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Optimal reconfiguration of constellation using adaptive innovation driven multiobjective evolutionary algorithm

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Abstract: Constellation reconfiguration is a critical issue to recover from the satellite failure, maintain the regular operation, and enhance the overall performance. The constellation reconfiguration problem faces the difficulties of high dimensionality of design variables and extremely large decision space due to the great and continuously growing constellation size. To solve such real-world problems that can be hardly solved by traditional algorithms, the evolutionary operators should be promoted with available domain knowledge to guide the algorithm to explore the promising regions of the trade space. An adaptive innovation-driven multi-objective evolutionary algorithm (MOEA-AI) employing automated innovation (AI) and adaptive operator selection (AOS) is proposed to extract and apply domain knowledge. The available knowledge is extracted from the final or intermediate solution sets and integrated into an operator by the automated innovation mechanism. To prevent the overuse of knowledge-dependent operators, AOS provides top-level management between the knowledge-dependent operators and conventional evolutionary operators. It evaluates and selects operators according to their actual performance, which helps to identify useful operators from the candidate set. The efficacy of the MOEA-AI framework is demonstrated by the simulation of emergency missions. It was verified that the proposed algorithm can discover a non-dominant solution set with better quality, more homogeneous distribution, and better adaptation to practical situations.

Keywords: constellation reconfiguration, emergency observations, rapid response, multi-objective optimization.

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1. Introduction

Marked by the SpaceX "Starlink" program, large-scale, low-cost, and low-orbit satellite giant constellations have become the frontier of space development, which have a significant impact on the traditional development and application of satellites. The satellite constellation pattern refers to the stable relative position and status of multiple satellites in order to achieve the desired goal. The constellation pattern directly affects the overall performance of space system operation and application. With the existence of satellite failure, space confrontation, and emergency requirement, constellation reconfiguration becomes the major problem that must be solved to recover from the failure, maintain the normal operation, and enhance the overall performance.

Constellation reconfiguration, defined as "a deliberate change of the relative arrangements of satellites in a constellation by addition or subtraction of satellites and orbital maneuvering in order to achieve desired changes in coverage or capacity" [1], has a wide range of applications in system recovery after satellite failure [2,3], constellation staged deployment [1], rapid emergency response[4], and so on. To positively respond to future uncertainties and rapidly recover or enhance system overall performance, constellation reconfiguration has profound significance in both civilian and military aspects. With the continued growth in the sizes of space systems and the development of in-orbit service technologies, the cost and risk of constellation reconfiguration have been reduced, and the capabilities of orbital maneuvering have been greatly enhanced. Meanwhile, the decision space for reconfiguration mission planning has also been expanded, and multiple conflicting objectives introduce more difficulties in decision making.

Recent research in constellation reconfiguration mainly focuses on how to reposition particular satellites into another configuration in a shorter time and at a lower cost. Weck et al. proposed a generic framework for reconfiguration problems using an auction algorithm to determine the optimal allocation efficiently and reliably and applied the framework to the optimal design of low-orbit communications constellations [1]. Soleymani et al. proposed a particle swarm/genetic hybrid algorithm based on

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Lambert’s theory to determine the optimal reconfiguration with two constraints: the total reconfiguration cost and the final pattern [2]. To achieve collision avoidance and to minimize the total fuel consumption during constellation reconfiguration, Fakoor et al. proposed a hybrid invasive weed optimization/particle swarm optimization (IWO/PSO) method to perform satellite assignment and design the orbits in the same step [3]. Chen et al. proposed a new adaptive variable-length multi-objective differential evolution algorithm for planning the optimal reconfiguration scheme for satellites in a short period of time. The main contribution of this approach is the use of fixed-length chromosome encoding schemes combined with expression vectors, and three coverage metrics were demonstrated to assess the reconfiguration performance [4]. The current research efforts are primarily oriented towards small or medium-sized constellations with around dozens of satellites. With the continued growth in sizes of the space systems, constellation reconfiguration problems also need focus on system-level resource allocation, which complicates the problem even further and poses great challenges to high-dimensional decision-making.

Multi-objective evolutionary algorithms with global optimization and interdisciplinary problem-solving capabilities are suitable for solving various types of nonlinear, discontinuous, and non-convex problems [4,5]. However, since the traditional evolution operators do not integrate any domain-relevant prior knowledge, the solution patterns for different problems are the same. Thus, the generality of these algorithms also restricts their capabilities to find global optima to some extent. To fully explore the decision space, solving practical problems should focus on the domain and use knowledge-related heuristics to facilitate the convergence of the algorithms. It has been shown that domain knowledge can guide algorithms to mine potential regions of the decision space, and integrating problem-related or domain-related knowledge into an evolutionary algorithm can effectively improve the search performance [6]. To address the problem of optimizing the design of Earth observation systems, Selva proposed a knowledge-intensive global optimization framework that applies domain-relevant knowledge as heuristics similar to the “IF-THEN” form, e.g., “removes random instrument from a random big satellite” to solve high-dimensional decision space exploration problems [7]. Knowledge-dependent operators are similar to variational operators in that they create offspring by perturbing an individual’s decision variables and control the population generation and evolutionary selection through the application of domain knowledge.

