

Article

Global Optimization Design of Large-Scale Constellations for Maritime Target Detection Based on Circular Scanning Radar

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Highlights

What are the main findings?

- A quantitative space-based multi-target tracking model is established to explicitly link the constellation revisit period, payload accuracy, target maneuverability, and maximum trackable density. This analytical model provides a theoretical foundation for constellation optimization.
- A three-objective optimization framework (constellation size, average revisit time, and coefficient of variation of revisit time) was developed under a space-ground integrated architecture, enabling Pareto-optimal trade-offs among system cost, tracking timeliness, and coverage uniformity using the NSGA-II algorithm.

What are the implications of the main finding?

- The algorithm quantifies the trade-offs among constellation cost, revisitation timeliness, and spatial uniformity, thereby validating the performance of the optimization framework.
- By synthesizing the quantitative multi-target tracking capability model with constellation optimization, this work provides a scientific, efficient, and deployable solution for the engineering design of maritime moving-target tracking constellations.

Abstract

Traditional Low Earth Orbit (LEO) satellite constellation design methods, primarily driven by geometric coverage, fail to satisfy the non-uniform and dynamic tracking requirements of moving targets. To address this, a multi-objective optimization framework for large-scale satellite constellations is proposed. This framework is task-driven, constraint-guided, and integrates space and ground segments. A quantitative model is established to characterize the multi-target tracking capability of space-based sensing systems. The model explicitly links the constellation revisit period, payload detection and positioning performance, target maneuverability, and the maximum trackable target density. These relationships are then formulated as optimization objectives and constraints. To capture temporal consistency in observation performance, the coefficient of variation of revisit time is introduced as an independent optimization objective. This yields a three-objective optimization problem that addresses tracking performance, coverage uniformity, and system cost, enabling Pareto-optimal constellation design solutions. Simulation results demonstrate that the proposed method improves track association performance in representative maritime target tracking scenarios when compared with

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conventional coverage-driven constellation designs. The proposed framework provides a systematic and implementable approach for constellation design by integrating capability modeling with multi-objective optimization at the system level.

Keywords: moving targets tracking; LEO satellite constellation; multi-objective optimization; the Non-dominated Sorting Genetic Algorithm II (NSGA-II)

1. Introduction

Maritime target tracking is critical for safeguarding maritime rights and interests [1], ensuring shipping safety [2], and supervising fishery resources [3]. Given their wide-area coverage, rapid revisit capabilities, and all-weather accessibility, Low Earth Orbit (LEO) satellite constellations are the primary space-based infrastructure for the persistent detection of large-scale and highly dynamic maritime targets [4]. In this work, spaceborne circular-scanning radar is considered as the primary observation modality, owing to its wide-swath coverage and continuous rotating beam operation. Traditional constellation design, however, focuses primarily on geometric metrics such as regional coverage rates and multiplicity. These traditional criteria do not address the heterogeneous requirements of dynamic target tracking tasks. This creates a gap between resource allocation and operational demands. Hotspot regions, such as international shipping lanes with dense traffic, require high-frequency revisits for precise track association; conversely, sparse deep-sea regions require only low-frequency revisitation of constellations to adequately maintain track continuity [5]. Consequently, uniform coverage leads to resource redundancy in low-traffic waters and insufficient tracking fidelity in high-value regions, limiting the efficiency of space-based assets [6]. In the context of space-based maritime moving target detection, a “large-scale” constellation refers to a highly dense, globally interconnected network composed of tens to thousands of LEO satellites distributed across tens of orbital planes [7] (in this paper, the search space bounds are parameterized as $50 \leq N_{\text{sat}} \leq 2000$). It features continuous overlapping fields-of-view (FOVs), heavy multi-satellite geometric intersections, and the capability of global multi-target persistent tracking.

This technical limitation originates from the separation of space-based constellation design and maritime target association methodologies, which has hindered the development of a space-ground integrated collaborative framework. On one hand, traditional design approaches do not incorporate mission-specific characteristics, such as target density and maneuverability, into the optimization of constellation parameters like revisit cycles and payload accuracy. Specifically, target motion parameters—such as target density and maneuverability—are not quantitatively mapped to constellation parameters like revisit cycles and payload detection accuracy. This yields designs that prioritize geometric uniformity or ideal coverage, rather than tailoring the constellation to the motion characteristics of moving targets. On the other hand, existing multi-target data association algorithms typically treat constellation revisit intervals as an exogenous prerequisite. Consequently, the analytical impact of space-based sensing parameters on data association performance remains largely unexplored, preventing the performance metrics of these algorithms from providing reverse, closed-loop driving forces for constellation optimization.

Recent advances in the multi-objective optimization of constellation configuration have primarily prioritized geometric coverage and temporal revisit metrics. To analyze the inherent trade-offs within LEO sparse constellations, Williams et al. employed a multi-objective genetic algorithm, revealing that average and maximum revisit periods operate as competing objectives that resist simultaneous optimization [8]. Similarly, Savitri et al. coupled a genetic algorithm with a semi-analytical method to optimize small LEO

constellations, validating the strict trade-offs between coverage percentages and revisit temporal windows [9]. Utilizing the Non-dominated Sorting Genetic Algorithm II (NSGA-II) framework, Melaku and Kim optimized CubeSat constellations to minimize global and regional average revisit periods while maximizing coverage rates; however, the distribution uniformity of revisit periods across spatially distinct target nodes was omitted from their objective space [10]. For rapid-response regional emergencies, Sun and Li [11] proposed a six-objective optimization model (including average revisit periods, total coverage durations, and maximum coverage gaps) and an NSGA-NN framework to accelerate convergence. For emergency Earth observation, Wu et al. [12] used sub-satellite point trajectory analysis to design a constellation for fixed and moving targets. They showed that an 8-satellite architecture could meet a 6 h revisit threshold for stationary targets and a 3 h threshold for dynamic missions. Furthermore, with the advancement of multi-objective evolutionary algorithms, satellite count is increasingly treated as an optimization objective, enabling the Pareto frontier between construction cost and coverage performance to be quantified. Based on the Walker- δ constellation model, Li and Shi utilized the NSGA-II algorithm to resolve simultaneous cost-coverage optimization, mapping the conflicting Pareto-optimal trade-offs that manifest alongside a cost increase [13]. In the context of LEO navigation augmentation, Han et al. leveraged MOO paradigms to downscale satellite infrastructure requirements while preserving baseline coverage capabilities [14]. In terms of algorithmic enhancements, a Walker constellation model aimed at short average revisit periods and minimal satellite counts was established by He et al. for regional remote sensing optimization, whereby an improved crayfish optimization algorithm (IMOCOA) was proposed. In their specific test cases, He et al. reported that IMOCOA outperformed NSGA-II, MOPSO, and MSSA in terms of convergence speed and population diversity [15]. Although significant advancements in terms of constellation geometric coverage and revisit timeliness have been achieved by the aforementioned optimization studies, current optimization objective systems remain predominantly tethered to bulk statistics (i.e., average or maximum revisit periods), with the spatial uniformity of revisit distributions across mission maritime zones and discrete target nodes being consistently underrepresented.

Although multi-target data association (MTDA) algorithms have been extensively addressed in the context of maritime target tracking, their development has not been integrated with orbital constellation design. Mušicki and Evans developed a joint integrated probabilistic data association (JIPDA) algorithm capable of maintaining tracks under multi-target, high-clutter environments; however, their formulation inherently presupposes a fixed and uniform sensor sampling interval [16]. In recent years, constellation revisit interval information has been directly incorporated into association formulations to enhance tracking fidelity. Hu et al. proposed an attention-guided track-pulse sequence target association network (AG-TPS-TAN), demonstrating that the coupled effect of the satellite revisit patterns and target dynamic characteristics leads to track fragmentation, which necessitates robust multi-satellite track association algorithms to preserve track continuity [17]. For dense dynamic targets in large-scale constellations with non-uniform coverage, Wang et al. [18] developed a track association method using an adaptive threshold and a multi-level assignment strategy. By dynamically parameterizing the average revisit period and detection errors, they achieved rapid screening and high-fidelity association. Nevertheless, these studies remain confined to algorithmic refinements under fixed, pre-determined constellation topologies. However, constellation design metrics, such as revisit uniformity, have not been incorporated into track association performance evaluation. A closed-loop feedback mechanism, where tracking performance drives constellation optimization, has not been realized. Therefore, a collaborative co-optimization

mechanism fusing constellation design with maritime target tracking missions is required to bridge this capability gap.

Compared to small-scale constellations, large-scale constellations introduce three fundamental challenges that complicate the optimization process. First, the search space expands exponentially with the number of orbital planes and satellites per plane. The decision variables—semi-major axis, inclination, number of planes, satellites per plane, and phase factor—interact nonlinearly, making exhaustive enumeration infeasible and requiring efficient multi-objective evolutionary algorithms such as NSGA-II. Second, the computational cost of performance evaluation scales with the satellite count; each objective evaluation requires propagating hundreds of satellites and computing visibility windows for thousands of satellite–target pairs, demanding parallel acceleration techniques [19]. Third, coverage uniformity becomes harder to achieve because adding satellites does not automatically balance revisit time distributions; inter-satellite phasing and orbital plane distribution must be carefully coordinated to avoid local oversampling or undersampling [20]. These challenges collectively motivate the constraint-guided, parallelized multi-objective optimization framework presented in this work.

Therefore, a collaborative co-optimization mechanism fusing constellation design with maritime target tracking missions is urgently required to bridge this capability gap. Given that spaceborne circular-scanning radar serves as the primary sensor for such missions due to its distinct rotating-beam geometry and wide-swath coverage, the contributions of this paper are established on its observation characteristics and are detailed as follows: First, a mathematical model for quantifying the multi-target tracking capability of space-based sensing systems is formulated. Grounded in the space-based circular-scanning radar observation mechanism, target kinematics model, and scan-differential velocity estimation, the analytical formulations for the position uncertainty radius, minimum resolution separation, and maximum resolvable density under a Poisson point process are systematically derived. Consequently, a capability quantification model for space-based multi-target tracking is established. This model quantitatively uncovers the intrinsic bounding constraints among the constellation revisit period, radar localization accuracy, target maneuvering capability, and the maximum trackable target density, thereby providing a theoretical foundation for constellation optimization. Second, an integrated space-ground synergistic constellation co-design framework is developed. By incorporating the derived capability quantification model as a core constraint, a multi-objective optimization (MOO) framework is established for LEO Walker-Delta constellations. A three-dimensional objective function specifically tailored for tracking missions is designed, targeting the concurrent optimization of the total constellation scale, average revisit time, and the coefficient of variation of revisit times. Utilizing the NSGA-II algorithm, a Pareto-optimal equilibrium among system cost, tracking performance, and coverage uniformity is successfully achieved, yielding optimized constellation design alternatives.

