1583. https://doi.org/10.1016/j.cor.2011.01.016

Ong KM, Ong P, Kiong SC (2021) A carnivorous plant algorithm for solving global optimization problems. Appl Soft Compput 98:106833. https://doi.org/10.1016/j.asoc.2020.106833

Qianzhou H, Yuan T, Cheng LD, Wenfeng L, Ming YJ (2021) Satellite imaging task planning using particle swarm optimization and tabu search. Paper presented 21st International Conference on Software Quality, Reliability and Security Companion IEEE; Hainan, China. https://doi.org/10.1109/QRS-C55045.2021.00090

She Y, Shuang L, Zhao Y (2018) Onboard mission planning for agile satellite using modified mixed-integer linear programming. Aerosp Sci Technol 72:204-216. https://doi.org/10.1016/j.ast.2017.11.009

Sheng J, Du Y (2023) Cooperative task assignment method of multiple UAVs under multiple constraints. Applied science and technology 50(5):46-53+148. https://doi.org/10.11991/yykj.202302033

Song YJ, Ma X, Li XJ, 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

Sun H, Cai X, Sulaman M, Fan Z (2017) An evolutionary many-objective optimization algorithm based on coverage and cache strategy. Paper presented *2017 International Conference on Industrial Informatics – Computing Technology, Intelligent Technology, Industrial Information Integration.* Wuhan, China https://doi.org/10.1109/ICIICII.2017.82

Sun X, Cao S (2020) A routing and wavelength assignment algorithm based on two types of LEO constellations in optical satellite networks. J Lightwave Technol 38(8):2106-2113.

Tianyang G, Xiaoxuan H, Wei X (2022) Constellation autonomous mission planning algorithm based on distributed co-evolution. Syst Eng Electron 44(5):1600-1608. https://doi.org/10.12305/j.issn.1001-506X.2022.05.21

Wang S, Zhao L, Cheng J, Zhou J, Wang Y (2019) Task scheduling and attitude planning for agile Earth observation satellite with intensive tasks. Aerosp Sci Technol 90:23-33. https://doi.org/10.1016/j.ast.2019.04.007

Wang X , Jian W, Zhong S, Zhao F, Zhonghe J (2022) Deep reinforcement learning-based autonomous mission planning method for high and low orbit multiple agile Earth observing satellites. Adv Space Res 70(11):3478-3493. https://doi.org/10.1016/j.asr.2022.08.016

Wang XW, 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

Wei L, Xing L, Wan Q, Song Y, Chen Y (2021) A multi-objective memetic approach for time-dependent agile earth observation satellite scheduling problem. Comput Ind Eng 159:107530. https://doi.org/10.1016/j.cie.2021.107530

Wu G, Liu J, Ma M, Qiu D (2013) A two-phase scheduling method with the consideration of task clustering for earth observing satellites. Comput Oper Res 40(7):1884-1894. https://doi.org/10.1016/j.cor.2013.02.009

Wu K, Zhang D, Chen Z, Chen J, Shao W (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

Wu X, Yang Y, Sun Y, Xie Y, Song X, Hang B (2022) Dynamic regional splitting planning of remote sensing satellite swarm using parallel genetic PSO algorithm. Acta Astronaut 204:531-551. https://doi.org/10.1016/j.actaastro.2022.09.020

Xhafa F, Sun J, Baroli A, Biberaj A, Barolli L (2012) Genetic algorithms for satellite scheduling problems. Mob Inf Syst 8(4):351-377. https://doi.org/10.3233/MIS-2012-00153

Yi J, Xing L, Wang G, Dong J, Vasilakos A (2020) Behavior of crossover operators in NSGA-ILI for large-scale optimization problems. Inf Scivol 509:470-487 https://doi.org/10.1016/j.ins.2018.10.005

Zhou Y, Yan Y, Huang X, Kong L (2015) Optimal scheduling of multiple geosynchronous satellites refueling based on a hybrid particle swarm optimizer. Aerosp Sci Technol 47:125-134. https://doi.org/10.1016/j.ast.2015.09.024