For knowledge-driven optimization (KDO) algorithms, the great challenge is to obtain and apply effective domain knowledge according to specific problems. There are two main types of traditional methods for acquiring domain knowledge: one is to make use of data visualization methods, such as self-organizing map (SOM) [8], biplots [9], and isomaps [10]. Data visualization based methods provide an intuitive presentation of a dataset to assist users in making analytical decisions. Data visualization based methods are highly subjective, and the results vary widely depending on individual preferences. Another class of methods extracts knowledge into explicit mathematical expressions, such as decision trees [11], fuzzy systems [12], and algorithm quasi-optimal learning (AQ) [13]. Machine learning algorithms are well suited for performing supervised learning on the optimized set of non-dominated solutions from available knowledge to aid future design. Bandaru et al. proposed an automated innovation algorithm to search for innovative design principles that reveal in the final or intermediate solution sets [14]. It automatically detected correlations between problem variables, objective functions, and constraints in the obtained optimal solution set using grid-based clustering algorithms. Meanwhile, over-reliance on knowledge will prevent the evolutionary algorithms from fully exploring the decision space, leading to premature convergence of the algorithm and producing a local optimal solution [15]. The performance of the operators changes dynamically during the optimization process and cannot be predicted in advance. An adaptive operator selection (AOS) provides a high-level operator management by dynamically evaluating and allocating operators to improve the efficiency and performance of the algorithm and reduce the operator sensitivity [16]. Hence, the key issue of the KDO algorithms is how to identify and reasonably apply effective knowledge-dependent operators to guide the algorithm.

To solve multi-objective optimization problems with high dimensionality and large decision spaces, domain knowledge should be extracted and applied to guide the algorithm’s search for promising regions of the decision space. This paper proposes an adaptive innovation-driven multi-objective evolutionary algorithm (MOEA-AI). Available innovation principles are extracted from final or intermediate solution sets by automated innovation mechanisms. Domain knowledge and innovation principles are integrated into an operator via AOS to control the population generation and the evolutionary selection. An integrated AOS operator management module is proposed to achieve the cooperative optimization of conventional and innovative operators and to prevent the overuse of a single operator caused by the “precocity” phenomenon. The efficacy of the MOEA-AI framework is demonstrated for the optimal reconfiguration of constellations for emergency situations.

This paper is organized as follows. In Section 2, the constellation in-orbit reconfiguration procedure is analyzed, and a multi-objective optimization problem model is constructed to meet the needs of emergency situations. In Section 3, an MOEA-AI framework is introduced, and the use of AOS and the innovation operator is demonstrated. In Section 4, the effectiveness of the model and methods proposed in this paper is analyzed and validated through simulations of a disaster response. Finally, the conclusions are discussed in Section 5.

2. Problem formulation

Generally, satellite constellations are deployed to perform long-term global or regional observation missions. When an urgent problem occurs, e.g., a disaster or satellite failure, constellation reconfiguration by in-orbit maneuvers is necessary to enable a rapid response. In this section, a mathematical model of constellation reconfiguration involving several critical steps for emergency situation requirements is analyzed and constructed. A multi-objective optimization problem model based on mission effectiveness metrics is proposed.

2.1 Reconfiguration procedure

To provide rapid response for emergency missions, constellation reconfiguration is required to perform assignment at first, the assigned satellites execute maneuvers to respond to urgent targets, and the un-assigned satellites also need to adjust the initial constellation configuration to reduce the effectiveness losses of the original system.

2.1.1 Satellite assignment

The aim of the satellite assignment task is to determine which satellites will respond to the emergency task based on the requirements. Because of the different fuel stocks of each satellite and the unpredictability of the fuel consumption required for in-orbit maneuvering, the assignment of satellites is based on a penalty function, which is high for satellites that will consume all the fuel or that do not have sufficient fuel to complete the maneuver. The penalty term will guide the optimization algorithm to discard excessively costly schemes and promote fast convergence of the algorithm. Meanwhile, reconfiguration inevitably has a significant impact on the initial constellation performance, reducing the performance of the original mission. Satellites that are not assigned a contingency mission must still choose whether to adjust the initial constellation configuration to reduce the effectiveness losses of the original system through phase-shift maneuvers.

The constellation reconfiguration problem for emergency missions first addresses the dynamic resource allocation problem of searching for the optimal combination of the configuration pattern and the orbital parameters. During the resource allocation phase, there are several options for each satellite, including participation in reconfiguration, phase adjustment, and state maintenance, as shown in Fig. 1.

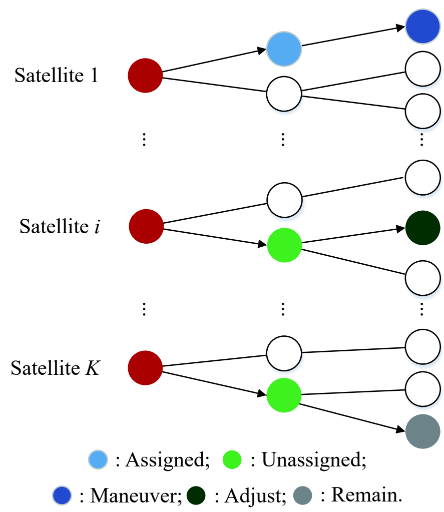
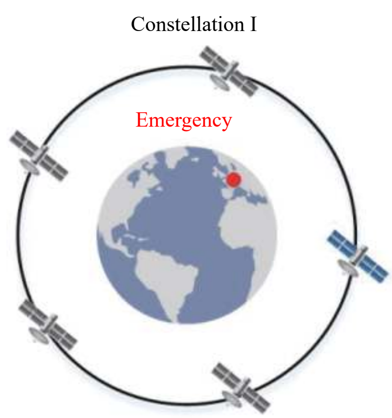