2. Quantitative Model for Multi-Target Tracking of Space-Based Detection Systems

2.1. Modeling of Space-Based Detection Systems and Target Kinematics

2.1.1. Observation Model of Circular Scanning Radar

Spaceborne circular-scanning radars are typically deployed on LEO satellites at altitudes of 500–600 km. These sensors use a wide-swath circular-scanning mode, with continuous antenna rotation in azimuth and a wide-beam or active scanning architecture in range. This enables a single pass to cover expansive maritime zones with a cross-track swath of hundreds of kilometers [21–23].

In the spaceborne circular-scanning radar imaging mode, the radar antenna is tilted on the satellite platform and possesses a 360° scanning capability around the satellite's +Z-axis. The angle between the normal direction of the radar antenna and the nadir direction of the satellite (the satellite's +Z direction) is designated as the radar look angle η . The azimuth angle φ is defined as the angle between the ground projection vector of the antenna beam direction and the satellite's nadir velocity vector. The imaging swath width S_w represents the cross-track distance between the outermost edges on the left and right sides when the satellite traverses the imaging region, while the antenna beam scans at an angular velocity ω . Based on the geometric model, multiple circular imaging zones are aggregated to expand the effective imaging width from tens of kilometers to thousands of kilometers. The schematic diagram of the observation modeling is illustrated in Figure 1.

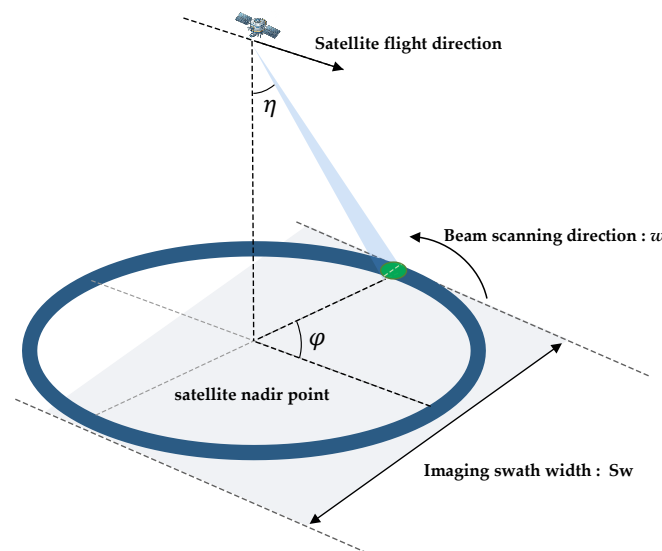


Figure 1. Illustrates the geometry of the spaceborne circular-scanning radar observation.

The temporal sampling interval of a constellation over a target zone depends on the orbital altitude, inclination, geometry, and area boundaries, ranging from minutes to hours. Due to orbital dynamics and Earth's rotation, consecutive observation intervals for a maritime region are non-uniform. To characterize this behavior, this paper defines the mean revisit time T_s as the statistical expectation of all time intervals between adjacent valid coverage time windows over the same region. This statistical mean, which serves as a critical design metric for space-based system synthesis, can be accurately evaluated through orbit propagation and geometric coverage simulation.

At each valid pass time t_k , the temporal interval between adjacent coverage windows is approximated as T_s , such that the k -th coverage window is formalized as $t_k = kT_s$ ($k = 0, 1, 2, \dots$). At time t_k , the measurement vector for the i -th ship is expressed as:

$$\hat{\mathbf{X}}_k^{(i)} = \mathbf{X}_k^{(i)} + \mathbf{W}_k^{(i)}, \mathbf{W}_k^{(i)} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}_2) \quad (1)$$

where $\mathbf{X}_k^{(i)}$ is the two-dimensional geodetic vector (latitude and longitude) defining the true position of the i -th ship at time t_k . As illustrated in Figure 1, the circular-scanning radar antenna is installed with a tilt on the satellite platform. The radar directly measures the slant range R (obtained via the time delay between transmission and echo reception) and the azimuth angle φ (obtained via the antenna pointing direction) of the target relative to the satellite platform. The geodetic position vector $\hat{\mathbf{X}}_k^{(i)}$ is derived from the raw radar measurements through coordinate transformation using satellite ephemeris and attitude information; $\mathbf{W}_k^{(i)}$ represents a generalized noise component that includes intrinsic receiver noise (e.g., thermal noise and quantization errors) and the coordinate

transformation errors from satellite ephemeris inaccuracies, attitude determination errors, antenna beam pointing calibration offsets, and atmospheric propagation delays. Consolidating these diverse error sources into zero-mean Gaussian white noise with a covariance matrix of $\sigma^2 \mathbf{I}_2$ is a standard simplification in radar tracking to ensure mathematical tractability. The parameter σ signifies the single-point localization standard deviation of the circular-scanning radar, which is modulated by factors such as slant-range error, beam-width, atmospheric propagation, and thermal noise. The single-point localization standard deviation $\sigma = 1$ km adopted in this study represents a conservative yet practically meaningful estimate for space-based circular-scanning radar systems in maritime wide-area detecting scenarios [22,24].

2.1.2. Target Dynamics Model

The motion of maritime ships is governed by navigation regulations, sea states, and operational maneuvers. This work adopts a local planar Cartesian coordinate system projected from latitude and longitude, neglecting Earth's curvature effects within localized regions. Consequently, the ship kinematics satisfy the following relationship:

$$\dot{\mathbf{X}}(t) = \mathbf{V}(t), \dot{\mathbf{V}}(t) = \mathbf{a}(t), \|\mathbf{a}(t)\| \leq a_{\max} \quad (2)$$

where $\mathbf{V}(t) = [V_x(t), V_y(t)]^\top$ represents the velocity vector; $\mathbf{a}(t)$ denotes the acceleration vector; $a_{\max}$ is the maximum possible acceleration magnitude, which is determined by the ship type and sea states. The parameter $a_{\max}$ reflects the target's maneuvering capability; that is, a higher agility of the target corresponds to a larger value of $a_{\max}$.

2.1.3. Velocity Error Estimation Based on Scanning Difference

Since only measured position rather than instantaneous velocities are obtained during each satellite pass, the measured position information from two consecutive passes must be utilized to estimate the average ship velocity between measurements. Let Δt_k be the actual epoch gap between the $(k-1)$ -th and k -th effective coverage, whose expectation is T_s . As an engineering baseline, T_s serves as the deterministic time step for velocity estimation:

$$\hat{\mathbf{V}}_k^{(i)} = \frac{\hat{\mathbf{X}}_k^{(i)} - \hat{\mathbf{X}}_{k-1}^{(i)}}{T_s} \quad (3)$$

The target index superscript i is omitted for notation clarity. Incorporating the observation equation (1) leads to:

$$\hat{\mathbf{V}}_k = \frac{(\mathbf{X}_k + \mathbf{W}_k) - (\mathbf{X}_{k-1} + \mathbf{W}_{k-1})}{T_s} = \frac{\mathbf{X}_k - \mathbf{X}_{k-1}}{T_s} + \frac{\mathbf{W}_k - \mathbf{W}_{k-1}}{T_s} \quad (4)$$

Defining the true velocity (taken as the interval midpoint or the average velocity) as $\mathbf{V}_k$, the velocity estimation error can be extracted as follows:

$$\hat{\mathbf{V}}_k - \mathbf{V}_k = \frac{\mathbf{W}_k - \mathbf{W}_{k-1}}{T_s} \quad (5)$$

Recognizing that $\mathbf{W}_k \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}_2)$ and $\mathbf{W}_{k-1} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}_2)$ are statistically independent, the covariance matrix of the velocity estimation error is derived as:

$$\text{Cov}(\hat{\mathbf{V}}_k - \mathbf{V}_k) = \frac{2\sigma^2}{T_s^2} \mathbf{I}_2 \quad (6)$$

The standard deviation of the velocity estimation error is given by:

$$\sigma_V = \sqrt{\frac{2\sigma^2}{T_s^2}} = \frac{\sqrt{2}\sigma}{T_s} \quad (7)$$

Within the tracking filter, this estimated velocity is commonly used to extrapolate the target state to the next pass epoch (from t_k to t_{k+1} , still adopting the mean interval T_s as the step size). The position uncertainty standard deviation caused by velocity error is formulated as:

$$\sigma_{V,\text{pos}} = \sigma_V \cdot T_s = \sqrt{2} \sigma \quad (8)$$

It can be inferred from the above that the position uncertainty stemming from the velocity estimation error depends exclusively on the single-target localization accuracy σ and is completely decoupled from the scanning period T_s . For this specific error source, increasing the revisit frequency (i.e., shortening T_s) does not reduce the position uncertainty induced by velocity estimation—which fundamentally reflects the inherent constraint imposed by single-point localization accuracy on velocity extrapolation errors.

2.1.4. Error Estimation Based on Dynamic Disturbance

A constant velocity model is employed for position extrapolation in maritime multi-target tracking algorithms. However, real-world maritime targets inherently exhibit random maneuvering accelerations, and this dynamic model mismatch introduces an additional position deviation [25]. Within the scanning interval T_s , when a target maneuvers along a single direction with its maximum acceleration, the resulting maximum position deviation is formulated as:

$$\|\Delta \mathbf{X}_{\text{dyn}}\| \leq \frac{1}{2} a_{\text{max}} T_s^2 \quad (9)$$

This deterministic deviation is approximated as the standard deviation of a uniform distribution, thereby yielding the dynamic perturbation error:

$$\sigma_{\text{dyn}} = \frac{1}{2} a_{\text{max}} T_s^2 \quad (10)$$

where this error increases with T_s^2 . In sharp contrast to the velocity estimation error analyzed in Section 2.1.3, the dynamic perturbation error exhibits a strong quadratic dependence on the revisit period T_s .

2.2. Variable Constraint Relationships of Space-Based Detection Systems

2.2.1. Sampling Uncertainty Radius of Space-Based Detection Systems

The position information of maritime targets can be acquired via space-based detection Systems. The radius of the target's position uncertainty is jointly determined by the fusion of three error sources: measurement noise, velocity estimation error, and dynamic perturbation. The total position uncertainty variance is derived as:

$$\sigma_{\text{total}}^2 = \sigma^2 + (\sqrt{2}\sigma)^2 + \left(\frac{a_{\text{max}} T_s^2}{2}\right)^2 = 3\sigma^2 + \frac{a_{\text{max}}^2 T_s^4}{4} \quad (11)$$

Equation (11) provides an engineering error budget, not a mathematically rigorous covariance combination. Treating these errors as decoupled modules is a standard practice in preliminary constellation design to avoid over-conservatism and complex cross-coupling mechanics [26].

According to the internationally recognized Guide to the Expression of Uncertainty in Measurement (GUM, JCGM 100:2008) [27], uncertainty components are classified into Type A (statistical evaluation) and Type B (evaluation by other means). The GUM explicitly states that both types are quantified by variances or standard deviations and are combined via the root-sum-square (RSS) method. The dynamic worst-case maneuvering displacement is therefore treated as an equivalent Type B standard uncertainty, following the GUM's treatment of bounded quantities with an assumed distribution. This RSS

combination is fully consistent with internationally accepted measurement uncertainty analysis methodology.

The position uncertainty quantization metric serves as a commonly used threshold for data association and track management [25]. In practical multi-target tracking engineering, a circular error probable with approximately 90% confidence level is typically adopted as the position uncertainty quantization metric; hence, the total uncertainty radius is given by:

$$r = 2 \sqrt{3\sigma^2 + \frac{a_{\max}^2 T_s^4}{4}} \quad (12)$$

Its physical significance is that, centered on the radar's single-observation plot, the true position of the target falls within the circle of radius r with a 90% probability, which serves as the direct criterion for determining whether multiple targets are conflated.

2.2.2. Minimum Safe Spacing for Multi-Target Tracking Data Association

The correct association between measurements and tracks is a prerequisite for maintaining stable tracking. To guarantee that the correct association rate meets engineering application requirements, a sufficient condition for accurate plot-to-track association is that the minimum center-to-center distance between any two targets must be no less than twice the uncertainty radius, namely:

$$d_{\min} \geq 2r \quad (13)$$

The criterion $d_{\min} \geq 2r$ is rooted in the fundamental principle of validation gate design in multitarget tracking. In tracking systems, an elliptical (or circular) validation gate is established around each track's predicted position: a measurement falling within this gate is considered associated with that track. When two targets are in close proximity, their respective uncertainty regions—determined by measurement noise, velocity estimation errors, and dynamic perturbations—may overlap. Such overlap creates ambiguity in measurement origin: a single measurement may fall within the validation gates of multiple tracks, or measurements from different targets may be incorrectly exchanged, leading to association errors, track coalescence, or track swapping [28].

The condition $d_{\min} \geq 2r$ ensures that the uncertainty circles of radius r centered at each target's estimated position are mutually non-overlapping. This eliminates any ambiguity in measurement-to-track association at the source, guaranteeing that each measurement can be assigned to at most one track and vice versa. Although this criterion is sufficient rather than necessary—correct association may still be possible in some cases when $d_{\min} < 2r$ —it provides a theoretically guarantee against association errors. This conservative design principle is widely adopted in radar tracking system engineering to ensure robust performance in dense target scenarios.

2.2.3. Maximum Resolvable Density Under Poisson Point Process

The 2-D maritime mission area is uniformly partitioned into square grids with a side length of $2r$, which corresponds to the minimum safe separation. According to geometric constraints, if two or more targets coexist within a single grid, the Euclidean distance between any two targets will be less than $2r$. This directly violates the minimum safe separation condition, thereby triggering a data association failure. Thus, a sufficient condition for multi-target tracking is that, with 90% confidence, each grid contains at most one target.

Assuming the spatial distribution of ships follows a homogeneous Poisson point process (PPP) [29] with density λ . The area of a single square grid is given by $A = (2r)^2 = 4r^2$. The number of targets N in the grid satisfies a Poisson distribution: $N \sim \text{Poisson}(\mu)$,

where $\mu = \lambda A$. Therefore, the mathematical expression of this constraint condition is given by:

$$P(N \leq 1) = e^{-\mu}(1 + \mu) \quad (14)$$

To satisfy the condition that the number of targets within the region is at most one with a 90% probability, by consulting the Poisson probability distribution table, it is found that the expected value $\mu \leq 0.5$, which yields $\lambda \cdot 4r^2 \leq 0.5$. The derivation is given as follows:

$$\lambda \leq \frac{0.5}{4r^2} = \frac{1}{8r^2} \quad (15)$$

Note that the target density λ is measured in ‘targets per ten thousand square kilometers’.

2.2.4. Quantitative Model for Multi-Target Tracking Constraints

Substituting the uncertainty radius gives the quantitative model:

$$\lambda_{\max} = \frac{1}{96 \sigma^2 + 8 a_{\max}^2 T_s^4} \quad (16)$$

This formula quantitatively relates the constellation revisit period, radar localization accuracy, and target maneuvering capability to the maximum trackable target density. Furthermore, this formula serves as the foundation for the subsequent optimization design of constellations tailored for multi-target tracking. All physical quantities must be converted to SI base units before substitution. Specifically, the localization accuracy σ (specified in kilometers) must be converted to meters (m), i.e., $\sigma = 1 \text{ km} = 1000 \text{ m}$; the target density λ (specified in ships/10⁴ km²) must be converted to ships per square meter (ships/m²), i.e., $1 \text{ ship}/10^4 \text{ km}^2 = 1 \times 10^{-9} \text{ ships}/\text{m}^2$; and the maximum target acceleration $a_{\max}$ is already specified in m/s². The revisit period T_s is expressed in seconds (s). All numerical results in this paper follow this SI-unit conversion convention.

The core quantitative model derived in this section serves as the theoretical foundation and is subsequently transformed into the critical revisit time constraint T_{crit} (in Equation (22)) within the downstream optimization framework. The logical progression mapping the quantitative model in Section 2 onto the constellation optimization problem in Section 3 is illustrated in Figure 2.

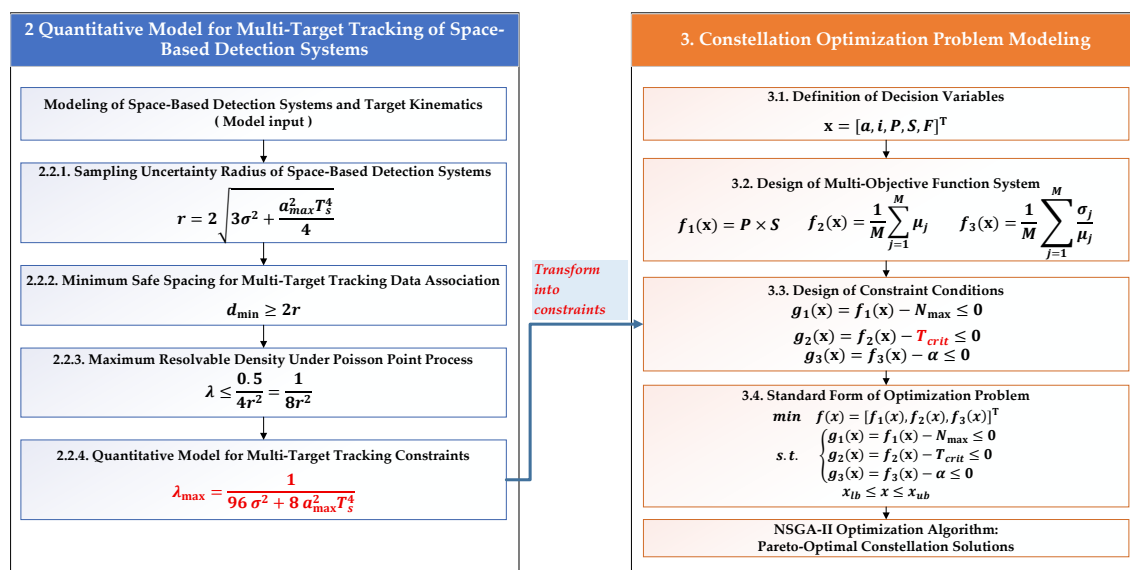


Figure 2. Logical relationship diagram between the quantitative tracking capability model (Section 2) and the constellation optimization problem (Section 3).

3. Constellation Optimization Problem Modeling

By integrating mission requirements with theoretical prerequisites, this study defines the core optimization objective as follows: to minimize system cost, maximize tracking performance, and optimize coverage uniformity under constraints of tracking capability, coverage balance, and constellation scale. The optimization coordinates key configuration variables, including the semi-major axis, inclination, number of planes, satellites per plane, and phasing factor. This process yields a set of Pareto-optimal constellation configurations to support engineering decision-making.

3.1. Definition of Decision Variables

The configuration parameters of a LEO satellite constellation directly determine its coverage characteristics, revisit performance, spatial geometry, and engineering implementation difficulty, serving as the core inputs for constellation optimization design. The constellation configuration is uniquely determined by five independent parameters, which collectively constitute the decision vector of the optimization problem:

$$\mathbf{x} = [a, i, P, S, F]^T \quad (17)$$

where a is the orbital semi-major axis, determining the orbital altitude $h = a - R_e$ ($R_e = 6378.137$ km is the reference radius of the Earth); i represents the orbital inclination, which sets the latitude coverage; P denotes the number of orbital planes, determining the distribution uniformity in the longitude direction; S is the number of satellites per orbital plane, determining the along-track coverage density; and F is the Walker phase factor, satisfying $0 \leq F < P$, which controls relative phase offsets and affects revisit uniformity.