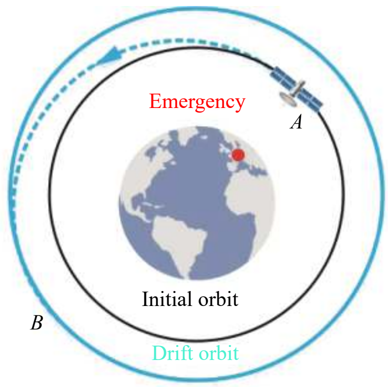
Fig. 1 Process of constellation reconfiguration for emergency

2.1.2 Reconfiguration maneuver

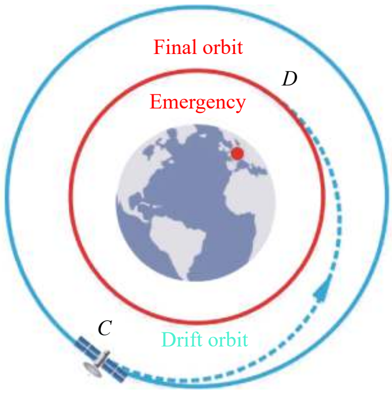
The essential purpose of the reconfiguration is to place satellites into new orbits to provide rapid emergency responses. Generally, the retasked and reconfigured satellites utilize coplanar orbital transfer for economic cost. The orbital transfer between coplanar circular orbits is accomplished by one or two Homan transfer maneuvers [17]. The process of constellation reconfiguration is illustrated in Fig. 2.



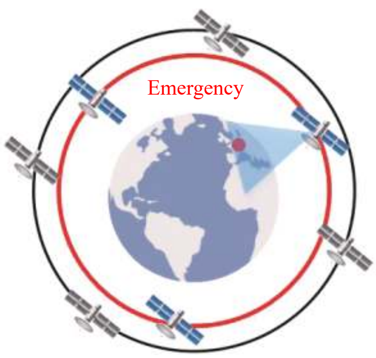
(a) Satellite assignment



(b) Transfer to drift orbit



(c) Transfer to final orbit



(d) Constellations after reconfiguration

Fig. 2 Process of constellation reconfiguration for emergency

First, the assigned satellite performs an initial propulsive maneuver Δv_A at point A of the initial orbit, with the same direction as the local velocity, into an elliptical drift orbit. A second propulsive maneuver Δv_B with the same direction as that of the local velocity is performed at point B after running half a revolution on the elliptical drift orbit. The satellite enters a circular transfer orbit with an altitude of $a_D = a_0 + \Delta h_D$, which is tangent to the elliptical drift orbit. For proper adjustment of the orbital state, the satellite waits in the circular transfer orbit for a period of time t_D. When proper orbital phasing occurs, the satellite performs a second Homan transfer to a final orbit with an altitude of a_F, which includes an initial propulsive maneuver Δv_C to enter the elliptical drift orbit and the final propulsive maneuver Δv_D to enter the desired orbit. The total transfer time is given as follows:

$$t_R = t_{T1} + t_D + t_{T2} \tag{1}$$

where t_{T1} is the duration of the satellite in the first drift orbit, which is equal to $\pi\sqrt{a_{T1}^3/\mu}$, and t_{T2} is the duration of the satellite in the first drift orbit, which is equal to $\pi\sqrt{a_{T2}^3/\mu}$. Additionally, μ is the Earth's gravitational constant. a_{T1} and a_{T2} are the altitudes of the two drift orbits, which can be calculated as follows:

$$a_{T1} = \frac{2a_0 + \Delta h_D}{2}, \tag{2}$$

$$a_{T2} = \frac{a_0 + \Delta h_D + a_F}{2}. \tag{3}$$

The total velocity change of the reconfiguration Δv_R can be calculated using the following equation:

$$\Delta v_R = \Delta v_A + \Delta v_B + \Delta v_C + \Delta v_D \tag{4}$$

where

$$\Delta v_A = \left|\sqrt{\frac{2\mu}{a_0} - \frac{\mu}{a_{T1}}} - \sqrt{\frac{\mu}{a_0}}\right|, \tag{5}$$

$$\Delta v_B = \left|\sqrt{\frac{2\mu}{a_D} - \frac{\mu}{a_{T1}}} - \sqrt{\frac{\mu}{a_D}}\right|, \tag{6}$$

$$\Delta v_C = \left|\sqrt{\frac{2\mu}{a_D} - \frac{\mu}{a_{T2}}} - \sqrt{\frac{\mu}{a_D}}\right|, \tag{7}$$

$$\Delta v_D = \left|\sqrt{\frac{2\mu}{a_F} - \frac{\mu}{a_{T2}}} - \sqrt{\frac{\mu}{a_F}}\right|. \tag{8}$$

During the reconfiguration process, the variations of the right ascension of the ascending node (RAAN) Ω_f and the phase angle M_f due to the influence of the J_2 harmonic perturbation term are given by the following equations:

$$\Omega_f = \Omega_0 + \dot{\Omega}_{T1} t_{T1} + \dot{\Omega}_D t_D + \dot{\Omega}_{T2} t_{T2}, \tag{9}$$

$$M_f = M_0 + \left(n_{T1} + \dot{\omega}_{T1} + \dot{M}_{T1}\right) t_{T1} + \left(n_D + \dot{\omega}_D + \dot{M}_D\right) t_D + \left(n_{T2} + \dot{\omega}_{T2} + \dot{M}_{T2}\right) t_{T2}, \tag{10}$$

where Ω_0 and M_0 are the initial orbital states, n_{T1}, n_D, n_{T2} are the mean motions at different stages, ω_{T1}, ω_D, ω_{T2} are the arguments of perigee, the relations for n, $\dot{\Omega}$, $\dot{\omega}$, $\dot{M}$ are given by

$$\dot{\Omega} = -\frac{3\sqrt{\mu}J_2R_E^2}{2a_s^{\frac{7}{2}}}\cos i_s, \tag{11}$$

$$\dot{\omega} = \dot{\Omega}\frac{1-5\cos^2 i_s}{2\cos i_s}, \tag{12}$$

$$\dot{M} = \frac{3J_2R_E^2}{2a_s{}^2}n\left(1-\frac{3}{2}\sin^2 i_s\right), \tag{13}$$

where R_E is the equatorial radius of the Earth, a_s is the semi-major axis, and i_s is the inclination.