3.2. Design of Multi-Objective Function System

3.2.1. Total Constellation Size

The total constellation size ($P \times S$) reflects manufacturing, launch, operations, and maintenance costs, and is a key constraint on engineering feasibility.

$$f_1(\mathbf{x}) = P \times S \quad (18)$$

Fewer satellites reduce complexity, increase reliability, and shorten construction time. Taking the total constellation size as an independent optimization objective to seek more cost-effective and engineering-feasible configurations ensures that the optimized schemes possess genuine practical value for implementation.

It is acknowledged that $f_1(\mathbf{x}) = P \times S$ constitutes a simplified cost metric. In actual space engineering, the total system cost is also heavily driven by other critical factors, such as the orbital altitude (which directly dictates the launch vehicle's energy requirements) and the number of orbital planes (which dictates the number of required launches and the operational complexity of inter-plane phase deployment). However, for the preliminary design phase targeted in this study, using the total number of satellites as a first-order proxy for system cost remains highly reasonable, as it directly scales with the primary cost drivers including manufacturing, assembly, integration, testing (AIT), and on-orbit operations. Incorporating altitude-dependent launch expenditures and plane-count-dependent deployment complexities into a higher-fidelity cost model heavily relies on explicit mission data regarding the specific launch vehicle capabilities and constellation insertion strategies. These details extend beyond the scope of this paper and are thus reserved for future investigation.

3.2.2. Average Revisit Time

Revisit time is a key metric for continuous tracking, track continuity, and positioning accuracy, and directly reflects mission performance. It is defined as the mean value of the average revisit times across all target points within the simulation region by satellites during the simulation period.

Given the set of target points $\mathcal{T} = \{t_1, t_2, \dots, t_M\}$, where the average revisit time of target t_j is denoted as μ_j , the global average revisit time is expressed as:

$$f_2(\mathbf{x}) = \frac{1}{M} \sum_{j=1}^M \mu_j \quad (19)$$

where f_2 directly characterizes tracking timeliness. A smaller f_2 means more frequent observations, higher track update rates, and better tracking of maneuverable ships. It is a critical indicator of overall tracking responsiveness.

3.2.3. Coefficient of Variation

Within a given mission area, the revisit time of different grid points may exhibit significant spatial disparities due to the non-uniform geometry of the constellation. Optimizing solely for the average revisit time can easily lead to a polarization phenomenon, where some sub-regions are revisited extremely frequently while others remain unobserved for extended periods. It is emphasized that the coefficient of variation defined in this paper characterizes the spatial uniformity of revisit times across different grid points within a specified mission area, rather than the uniformity across multiple geographically separated maritime regions. This intra-regional uniformity metric directly affects the consistency of track association performance within the surveillance region.

Let the target point set be denoted as $\mathcal{T} = \{t_1, t_2, \dots, t_M\}$. The coefficient of variation is defined as the ratio of the standard deviation to the mean of the global average revisit times:

$$f_3(\mathbf{x}) = \frac{1}{M} \sum_{j=1}^M \frac{\sigma_j}{\mu_j} \quad (20)$$

where μ_j and σ_j represent the mean and standard deviation of the revisit intervals of the constellation for target t_j , respectively. f_3 quantifies the coverage uniformity, with a smaller value indicating more consistent revisit characteristics of the constellation across different sub-regions.

3.3. Design of Constraint Conditions

The constellation optimization problem searches for optimal solutions within engineering and mission performance bounds. The constraints on scale, performance, and coverage ensure that solutions are both feasible and implementable.

3.3.1. Constellation Scale Upper Limit Constraint

The number of satellites is one of the most sensitive cost drivers in aerospace engineering. From an economic perspective, the manufacturing, launch, and on-orbit operational costs of satellites scale approximately linearly with the constellation size, whereas indirect expenditures—such as ground segment operations and frequency spectrum coordination—exhibit super-linear growth. From a technological perspective, the launch capacity of launch vehicles, the availability of viable launch windows, and the engineering feasibility of completing multi-satellite deployment within a reasonable timeframe impose rigid constraints on the number of orbital planes. An excessive number of satellites

degrades system reliability, increases scheduling complexity, and escalates operational costs. Consequently, a strict upper bound on the total number of satellites ($N_{\max}$) must be established to confine the optimized solutions within a reasonable scope of engineering scale.

The constraint stipulating that the total number of satellites shall not exceed the engineering upper limit $N_{\max}$ is expressed as:

$$g_1(\mathbf{x}) = f_1(\mathbf{x}) - N_{\max} \leq 0 \quad (21)$$

This constraint ensures that the finalized Pareto-optimal solutions represent highly engineerable schemes that can be practically designed, manufactured, launched, and operated.

3.3.2. Multi-Target Tracking Capability Constraint

This constraint establishes a quantitative mapping between the kinematic characteristics of maritime targets and the space-based system parameters. Consequently, the resulting constellation configuration directly addresses the tracking requirements of the designated mission area. Depending on the designated space-based detection zones, vessel target densities and kinematic behaviors vary significantly across different maritime regions. Consequently, the constellation configuration must be adaptively tailored to the explicit mission requirements of heterogeneous sea sectors. This constraint precisely acts as the quantitative bridge to achieve such “mission-to-configuration” adaptation. As mathematically derived in Section 2.2, the multi-target tracking capability of a space-based surveillance system is jointly determined by the target density λ , payload localization accuracy σ , maximum target maneuverability $a_{\max}$, and the revisit interval T_r . By substituting the region-specific λ and $a_{\max}$ of different maritime zones into the formulation, distinct critical revisit thresholds T_{crit} are obtained, which subsequently drive the optimization algorithm to search for constellation configurations that match the operational demands of each respective maritime mission.

This constraint originates from the quantitative model of space-based detection systems for multi-target tracking, reflecting that the constellation’s revisit performance must satisfy the minimum requirements for continuous target tracking. The critical revisit time T_{crit} is expressed as:

$$T_{crit} = \left[\frac{1}{8a_{\max}^2} \left(\frac{1}{\lambda} - 96\sigma^2 \right) \right]^{1/4} \quad (22)$$

where λ is the density of target ships in the sea area (ships/10⁴ km²); σ denotes the satellite payload detection error (meters); $a_{\max}$ represents the maximum maneuvering acceleration of the target (m/s²). The constraint formulation is given by:

$$g_2(\mathbf{x}) = f_2(\mathbf{x}) - T_{crit} \leq 0 \quad (23)$$

Long revisit times cause rapid accumulation of maneuvering distance and heading uncertainty, leading to track breakage, association failure, and invalid localization. Thus, the average revisit time must be strictly less than T_{crit} .

3.3.3. Coverage Uniformity Constraint

This constraint addresses the internal observation consistency requirements within specific target zones. Given a designated mission sector, even if the target density is relatively uniform as a whole, a poorly designed constellation configuration can still induce spatial polarization. Such non-optimized configurations lead to temporary oversampling or localized coverage gaps within the same region. This temporal non-uniformity compromises the data association performance across the tracking domain. Specifically,

because the selection of validation gating thresholds typically depends on the statistical profiles of the global observation intervals, anomalous fluctuations in localized revisitation gaps will cause a mismatch in association parameters, thereby triggering localized track fragmentation.

To suppress local coverage blind spots, it is required that the coefficient of variation of the revisit time does not exceed the engineering threshold α :

$$g_3(\mathbf{x}) = f_3(\mathbf{x}) - \alpha \leq 0 \quad (24)$$

where $\alpha = 1.5$. This ensures stable observation frequencies across sub-regions, improving tracking efficiency and robustness.

The conceptual architecture illustrating the interrelations among these constellation optimization design constraints is presented in Figure 3:

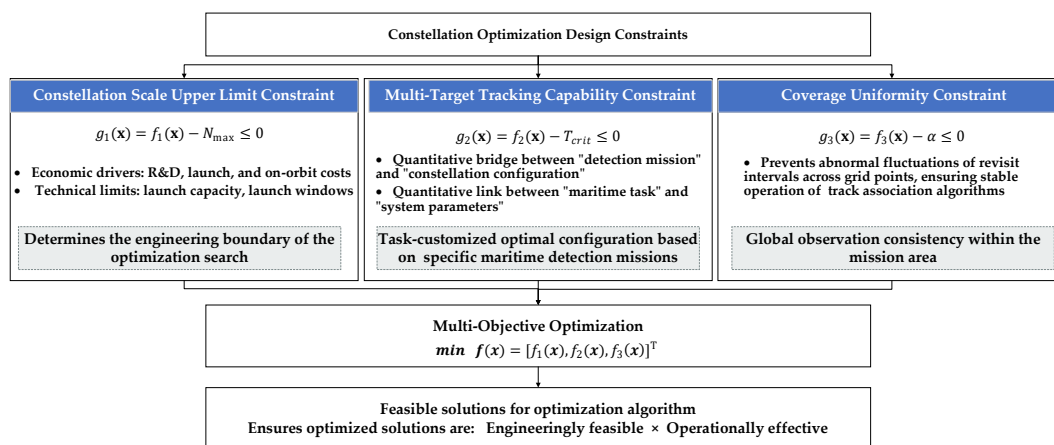


Figure 3. Schematic diagram of constellation design constraints.

3.4. Standard Form of Optimization Problem

To summarize, the standard mathematical formulation of the maritime-target-tracking-oriented constellation optimization problem is given as follows:

$$\begin{aligned} \min \quad & \mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x})]^T \\ \text{s. t.} \quad & \begin{cases} g_1(\mathbf{x}) = f_1(\mathbf{x}) - N_{\max} \leq 0 \\ g_2(\mathbf{x}) = f_2(\mathbf{x}) - T_{crit} \leq 0 \\ g_3(\mathbf{x}) = f_3(\mathbf{x}) - \alpha \leq 0 \end{cases} \\ & x_{lb} \leq \mathbf{x} \leq x_{ub} \end{aligned} \quad (25)$$

It must be emphasized that the objective function vector $\mathbf{f}(\mathbf{x})$ in (25) is composed of three independent objective functions. The optimization incorporates the Pareto dominance criterion: a solution $\mathbf{x}_1$ is said to dominate another solution $\mathbf{x}_2$ if and only if $\mathbf{x}_1$ is no worse than $\mathbf{x}_2$ across all three objectives, and strictly better than $\mathbf{x}_2$ in at least one objective. By avoiding the subjectivity inherent in manual weight selection, this approach enables the algorithm to uncover the intrinsic trade-offs among the three objectives. Ultimately, the optimization outputs a set of Pareto-optimal solutions, thereby providing comprehensive decision support for engineering design.

The model collaboratively optimizes cost, timeliness, and uniformity, while three inequality constraints guarantee scale feasibility, tracking capability, and coverage stability.

4. Multi-Objective Optimization Algorithm for Large-Scale Constellation Oriented to Multi-Target Tracking

4.1. Algorithm Solving Framework

This study adopts a constraint-adaptive non-dominated sorting genetic algorithm II (NSGA-II) as the optimization framework. Based on fast non-dominated sorting, an elitism-preservation strategy, and a crowding distance mechanism, NSGA-II has been widely applied in the field of multi-objective optimization. Considering that the maritime target tracking constellation optimization problem features moderate decision variable dimensions, explicit constraints, and computationally expensive objective functions, parallel evaluation and the constraint-domination principle are incorporated to develop an efficient and robust solving procedure. The algorithm is shown in Figure 4. The specific steps of the algorithm are outlined below:

(S1) Parameter configuration: Set population size N , maximum evolutionary generation $G_{\max}$, crossover distribution index η_c , mutation distribution index η_m , initial crossover probability p_c , and mutation probability p_m .

(S2) Population initialization: Each individual is represented as a design variable vector $[a, i, P, S, F]$. Orbital semi-major axis and inclination adopt continuous real-number coding, while the number of orbital planes, number of satellites per orbit, and phase factor adopt integer constraints. Boundary constraint verification and feasibility corrections are executed to jointly construct the decision space for constellation optimization oriented toward maritime target tracking.

(S3) Parallel evaluation: Synchronously calculate the objective function values (constellation scale f_1 , average revisit time f_2 , and coverage uniformity f_3) and constraint violation degree of all individuals in the population.

(S4) Non-dominated sorting and crowding calculation [30]: Perform fast non-dominated sorting based on the constraint dominance principle, and calculate the crowding distance of individuals within the same Pareto frontier.

(S5) Optimal solution set archiving: Record the first non-dominated frontier of the current generation as the dynamically updated Pareto optimal solution set.

(S6) Termination judgment: If the current evolutionary generation reaches $G_{\max}$, output the final Pareto frontier and terminate the algorithm; otherwise, continue to execute subsequent evolutionary steps.

(S7) Offspring generation: Employ binary tournament selection to choose parent individuals [30], sequentially perform simulated binary crossover (SBX) [31] and polynomial mutation operations [30] to generate offspring population of size N .

(S8) Offspring evaluation: Parallely calculate the objective function values and constraint violation degree of offspring individuals.

(S9) Elite environmental selection [30]: Merge the parent and offspring populations (size $2N$), re-perform non-dominated sorting and crowding calculation, and preferentially retain N individuals according to the principle of dominance level priority and crowding degree sub-optimal to form a new generation population.

(S10) Iterative loop: Return to S3 and continue to execute the evaluation-sorting-selection process until the termination condition is satisfied.

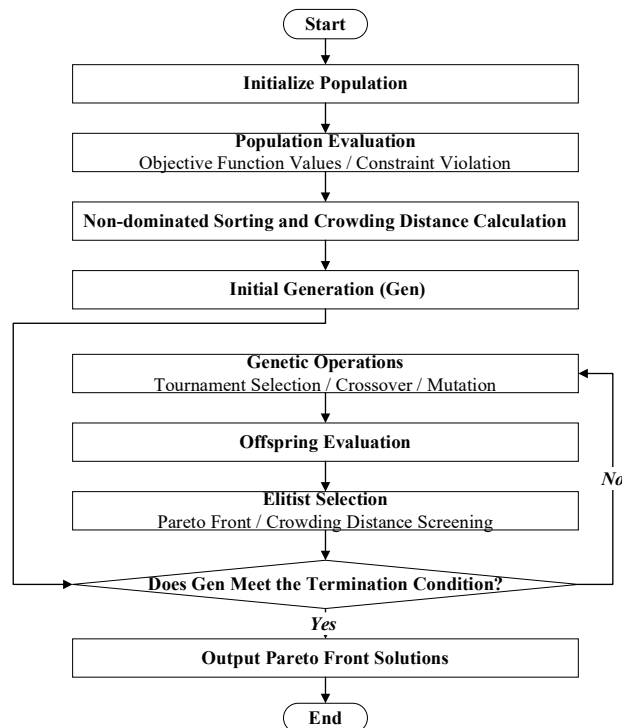


Figure 4. Algorithm flowchart.

The NSGA-II algorithm is chosen as the core optimizer for this problem due to three considerations. First, the optimization problem formulated in Equation (25) features three conflicting objectives and mixed-integer decision variables, which matches the problem class that NSGA-II is designed to address. Second, NSGA-II has been extensively validated in satellite constellation design applications, demonstrating reliable convergence and diversity preservation through its fast non-dominated sorting, crowding distance, and elitism mechanisms. Third, the constraint-domination principle of NSGA-II can be extended to handle the three inequality constraints in Equation (25). Although alternative multi-objective algorithms—such as MOPSO and MSSA—could also be applied, NSGA-II offers a favorable balance between solution quality, computational efficiency, and algorithmic maturity for the Walker constellation optimization problems addressed in this work [32].

4.2. Offspring Evaluation Strategy

In the multi-objective constellation optimization framework, the evaluation of offspring individuals serves as the core link that drives algorithmic convergence. This section proposes a fast evaluation mechanism tailored for revisit time analysis. By constructing a standardized workflow—comprising region discretization, geometric visibility determination, time window aggregation, and statistical metric mapping—an offspring evaluator is established to enable the rapid assessment of constellation alternatives.

4.2.1. Observation Area Discretization and Target Grid Construction

To quantify the coverage performance of the constellation over a specified geographical area, the continuous latitude-longitude space must be discretized into a finite number of independent observation target points. Let the latitude range of the target region be $[\varphi_{\min}, \varphi_{\max}]$ and the longitude range be $[\lambda_{\min}, \lambda_{\max}]$, with step sizes denoted as $\Delta\varphi$ and $\Delta\lambda$ respectively. Through this region discretization, the target point set $\mathcal{T} = \{t_1, t_2, \dots, t_M\}$ is established, where M represents the total number of target points. By calculating the time windows of each satellite in every constellation generation relative to each grid point,

the evaluator ultimately maps the statistical results of the time windows into the objective vector $f(\mathbf{x})$ of the optimization problem.

4.2.2. Geometric Visibility Determination Model

As illustrated in Figure 5, for simplicity, the Earth is assumed to be an ideal sphere, and the astrodynamics of the satellite are described in the J2000 Earth-Centered Inertial (ECI) frame with its origin at the Earth's center. Here, S and T denote the satellite and the observation target, respectively. The half-field-of-view (half-FOV) angle of the satellite sensor is denoted by θ_{half} , and the sensor optical axis is assumed to point toward the geocenter. For the circular-scanning radar observation geometry detailed in Section 2.1.1 (Figure 1), the antenna boresight is oriented with a fixed look angle η relative to the nadir direction. In this configuration, the half-FOV angle θ_{half} is numerically equal to the look angle η , since both quantities describe the angular deviation of the beam center from the nadir direction. The visibility time window between the satellite and the moving target is determined by the condition that the angle β between the satellite-to-target vector and the satellite-to-geocenter vector does not exceed θ_{half} , i.e., $\beta \leq \theta_{half}$. In ECI frame, $\vec{r}_S$ denotes the position vector of the satellite, and $\vec{r}_T$ denotes the position vector of the moving target. Thus, angle β is calculated as follows:

$$\cos \beta = \frac{(\vec{r}_T - \vec{r}_S) \cdot (-\vec{r}_S)}{|\vec{r}_T - \vec{r}_S| |\vec{r}_S|} \quad (26)$$

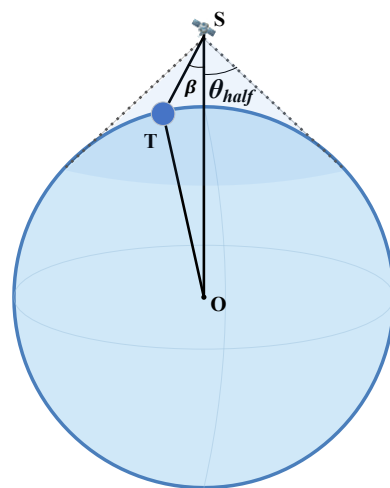


Figure 5. Space-based system detection model.

In this study, the 8 h simulation window is justified by the following considerations: (1) the large-scale constellation under optimization comprises up to hundreds of satellites, providing dense temporal and spatial sampling that accelerates the convergence of statistical metrics; (2) the revisit time statistics are computed as ensemble averages over multiple target grid points (M grid points) and multiple satellites, reducing the sensitivity to the exact simulation start time; and (3) the primary purpose of this simulation is relative comparison among constellation candidates within the NSGA-II optimization framework, rather than absolute prediction of revisit times for a specific operational scenario. The Pareto ranking of candidate solutions, which drives the optimization, is robust to constant offsets in absolute revisit time values.

The spherical Earth assumption is used solely for visibility geometry determination—i.e., calculating the elevation angle and geocentric angle between the satellite and the target to determine whether the target falls within the satellite's field of view. This is a widely adopted simplification in radar coverage analysis that ensures geometric clarity

and computational efficiency, and it does not reflect the fidelity level of the orbital dynamics modeling. Orbital propagation is performed in the J2000 ECI frame using J_2 perturbed orbit model.

4.2.3. Time Window Aggregation and Revisit Time Calculation

Given a specific constellation configuration $\mathbf{x} = [a, i, P, S, F]^T$, the total number of satellites is determined by $N_{\text{sat}} = P \times S$. Each satellite operates independently in its orbit and performs visibility judgment on the global target grid point set $\mathcal{T} = \{t_1, t_2, \dots, t_M\}$.