2.2 General formulation of multi-objective optimization

2.2.1 Optimization objectives

In this paper, the constellation reconfiguration problem for emergency missions is treated as a search for the optimal combination of the configuration pattern and orbital parameters to achieve the optimization objectives, including maximizing the effectiveness of the reconfiguration and minimizing the propulsive fuel consumption and maneuver time.

(i) Total coverage time (TCT)

The TCT one of the fundamental in-dicators for evaluating the observation performance, which is obtained by summing the durations of each access window [18]. In reconfiguration missions, the performance of the original conventional mission must be taken into account. Therefore, the TCT is evaluated uni-formly for both conventional and emergency targets along with weights:

$$\mathrm{TCT} = \sum_{i=1}^{K}\sum_{j=1}^{p^i}\omega_{\text{target}}\left(\omega_{end}^{i,j}-\omega_{\text{begin}}^{i,j}\right) \tag{14}$$

where K is the total count of satellites, p^i is the number of all coverage windows for the ith satellite. The jth coverage window of the ith satellite is recorded by the start time $\omega_{\text{begin}}^{i,j}$ and the end time $\omega_{\text{end}}^{i,j}$, and ω_{target} denotes the weight of the target. The weight of the emergency target is generally greater than that of the conventional target.

(ii) Average revisit time (ART)

The revisit time, which is generally obtained by calculating the interval between adjacent access windows, can be used to effectively evaluate the frequency of visits. The ART is calculated by the following equation:

$$\mathrm{ART} = \frac{\sum_{i=1}^{K}\sum_{j=1}^{m^i}\omega_{\text{target}}\left(g_{\text{end}}^{i,j}-g_{\text{begin}}^{i,j}\right)}{\sum_{i=1}^{K}m^i} \tag{15}$$

where m^i is the number of all gap windows for the ith satellite. The jth gap window of the ith satellite is recorded by the start time $g_{\text{begin}}^{i,j}$ and the end time $g_{\text{end}}^{i,j}$.

(iii) Total ΔV

In this paper, the energy replenishment of in-orbit satellites is not considered. To ensure that the reconfiguration does not overly affect the lifetime of the satellites, the energy consumption during the reconfiguration must be minimized to achieve a rapid response at the lowest economic cost:

$$\Delta V_{\text{Total}} = \sum_{i=1}^{K}\Delta v_R^i \tag{16}$$

where Δv_R^i is the velocity change of the orbital maneuver of the ith satellite.

(iv) Maximum maneuvering time (MMT)

It is assumed that all satellites start maneuvering at the same moment, so that the MMT is the maximum time of the satellites in the constellation reconfiguration:

$$\mathrm{MMT} = \max\left\{t_R^i \middle| 1 \leqslant i \leqslant K\right\} \tag{17}$$

where t_R^i is the maneuvering time of the ith satellite.

2.2.2 Formulation

Based on the requirement of the emergency situations and the initial parameters of the constellation, the reconfiguration problem model can be expressed by

$$\begin{cases} \text{Maximize TCT} \\ \text{Minimize ART}, \Delta V_{\text{Total}}, \text{MMT} \\ \text{s.t.} \quad \Delta v_R^i \leqslant \Delta v_{\max}^i, \forall i \leqslant K \end{cases}$$

where $\Delta v_{\max}^i$ is the maximum surplus of the velocity changes of the ith satellite. Constellation reconfiguration problems for emergency missions are non-linear and non-convex practical problems, which are well suited for multi-objective evolutionary algorithms.

3. MOEA-AI framework

3.1 Optimization framework

A multi-objective optimization framework that employs AOS and automated innovation to solve the nonlinear and nonconvex problem of constellation reconfiguration is proposed. AOS, as a top-level strategy for the management of operations, is combined with automated innovation to extract knowledge-dependent principles that may make contributions to the convergence of algorithms and help guide the algorithms to explore the promising regions of a decision space. As shown in Fig. 3, the workflow of the optimization framework can be divided into two main branches. One performs conventional evolutionary operations, such as offspring evaluation and population updating, which are independent of the domain knowledge. The other starts with intermediate solutions obtained from several increment iteration runs. To overcome the low quality of useful knowledge extracted from the previously discovered solutions, we employ significance to indicate the quality of knowledge-dependent operators. Only when the significance of an operator meets the demand of the minimum value is it inserted into a candidate set to perturb or recombine solutions in the evolutionary operation. Additionally, the AOS evaluates and selects operators based on their performance, which helps to identify useful operators from the candidate set.