The simulation period T_{sim} is discretized into $N_{\text{step}} = T_{\text{sim}}/\Delta t$ time steps. For each satellite s ($s = 1, 2, \dots, N_{\text{sat}}$) and each target point t_j ($j = 1, 2, \dots, M$), the visible time steps are recorded based on the geometric visibility condition (Figure 5). Consecutive visible steps are subsequently merged into indivisible, continuous access time windows:

$$\left[t_{\text{start}}^{(s,j,k)}, t_{\text{end}}^{(s,j,k)} \right], k = 1, 2, \dots, K_{s,j} \quad (27)$$

where $K_{s,j}$ denotes the number of independent passes of satellite s over target t_j .

For a fixed target point t_j , the access time windows of all satellites are merged in chronological order (adjacent time windows with overlapping time are merged) to obtain the composite access time window sequence of target point t_j . Let the merged windows be denoted as:

$$\left[T_{\text{start}}^{(j,\ell)}, T_{\text{end}}^{(j,\ell)} \right], \ell = 1, 2, \dots, L_j \quad (28)$$

where L_j represents the total number of composite access windows for target t_j after consolidating the intervals from all satellites.

The final revisit intervals for target t_j are defined as the duration between the start time of the subsequent time window and the end time of the preceding time window:

$$\Delta_{j,\ell} = T_{\text{start}}^{(j,\ell+1)} - T_{\text{end}}^{(j,\ell)}, \ell = 1, 2, \dots, L_j - 1 \quad (29)$$

Thus, the revisit interval sequence $\{\Delta_{j,1}, \Delta_{j,2}, \dots, \Delta_{j,L_j-1}\}$ of target point t_j is obtained.

In summary, the average revisit time of target t_j is calculated as follows:

$$\mu_j = \frac{1}{L_j - 1} \sum_{\ell=1}^{L_j-1} \Delta_{j,\ell} \quad (30)$$

When $L_j - 1 \geq 2$, the standard deviation of the revisit time for target t_j is given by:

$$\sigma_j = \sqrt{\frac{1}{L_j - 2} \sum_{\ell=1}^{L_j-1} (\Delta_{j,\ell} - \mu_j)^2} \quad (31)$$

The coefficient of variation (CV) for target t_j is formulated as:

$$CV_j = \frac{\sigma_j}{\mu_j} \quad (32)$$

Following the aggregation of the revisit intervals for all target points, these metrics are utilized in the subsequent formulation of objective functions and constraint conditions.

4.2.4. Quantitative Construction of Objective Functions and Constraint Conditions

According to the multi-objective function system defined in Section 3, the above statistical results are standardized and mapped into objective vectors and constraint violations that can be directly called by the optimization algorithm. The objective function

vector is formulated as: $\mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x})]^T$, where the total constellation size is expressed as: $f_1(\mathbf{x}) = P \times S$.

Global average revisit time is given by:

$$f_2(\mathbf{x}) = \frac{1}{M} \sum_{j=1}^M \mu_j = \frac{1}{M} \sum_{j=1}^M \left(\frac{1}{L_j - 1} \sum_{\ell=1}^{L_j-1} \Delta_{j,\ell} \right) \quad (33)$$

The spatial average of the coefficient of variation for the revisit time is defined as:

$$f_3(\mathbf{x}) = \frac{1}{M} \sum_{j=1}^M C V_j = \frac{1}{M} \sum_{j=1}^M \frac{\sigma_j}{\mu_j} \quad (34)$$

The corresponding constraint conditions are respectively defined as follows:

- (1) Scale constraint: $f_1(\mathbf{x}) \leq N_{\max}$, controlling the upper limit of constellation construction and operation costs;
- (2) Task timeliness constraint: $f_2(\mathbf{x}) \leq T_{\text{crit}}(\lambda, \sigma, a_{\max})$, representing the theoretical critical revisit threshold derived from target scene density, positioning error, and maneuvering capabilities;
- (3) Uniformity constraint: $f_3(\mathbf{x}) \leq \alpha$, ensuring the engineering stability of regional revisit time distribution.

The constraint violations are normalized and subsequently accumulated into penalty values. This penalty value is coupled with the non-dominated sorting mechanism to ensure that infeasible solutions are effectively eliminated during environmental selection.

5. Simulation Design and Result Analysis

To verify the effectiveness of the proposed algorithm, validation is conducted from two distinct perspectives: constellation optimization design and constellation system application. At the constellation optimization design level, simulation analyses are performed focusing on dimensions such as algorithmic convergence performance and objective function trade-offs, thereby demonstrating the superiority of the proposed framework in maritime target tracking constellation optimization. At the constellation system application level, the analysis centers on the track-matching success rate metric. By comparing the simulation results of solutions on the Pareto front against those off the front, the efficacy of the optimization framework for multi-target tracking missions is further substantiated.

5.1. Simulation Design

5.1.1. Constellation Optimization Variables and Boundary Constraints

The value ranges of constellation optimization variables are shown in Table 1. The satellite payload detection error follows a Gaussian distribution, with the standard deviation of the payload noise set to 1 km. The algorithmic configuration parameters are set as follows: the population size $N_{\text{pop}} = 200$, the maximum evolutionary generation $G_{\text{max}} = 150$, the crossover distribution index $\eta_c = 10$, the mutation distribution index $\eta_m = 10$, the initial crossover probability $p_c = 0.9$, and the mutation probability $p_m = 0.5$.

Table 1. Range of decision variables for constellation optimization.

Parameter Name	Lower Limit	Upper Limit
Orbital Altitude (km)	500	600
Orbital Inclination (°)	50	90

Number of Orbital Planes P	5	50
Number of Satellites per Plane S	10	50
Phase Factor F	0	P – 1

The constraint conditions include the following:

Critical revisit time constraint: According to the target density of 50 ships per 10,000 square kilometers, the calculated revisit time constraint yields $T_{crit} = 1898.83$ s. The detailed derivation process of the revisit time constraint is formulated as follows:

The critical revisit time T_{crit} is calculated from Equation (22). Following the unit conversion rule stated in Section 2.2.4, all quantities are first converted to SI base units: Target density $\lambda = 50$ ships/ 10^4 km² = $50 \times 10^{-9} = 5 \times 10^{-9}$ ships/m²; Localization accuracy $\sigma = 1$ km = 1000 m; Maximum target acceleration $a_{max} = 0.001$ m/s². Substituting these SI-unit values into Equation (22) gives:

$$\begin{aligned}
 T_{crit} &= \left[\frac{1}{8a_{max}^2} \left(\frac{1}{\lambda} - 96\sigma^2 \right) \right]^{1/4} \\
 &= \left[\frac{1}{8 \times 0.001^2} (5 \times 10^{-9} - 96 \times (1000)^2) \right]^{1/4} \\
 &= 1898.83 \text{ s.}
 \end{aligned}$$

Revisit uniformity constraint: Let $\alpha = 1.5$. This threshold primarily serves a boundary-limiting purpose, leaving the optimization process to be dominated by the objective functions.

Total constellation size upper limit constraint: The upper bound of the constellation size is constrained by $N_{max} = 2000$.

5.1.2. Detection Region and Target Motion Model

The simulation area is designated with a latitude range of 5°N to 15°N and a longitude range of 85°E to 95°E, within which the target density is constrained to 50 ships/ 10^4 km². The initialization parameters for each ship's trajectory consist of the starting point, initial velocity, heading angle, and a small-magnitude random acceleration. Detailed parameters are shown in Table 2. The generated tracks are stored in JSON format, containing information such as the ground-truth latitude, longitude, and velocity at each time step.

Table 2. Vessel motion design parameters.

Parameter Name	Parameter Value
Target Density (ships/ 10^4 km ²)	50
Time Range	6 July 2025 04:00:00 to 6 July 2025 12:00:00
Motion Region	[5°N~15°N, 85°E~95°E]
Velocity Range (knots)	20~35
Acceleration Variation Range (m/s ²)	0.001
Heading Angle Range (°)	20°~100°

5.1.3. Design of Evaluation Metric System

(1) Global Matching Success Rate for Target Tracking

Let the set of true targets be denoted as $\mathcal{T} = \{T_1^t, T_2^t, \dots, T_N^t\}$ and the set of fused tracks be $\mathcal{F} = \{T_1^f, T_2^f, \dots, T_K^f\}$. The Hungarian algorithm [33–35] is used to solve the maximum cardinality matching, ensuring that each true target is matched with at most one fused track. The resulting number of successful matches is obtained as $N_{matched}$.

The final success rate (SR) of track matching is defined as follows:

$$SR = \frac{N_{matched}}{N_{true}} \times 100\% \quad (35)$$

This metric directly reflects the tracking completeness of the algorithm at the target level. $SR = 100\%$ means all true targets are correctly tracked; $SR < 100\%$ implies the presence of target loss or track confusion.

(2) Hypervolume Indicator

The hypervolume (HV) indicator is a comprehensive metric used to evaluate both the convergence and distribution performance of multi-objective optimization algorithms. It is defined as the volume of the objective space enclosed by the non-dominated solution set and a predefined reference point [36,37].

Given a fixed reference point $\mathbf{r} = (r_1, r_2, r_3) = (2500, 2000, 3)$, the components correspond sequentially to the baseline reference values of the constellation scale $f_1(\mathbf{x})$, the average revisitation time $f_2(\mathbf{x})$, and the revisitation uniformity $f_3(\mathbf{x})$. For the non-dominated solution set $\mathcal{P}_s$ obtained from the s -th independent simulation run, its hypervolume is calculated as:

$$HV_s = \Lambda \left(\bigcup_{\mathbf{y} \in \mathcal{P}_s} [\mathbf{y}, \mathbf{r}] \right) \quad (36)$$

where $\Lambda(\cdot)$ denotes the Lebesgue measure, and $[\mathbf{y}, \mathbf{r}]$ represents the hypercube spanned by the objective vector of solution $\mathbf{y}$ and the reference point $\mathbf{r}$. A larger HV value signifies that the solution set simultaneously achieves superior convergence and a better distribution within the objective space.