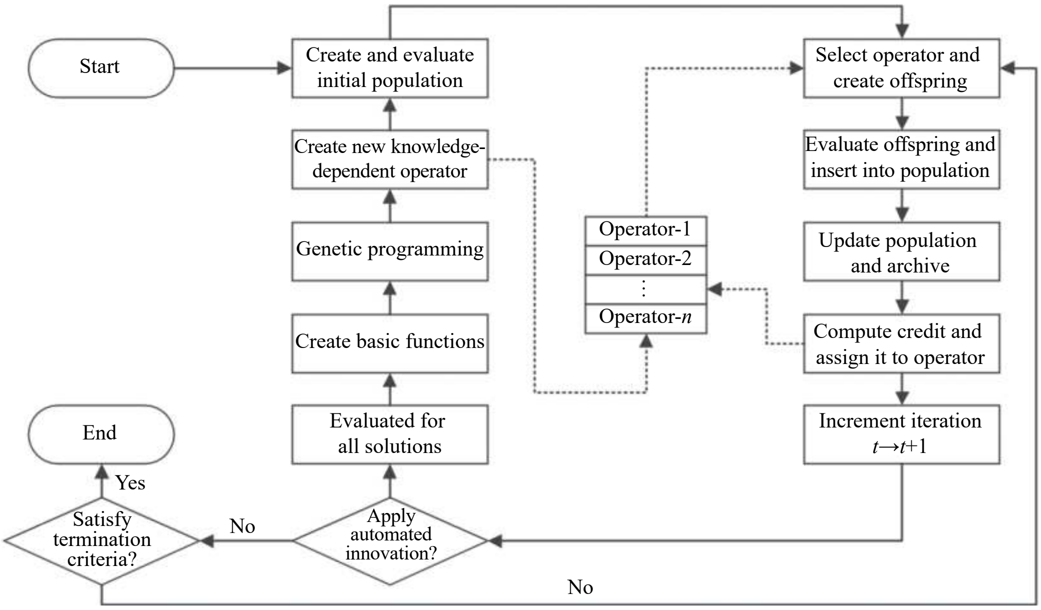


Fig. 3 Optimization framework of agile satellite constellation design

Algorithm 1 gives the pseudo-code of the MOEA-AI framework. Lines 1–3 show the initialization of the algorithm, including the setup of the population and elite profiles. Starting from line 4, the iterative operation of the genetic algorithm is performed until the terminal condition is met. In lines 7–10, the algorithm selects the appropriate operator o_i via AOS and the individuals involved in operator o_i in the generation. After completing the operation, the algorithm evaluates the offspring through fitness functions to assess whether the offspring enters the next generation. In line 13, the algorithm assigns credits to the operator based on the dominance of that offspring. In lines 15–18, the algorithm automatically innovates based on the current solution set and exploits the operator with a high level of significance. The operator is added to the operator sequence when its significance satisfies the requirement.

Algorithm 1 Framework pseudocode

1 $P \leftarrow$initializePopulation();
2 $A_{\text{best}} \leftarrow$initializeBestArchive();
3 iteration $t \leftarrow 0$;
4 **while** Termination criteria have not been satisfied **do**
5 $P_0 \leftarrow \phi$ **while** $|P_0| < n$ **do**
6 $t++$;
7 $o_i \leftarrow$selectOperator();
8 $\gamma \leftarrow$selectParentSolutions();
9 $x^{o_i,t} \leftarrow o_i$.operate(γ);
10 evaluate$(x^{o_i,t})$;
11 $P_0 \leftarrow P_0 \cup \{x^{o_i,t}\}$
12 updateBestArchive$(x^{o_i,t})$
13 rewardOperator(o_i);
14 **end while**
15 **If** apply innovation **then**
16 knowledge= automaticInnovation(A_{best});
17 updateOperators(knowledge);
18 **end if**
19 $P \leftarrow$ select$(P \cup P_0)$
20 **end while**

3.2 Automated innovation

Automated innovation combines the problem variables, the objective and constraint functions, and their linear combinations as basic functions to form $\varphi(x)$, and an alternative set $T = \{\varphi_1, \varphi_1, \cdots, \varphi_N\}$ consists of N basic functions. The mathematical expression for a design principle $\psi(\varphi(x))$ is constructed by a linear combination of the basic functions. A numerical value c can be calculated by the design principle and each vector in the given solution set. The distribution of c values is used to determine whether the design principle expresses important relationships hidden in the set of solutions. The expression for a design principle [16] is given by the following formula:

$$\psi(\varphi(x)) = \prod_{j=1}^{N} \varphi_j(x)^{a_j b_j} = c \tag{18}$$

where a_j is a Boolean variable indicating whether $\varphi_j(x)$ is selected or not, and b_j is the power of $\varphi_j(x)$. By definition, when a design principle is valid, it means that $\prod_{j=1}^{N} \varphi_j(x)^{a_j b_j} = c$ is correct for most of the undominated solution sets.

The formula cannot remain constant due to the approximation of the undominated solution set. Therefore, the distribution of c values must be clustered to find a design principle that is general for more cases. An optimization model is constructed to minimize the number of clusters and the percentage coefficients of the variables in each cluster to obtain an effective design principle [19]. The optimization problem model is represented by the following expression:

$$\begin{gathered}\text{Minimize } C + \sum_{k=1}^{c} c_v^{(k)} \times 100\%, \\ c_v^{(k)} = \frac{\sigma_c}{\mu_c},\ \forall c \in \text{ the } k\text{th cluster},\end{gathered} \tag{19}$$

where C is the number of clusters, σ_c is the standard deviation, and μ_c is the mean of the c values, respectively.

Automated innovation uses genetic programming (GP) to solve the above optimization model. In general, the initial population of GP is randomly generated by a given function set F and termination set T combined with parameters. We can treat the events of the randomly generated individuals as elements randomly obtained from the function set and termination set, creating nodes (root or child nodes) and specifying random processes for their connected random child nodes. Expressions for arbitrary design principles $\psi(\varphi(x))$ can be represented by a tree structure.