The total number of independent simulation runs is set to $N_{sim} = 10$. The HV value of the Pareto front at each generation is recorded independently for each simulation run. They are further computed as mean hypervolume $\overline{HV}^{(g)}$ and hypervolume standard deviation $\sigma_{HV}^{(g)}$ at generation g :

$$\overline{HV}^{(g)} = \frac{1}{N_{sim}} \sum_{s=1}^{N_{sim}} HV_s^{(g)} \quad (37)$$

$$\sigma_{HV}^{(g)} = \sqrt{\frac{1}{N_{sim} - 1} \sum_{s=1}^{N_{sim}} (HV_s^{(g)} - \overline{HV}^{(g)})^2} \quad (38)$$

where $HV_s^{(g)}$ denotes the HV value of the Pareto front at the g -th generation during the s -th simulation run. This study utilizes the HV calculation module within the pymoo framework, fixing the reference point at (2500, 2000, 3) to unify the dimensions and scales. Throughout the evolutionary process, the overall convergence trend of the algorithm is assessed via the variation curve of the mean hypervolume versus the iteration count, while the stability across multiple independent runs is evaluated using the hypervolume variance.

To enable a scale-independent comparison of the algorithm's stability across different evolutionary stages, the relative standard deviation (coefficient of variation, CV) of the hypervolume is defined as:

$$CV_{HV}^{(g)} = \frac{\sigma_{HV}^{(g)}}{\overline{HV}^{(g)}} \times 100\% \quad (39)$$

Throughout the convergence analysis, $CV_{HV}^{(g)}$ is used to complement the absolute standard deviation, providing a robust, dimensionless measure of algorithmic stability across stages.

(3) Convergence Curves of Objective Means

Let the population size of the g -th generation be denoted as N_{pop} , and the individuals within the population be represented as $\mathbf{x}^{(g,k,s)}$ ($k = 1, 2, \dots, N_{pop}$; $s = 1, 2, \dots, N_{sim}$). To

observe the overall evolutionary trend of each optimization objective, the arithmetic means of the three objective functions within the population are calculated for each generation.

$$\mu_{f_1}^{(g,s)} = \frac{1}{N_{\text{pop}}} \sum_{k=1}^{N_{\text{pop}}} f_1(\mathbf{x}^{(g,k,s)}) \quad (40)$$

$$\mu_{f_2}^{(g,s)} = \frac{1}{N_{\text{pop}}} \sum_{k=1}^{N_{\text{pop}}} f_2(\mathbf{x}^{(g,k,s)}) \quad (41)$$

$$\mu_{f_3}^{(g,s)} = \frac{1}{N_{\text{pop}}} \sum_{k=1}^{N_{\text{pop}}} f_3(\mathbf{x}^{(g,k,s)}) \quad (42)$$

To illustrate the average convergence behavior of the algorithm across multiple simulation runs, the mean values of the objective functions over all simulations are computed as follows:

$$\bar{\mu}_{f_1}^{(g)} = \frac{1}{N_{\text{sim}}} \sum_{s=1}^{N_{\text{sim}}} \mu_{f_1}^{(g,s)} \quad (43)$$

$$\bar{\mu}_{f_2}^{(g)} = \frac{1}{N_{\text{sim}}} \sum_{s=1}^{N_{\text{sim}}} \mu_{f_2}^{(g,s)} \quad (44)$$

$$\bar{\mu}_{f_3}^{(g)} = \frac{1}{N_{\text{sim}}} \sum_{s=1}^{N_{\text{sim}}} \mu_{f_3}^{(g,s)} \quad (45)$$

The mean values $\bar{\mu}_{f_1}^{(g)}$, $\bar{\mu}_{f_2}^{(g)}$, and $\bar{\mu}_{f_3}^{(g)}$ quantify the convergence performance of each objective for the algorithm across multiple simulation runs.

5.2. Simulation Results and Analysis

5.2.1. Optimization Design Results and Algorithm Convergence Analysis

(1) Convergence Analysis of Hypervolume Indicator

The hypervolume (HV) indicator serves as a comprehensive and classic metric to simultaneously evaluate the convergence and distribution performance of the obtained Pareto front. Figure 6 presents the HV evolution curve over generations, and Table A1 lists the per-generation statistics. Overall, the HV value increases continuously from 1.1977×10^7 in the initial generation to 1.2989×10^7 at the 150th generation, representing an overall improvement of approximately 8.45%. The evolutionary process can be divided into three distinct phases:

Rapid ascent phase (Generations 0–10): HV rises sharply from 1.1977×10^7 to 1.2671×10^7 , a gain of about 5.80%. In this phase, the algorithm quickly discovers a large number of high-quality non-dominated solutions, driving the Pareto front close to the true frontier.

Steady growth phase (Generations 11–50): HV increases steadily from 1.2694×10^7 to 1.2952×10^7 , with a growth rate of roughly 2.03%. During this stage, the crossover and mutation operators continuously generate better offspring, progressively improving the coverage and convergence quality of the front.

Plateau convergence phase (Generations 51–150): HV fluctuates gently around 1.298×10^7 , reaching 1.2989×10^7 at generation 150—only about 0.029% higher than at

generation 50, with fluctuation amplitudes well below 1% throughout. Concurrently, the standard deviation of HV drops from 3.84×10^5 in the initial generation to about 2.97×10^4 at the final stage, and the relative standard deviation decreases from 3.20% to 0.23%, indicating that multiple independent runs yield highly consistent results and the algorithm exhibits excellent stability. These findings provide strong evidence that NSGA-II has fully converged to a stable Pareto front, achieving balanced optimal trade-offs among the three objective dimensions: constellation size, average revisit time, and revisit time uniformity.

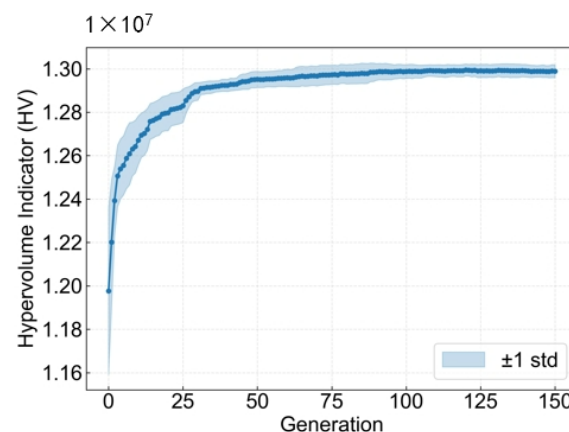


Figure 6. Hypervolume indicator iteration diagram.

(2) Convergence Trend Analysis of Population Objective Means

The population objective means reflect the overall evolutionary trajectory of each optimization objective during the generational process. As indicated by the data in Table A1 of Appendix A and the trends illustrated in Figure 7:

The mean constellation size decreases monotonically from 821 satellites in the initial generation to 678 at generation 150, representing a total reduction of approximately 17.4%. The decline is most rapid during the first 10 generations (from 821 to 754, a drop of about 8.2%), after which the descent gradually slows: the mean size reaches about 717 at generation 50, 685 at generation 100, and 678 at generation 150. This sustained downward trend demonstrates that the algorithm continuously eliminates large-scale candidates throughout evolution, autonomously converging toward more economical and compact constellation configurations.

The mean average revisit time exhibits an opposite upward trend, increasing from 187.9 s initially to 366.6 s at generation 150, a total gain of about 95.1%. The rise is steeper in the first 10 generations (reaching 207.1 s), then continues to grow to 267.0 s at generation 50 and 322.5 s at generation 100, before gradually flattening toward the end. This inverse relationship clearly reveals the inherent trade-off between constellation size (cost) and tracking timeliness—the algorithm does not minimize revisit time without bound, but rather seeks a reasonable performance compromise under cost constraints.

The mean coefficient of variation of revisit time drops sharply at the beginning of evolution, from an initial value of 1.1087 to 0.6579 by generation 5, a reduction of over 40%. Thereafter, it fluctuates within the range of 0.65–0.83, stabilizing at 0.8295 at generation 150. Throughout the entire process, this metric remains far below the engineering constraint threshold $\alpha = 1.5$, demonstrating that the algorithm effectively maintains spatial uniformity of revisit times across the mission area while optimizing the average revisit performance. The early rapid decline followed by steady behavior confirms that NSGA-II can quickly improve coverage uniformity and sustain it robustly over later generations.

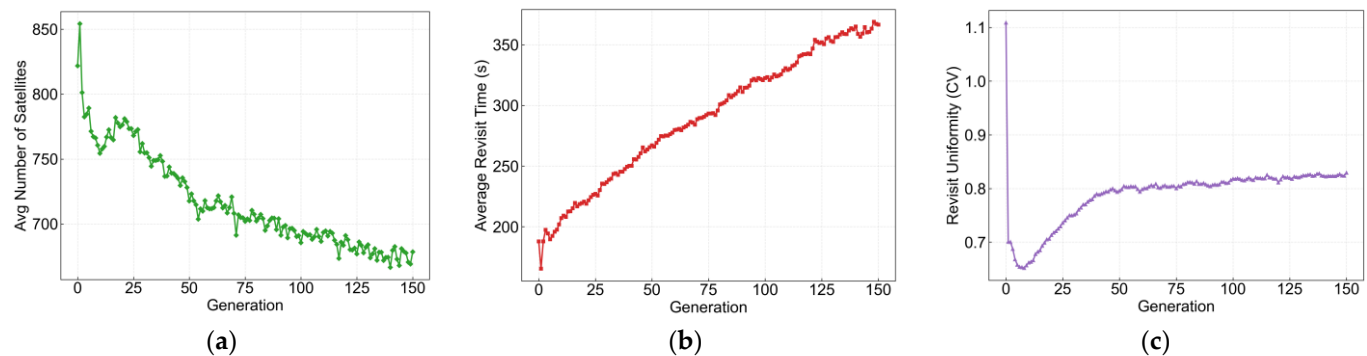


Figure 7. Iterative evolution diagram of objective functions: (a) Iterative diagram of average number of satellites; (b) Iterative diagram of average revisit time; (c) Iterative diagram of revisit time uniformity.

(3) Trade-off Analysis of Objective Functions

- Trade-off Analysis between Cost and Performance

A prominent trade-off relationship between the total constellation scale and the mean revisit time can be clearly observed from the obtained Pareto front, which substantiates the necessity of employing multi-objective optimization. Details are shown in Figure 8a,b.