In GP, fitness functions are assessed by a grid-based clustering algorithm [20], which ranks the c values obtained by arbitrary design principles. The grid-based clustering algorithm marks the divisions with c values less than $\lfloor m/d \rfloor$ as non-clustered, where m is the total number of c values, and d is the number of divisions, which is treated as the design variable to optimize. The adjacent divisions with c values no less than $\lfloor m/d \rfloor$ become a cluster, so that the final accumulative number of clusters is evaluated as the fitness of one innovation solution. Finally, the commonality and practicability of a design principle $\psi(\varphi(x))$ is called the significance [20], which is defined as follows:

$$S = \frac{m - U'}{m} \times 100\% \tag{20}$$

where U' is the number of un-clustered values, which is calculated by the accrued with divisions less than $\lfloor m/d + \varepsilon \rfloor$ values, and ε is a small integer value chosen by the user. When the significance S of an obtained principle has a requirement, e.g., a value of 80%, the design principle can be applied in the algorithm as an innovation operator.

The influence of an innovation operator can be deemed to be a repair process of the offspring. The input of an innovation operator is a single individual of the offspring. According to the power-law form of the innovation operator described above, the base function $\varphi_i(x)$ is randomly selected to perform the repair operation, which is represented by the following expression:

$$\varphi_i(x) = \left(\frac{\bar{c}}{\prod_{j \neq i} \varphi_j^{b_j}(x)} \right)^{\frac{1}{b_i}} \tag{21}$$

where $\bar{c}$ is the average value of c values calculated in the automated innovation.

3.3 Adaptive operator selection

The AOS consists of two parts: an operator selection strategy and a credit assignment strategy. The operator selection strategy is responsible for selecting the operators that can produce high-quality solution sets to proceed to the next evolutionary iteration. The credit assignment evaluates the performance of the operators based on the contribution of the offspring to the population. AOS selects the appropriate operator to complete the evolutionary operation based on the quality of the solution set created by the operator and the performance of the operator during the evolutionary process. To balance the impact of knowledge and the evolutionary algorithm itself on the solution set, in addition to using knowledge-related operators learned by automated innovation, typical evolutionary operations, including crossovers and mutations, are also needed.

3.3.1 Operator selection

Since the performance of the operators is dynamically changing, trade-offs of different operators are crucial. Given a finite set of operators O, the operator $o_{i,t} \in O$, which is applied in each iteration, is selected according to the probability $p_{i,t}$. The selection probability is calculated as follows:

$$p_{i,t+1} = \begin{cases} p_{i,t} + \beta \cdot (p_{\max} - p_{i,t}), & o_i = \arg\max_{o_i \in O} q_{i,t} \\ p_{i,t} + \beta \cdot (p_{\min} - p_{i,t}), & \text{otherwise} \end{cases} \tag{22}$$

where $q_{i,t}$ is the quality of the operator $o_{i,t}$ at iteration t, which is determined by the credit $h_{i,t}$, as follows:

$$q_{i,t+1} = (1 - \alpha) \cdot q_{i,t} + \alpha \cdot h_{i,t}. \tag{23}$$

In this paper, the selection probabilities are handled with the adaptive pursuit (AP) method [21]. In AP, a minimum selection probability $p_{\min}$ and a maximum selection probability $p_{\max}$ are employed to balance the selection between the low- and high-performance operators. The minimum selection probability can foster the exploration of poorly performing operators. The maximum selection probability $p_{\max}$ prevents the algorithm from overusing the well-performing operators with a high credit $h_{i,t}$, which is defined as follows:

$$p_{\max} = (1-(|O|-1)\cdot p_{\min}). \tag{24}$$

3.3.2 Credit assignment

In population-based searches, it is fundamental to assign a high credit to well-performing operators. Pareto dominance is a popular choice for credit assignment to measure the performances of operators [22]. The input of dominance-based credit assignment is implemented by the dominance relationship between an offspring $x^{o_{i,t}}$ generated by operator $o_{i,t}$ and its parent x^p:

$$h_{i,t}=\begin{cases} 1, & x^{o_{i,t}} \prec x^p \\ 0, & \text{otherwise} \end{cases} \tag{25}$$

where $h_{i,t}$ is the credit assigned to the operator $o_{i,t}$ at iteration t.

4. Simulation

4.1 Scenario assumption

Taking a tsunami as an example, several simulation cases were developed to investigate the optimal constellation reconfiguration using MOEA-AI. We suppose that a Walker 30/6/1 constellation with an orbital altitude of 410.0 km has been deployed to perform a long-term global observation mission, and the orbital inclination i is equal to 60.8°. It is assumed that a tsunami occurs at 22:18 UTC on December 12, 2022, and has an extreme impact on port cities. The coastline has an urgent demand for observation. In Fig. 4, the black dots indicate the initial regular targets, and the red dots indicate the emergency targets that require rapid observation.

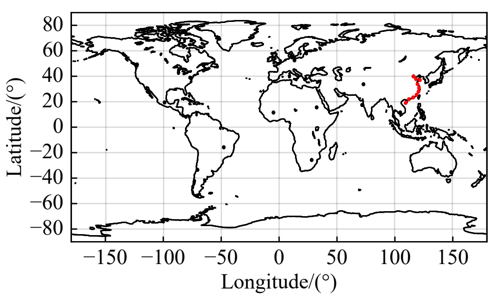


Fig. 4 Regular and emergency target distribution

A comparative study was conducted to investigate the performance of the AI operators and the effect of the AOS. The first case established a baseline design using the dominance-based multi-objective optimization algorithm non-dominated sorting genetic algorithm-II (NSGA-II) with conventional evolutionary operator differential evolutionary (DE/rand/1), simulated binary crossover, uniform mutation (UM), and parent-centric crossover. This case is denoted as MOEA-0. Another class of operators considered the credit-based AOS algorithm for assignment, dominance-based credits. The collection and use of the NSGA-II is referred to as MOEA-AOS. To apply the optimization algorithm, we designed the AOS algorithm based on the application of innovative principles, which is referred to as MOEA-AI. To ensure the consistency of the algorithm baseline, the algorithm base parameters are shown in Table 1 [23].

Table 1 Algorithm parameters

Mission parameter	Value
Population size	300
Generation	200
Crossover probability	0.5
Mutation probability (n is the number of variables)	$1/n$
Probability of selecting mating pool	0.9
Minimum probability of selecting an operator $p_{\min}$	0.1

4.2 Results and discussion

4.2.1 Search performance

The convergence, uniformity, and universality of different sets of solutions were compared with hypervolume (HV). The HV evaluation method was first proposed by Zitzler et al., which represents the volume of a hypercube surrounded by the individual and reference points in the target space [24]. The HV can simultaneously evaluate the convergence and the diversity without knowing the real Pareto Frontier or reference set, so it has become a very popular multi-objective optimization algorithm evaluation index [25].

The optimization cases were simulated for 30 trials each. Fig. 5 represents the historical curve of the HV as a function of the number of iterations. The shaded areas present the upper and lower bounds of the historical data, and the lines indicate the average values of 30 runs. The red, blue, and green curves and shaded areas correspond to the MOEA-AI, MOEA-AOS, and MOEA-0, respectively. The comprehensive performance of the MOEA-AI was better than the others since the AI operators were generated at the 300th iteration. The highest HV value of the MOEA-AI reached 0.971 3, which was proven to be a suitable indicator of the near-optimal solutions. The historical curves of the MOEA-0 and the MOEA-AOS remained flat through the entire optimization process. This indicated that the traditional evolutionary algorithms with conventional evolutionary operators had difficulty with the constellation reconfiguration problem with a high dimension and an extremely large decision space. Additionally, the AOS strategy for promoting the high-performance operators had little effect on the convergence of the algorithms without domain knowledge. As a result, the conventional evolutionary operators made full use of the random selection and evolutionary operation, which could not significantly promote the exploration process. The automatic innovation module worked as an inspector to extract and create useful design principles over the intermediate solutions. Only if the significance of the extracted principle was beyond 90% could it be applied in the optimization as an operator. Therefore, the HV indicators demonstrated that the automatic innovation operators associated with valid design principles are helpful for guiding the algorithms to search for promising solutions and quickly converge.

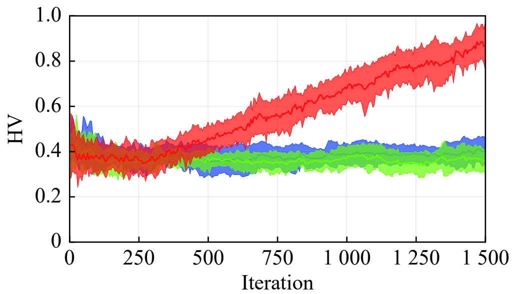


Fig. 5 HV history of three cases for 30 trials

4.2.2 Optimization efficiency

To analyze the optimization efficiency of the overall framework under different schemes, three kinds of simulations were developed with different scales of issues. To eliminate additional confounding factors, we selected the original pattern of the constellation as the varying parameter to test the maximum optimization capacity. The metrics of the median HV, the average computing time (ACT) of one iteration, and the average number of iterations (ANI) required to attain 90% of HV* were employed to quantify the optimization efficiency of the overall framework. The algorithm parameters are given in Table 1, and the maximum total numbers of satellites were set to 100, 300, and 1 000. Table 2 shows the calculation results of the simulations for 30 runs each where a higher value of the median HV signifies that the solutions were closer to the true Pareto frontier. The median HV values of three simulations reached convergence levels of 90% of HV*, which was generally equal to 0.9. As the number of satellites increased, the computation cost of the overall framework increased due to the time-consuming propagation of the satellites. The ACT of one iteration was basically proportional to the number of satellites. Meanwhile, the ANI to attain 90% of HV* did not change significantly, which demonstrated that the AOS strategy aided the algorithm in finding well-performing solutions with fewer evaluations. As a result, this indicated that the limit of the maximum optimization capacity primarily depended on the propagation of satellites for coverage analysis. The proposed strategy was efficient and robust for any number of satellites, and in some cases it decreased the number of unnecessary calculations of propagation by helping the algorithm to rapidly converge.

Table 2 Metrics of simulation results

Original pattern	Median HV	ACT/s	ANI
Walker 30/6/1	0.870 1	73.189 0	1 300.7
Walker 300/20/12	0.813 4	435.010 5	1 354.3
Walker 800/50/6	0.809 7	813.332 7	1 317.1

4.2.3 Operator selection history

The historical selection during the search process provides further insight into the benefit of the design principle at each iteration. In Fig. 6, the red curve shows the total historical selection of the innovation operators for 30 trials, and the blue curve shows the total historical selection of the conventional evolutionary operators. At first glance, it is evident that the AOS preferred the innovation operators rather than the conventional evolutionary operators, even when the innovation operators were just generated. According to the AOS strategy described in the previous section, the prior choice of operators was determined by their searching performance and the ability to produce elite offspring. Since the selection probabilities were handled with the AP method, a minimum selection probability and a maximum selection probability were employed to balance the selection between low-performance and high-performance operators. The conventional evolutionary operators still had opportunities to be selected. However, the performance of knowledge-independent operators remained at a low-level. Additionally, the peak distribution of operator selection can be interpreted as the influence of random probability.

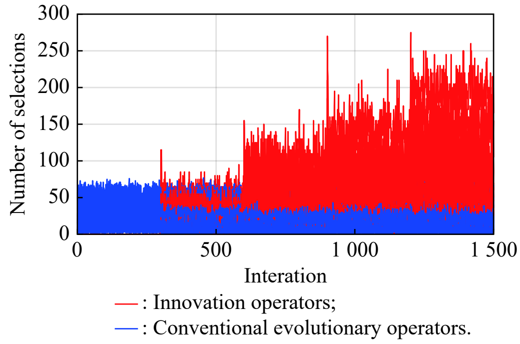
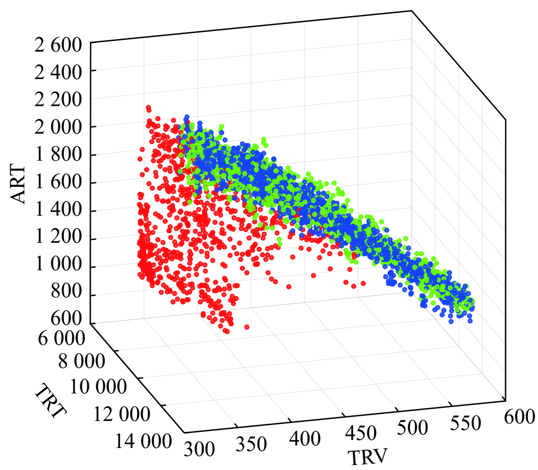


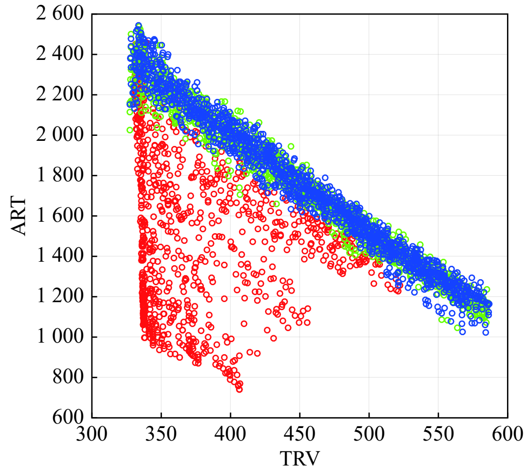
Fig. 6 Selection history of MOEA-AI for 30 trials

4.2.4 Solution quality

The visualization of the distribution of the optimal solutions provides an intuitive and expansive view of the decision space. In Fig. 7(a), the red dots correspond to the solutions of the MOEA-AI. The results indicate that the MOEA-AI discovered a more promising region of the solution space than the MOEA-0 and the MOEA-AOS did. For constellation reconfiguration, the target is to achieve the maximum coverage performance with a minimum cost. Fig. 7(b) demonstrates that even with the lowest reconfiguration energy consumption, the solutions of the MOEA-AI provided smaller ARTs than the lowest values that the MOEA-0 and the MOEA-AOS could achieve. The results indicate that the solutions of the MOEA-AI were nondominated, which is consistent with the results of the HV indices. Due to the extremely large search spaces of real-world problems, the MOEA-0 and the MOEA-AOS require significantly more generations to discover the feasible solutions due to the limited capabilities of conventional evolutionary operators without domain knowledge.



(a) Three-dimensional distribution of the solutions



(b) ART vs. TRV

Fig. 7 Distribution visualization of the solutions

From the solution set of the MOEA-AOS, we selected three solutions for comparison with original constellation. As shown in Table 3, the coverage metrics of original constellation towards emergency targets were undesired. With the optimal reconfiguration of original constellation using the proposed method, the capability of emergency response has been enhanced to varying degrees. Solution 1 provides an option of prominent increase on TCT and decrease on ART for emergency targets with inevitable loss of original effectiveness. It seems that solution 2 provides a low-cost choice with desired performance. Meanwhile, solution 3 seems take a high cost of reconfiguration, but it achieves an excellent TCT for both emergency and original targets. In summary, after obtaining a non-dominant solution set with outstanding performance by the proposed method, decision makers need to select a final solution that combines their own preferences and practical needs.

Table 3 Simulation results

Solution	TCT of original targets/h	TCT of emergency targets/h	ART/h	TotalΔV/(m/s)	MMT/h
Original constellation	538.2	331.6	17.2	0.0	0.0
Solution 1	359.4	613.3	10.7	405.1	3.5
Solution 2	471.8	531.8	16.3	361.8	3.1
Solution 3	519.8	522.3	18.6	466.0	4.7

5. Conclusions

This work focused on the problem of multi-objective optimization for constellation reconfiguration, and an MOEA-AI is proposed to solve real-world problems with high dimensionality and large decision spaces. An in-depth analysis of the system-level scheduling problem of constellation reconfiguration and the combinatorial strategy model is conducted. Automated innovation techniques are used to extract effective design principles from the set of non-dominant solutions to guide the optimal design algorithms to search for potential regions of the decision space. Main innovations are as follows:

(i) Classical constellation reconfiguration problems just focused on the orbital adjustment to meet the urgent needs. The problem model in this paper is constructed from system view to enhance the overall performance of original and emergency missions.

(ii) The proposed method distinguishes from traditional algorithms in favor of the extraction and application of domain knowledge, which helps solving such non-deterministic polynominal-time hard (NP-hard) problems, also it may be beneficial for future design.

(iii) An integrated AOS operator management module is proposed to achieve the cooperative optimization of conventional and innovative operators and to prevent the overuse of a single operator caused by the "precocity" phenomenon. The AOS is confirmed to promote the rapid convergence of the algorithm to global optima.

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