The Pareto front spans a range of mean revisit times from 35.59 s (corresponding to a large-scale constellation) to 1799.83 s (corresponding to a small-scale constellation). This corresponds to a variation in the number of satellites from 2000 down to 50, thereby fully covering the predefined search bounds of the constellation scale. Specifically, when the constellation size expands from 50 to 250 satellites, the mean revisit time drops sharply from 1799.83 s to 287.45 s. Conversely, as the scale further increases from 1023 to 2000 satellites, the revisit time merely decreases from 69.94 s to 35.59 s, demonstrating a distinct law of diminishing marginal utility. These numerical insights provide a critical foundation for engineering decision-making: a cost-effective equilibrium must be carefully identified to balance system expenditures against the desired revisit performance.

- Trade-off Analysis between Cost and Revisit Uniformity

As illustrated in the Figure 8a,c, the constellation scale and the revisit time uniformity exhibit a non-monotonic, highly complex, funnel-shaped scattering distribution. This distribution fundamentally contradicts the conventional linear assumption that a larger number of satellites inherently guarantees better uniformity, thereby highlighting the unique value of multi-objective optimization.

For small-scale constellations (50~250 satellites), the uniformity indicator exhibits an extremely wide distribution range (0.18~1.50). This implies that when the number of available satellites is strictly constrained, the geometric design of the constellation architecture plays a decisive role. A rationally optimized constellation configuration can yield a coverage uniformity that is significantly superior to peer solutions of the same scale; conversely, an improper structural design easily induces severe coverage non-uniformity.

For medium-to-large-scale constellations (250~1000 satellites), as the number of satellites increases, the upper bound of the uniformity indicator drops significantly, and the overall distribution converges toward the bottom. Within this interval, the constellation performance generally tends to be robust. However, distinct variations in uniformity persist even among configurations of identical scales, confirming that design optimization remains vital.

For ultra-large-scale constellations (above 1000 satellites), the distribution interval of the revisit uniformity is further compressed, concentrating primarily between 0.80 and

1.08. At this stage, the redundant coverage provided by the massive constellation scale renders its uniformity highly stable, leaving marginal room for further improvement.

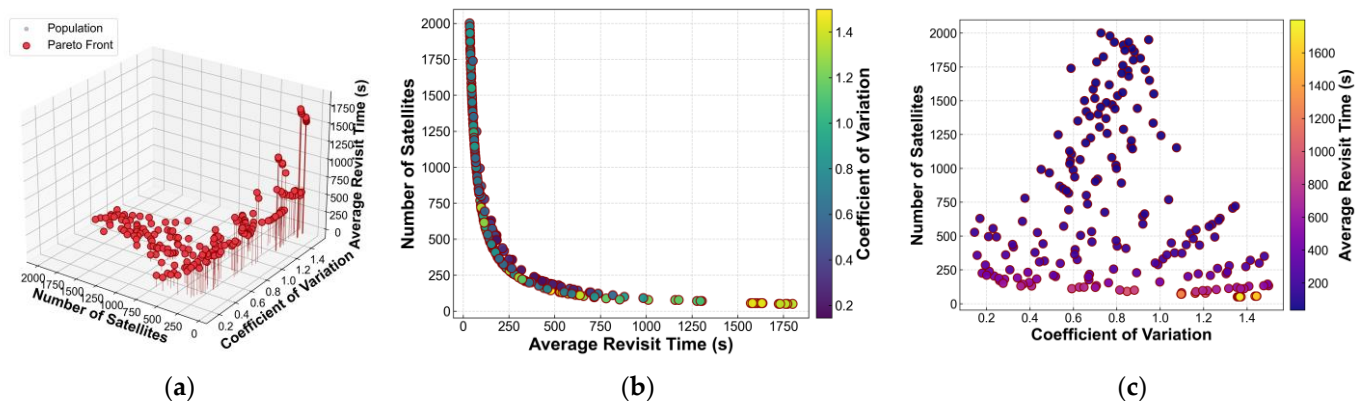


Figure 8. Pareto front solutions of the 150th generation: (a) Three-dimensional Pareto front solutions; (b) Two-dimensional diagram of average revisit time versus constellation size; (c) Two-dimensional diagram of revisit time uniformity versus constellation size.

5.2.2. Localization Accuracy Sensitivity Analysis

To further evaluate the impact of payload localization accuracy on system tracking performance, a sensitivity analysis was conducted based on the quantitative model derived in Section 2.2. Treating the single-point localization standard deviation σ as the independent variable, we investigated the behavioral variations of two critical metrics: the maximum trackable target density $\rho_{\max}$ (Equation (16)) and the critical revisitation time T_{crit} (Equation (22)). Two distinct operational mission scenarios were established for this evaluation:

- (1) Scenario 1: Fixing the maximum target maneuverability $a_{\max} = 0.001 \text{ m/s}^2$ and the orbital revisitation interval $T_r = 1898.83 \text{ s}$ to calculate the variation profile of the maximum resolvable target density $\rho_{\max}$ as a function of σ .
- (2) Scenario 2: Fixing $a_{\max} = 0.001 \text{ m/s}^2$ and the operating target density $\rho = 50 \text{ ships}/10^4 \text{ km}^2$ (matching the baseline deployment conditions in Section 5.1) to compute the response curve of the critical revisitation time T_{crit} against σ .

For simulation Scenario 1, $\rho_{\max}$ exhibits extreme sensitivity toward variations in σ . As illustrated in Figure 9, $\rho_{\max}$ decreases monotonically with the increase of σ , with the drop-off being particularly severe in the low- σ regime. Under ideal tracking conditions ($\sigma = 0 \text{ km}$), the system can resolve up to $\rho_{\max} = 96 \text{ ships}/10^4 \text{ km}^2$. This metric degrades to $77 \text{ ships}/10^4 \text{ km}^2$ when $\sigma = 0.5 \text{ km}$, and collapses to $\rho_{\max} = 50 \text{ ships}/10^4 \text{ km}^2$ at the baseline specification of $\sigma = 1 \text{ km}$ adopted in this study. This pronounced sensitivity confirms that the $96\sigma^2$ denominator term in Equation (16) dominates the theoretical bound of tracking capability. More crucially, this outcome provides empirical counter-evidence validating the absolute necessity of adopting a conservative σ margin: any optimistic underestimation of σ will lead to a severe overestimation of the system's true tracking capacity, thereby resulting in non-viable constellation configurations that are highly prone to mission failure under actual on-orbit conditions.

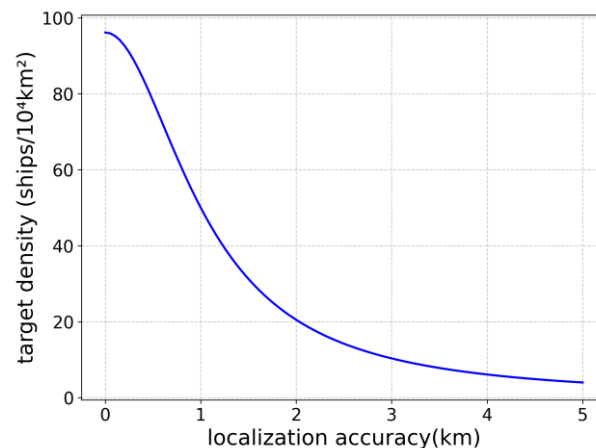


Figure 9. Variation curve of $\rho_{\max}$ versus σ .

For simulation Scenario 2, T_{crit} exhibits a monotonic decay as σ increases. As shown in Figure 10, larger localization uncertainties restrict the maximum allowable tracking gap, which exponentially drives up the coverage density and deployment scale requirements of the satellite constellation. Within the interval of 0 to 1.2 km, the degradation rate of T_{crit} remains relatively stable and linear, contracting by approximately 20%. However, as σ approaches 1.4 km, T_{crit} decreases nonlinearly. This threshold characteristic indicates that reasonable stochastic fluctuations of σ around the 1 km operating point fall within an acceptable engineering tolerance, proving that the proposed optimization framework is highly robust against sensor estimation noise. Concurrently, it is observed that once σ surpasses the asymptotic limit of $1/\sqrt{96\lambda} \approx 1.44$ km, the multi-target tracking continuity constraints cannot be satisfied under any physical constellation architecture, regardless of its configuration.

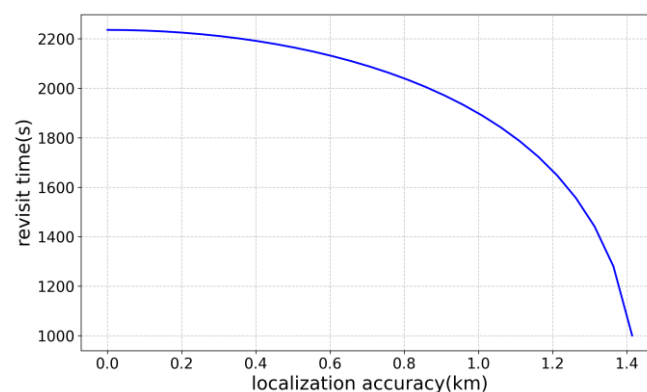


Figure 10. Variation curve of T_{crit} versus σ .

These sensitivity metrics quantify the trade-offs between sensor performance and orbital deployment costs. They quantitatively demonstrate that enhancing payload localization precision (minimizing σ) significantly relaxes the rigid constraints imposed on satellite revisit intervals while allowing the system to sustain substantially higher target densities, thereby establishing a transparent trade-off space between sensor performance and orbital deployment costs. Should future on-orbit geometric calibration refine the systemic localization precision down to $\sigma = 0.5$ km, the constellation can be adaptively re-optimized within the identical framework using the updated parameter envelope to yield a highly downscaled, more cost-effective constellation scheme. Conversely, the conservative assignment of $\sigma = 1$ km maintained throughout this study guarantees that the synthesized constellation architectures retain highly dependable tracking performance

envelopes under realistic flight conditions—fully satisfying the primary criteria for engineering deployment.

5.2.3. Effectiveness Analysis of Revisit Uniformity Metrics for Multi-Target Tracking

To verify the effectiveness of the constellation optimization design for multi-target tracking tasks, a small-scale constellation scenario is selected for simulation validation. The simulation configuration constrains the maximum total number of satellites to 100, with the semi-major axis (orbital altitude) fixed at 6878 km and the orbital inclination varying from 50° to 60°. The resulting Pareto-optimal front solutions are illustrated in Figure 11:

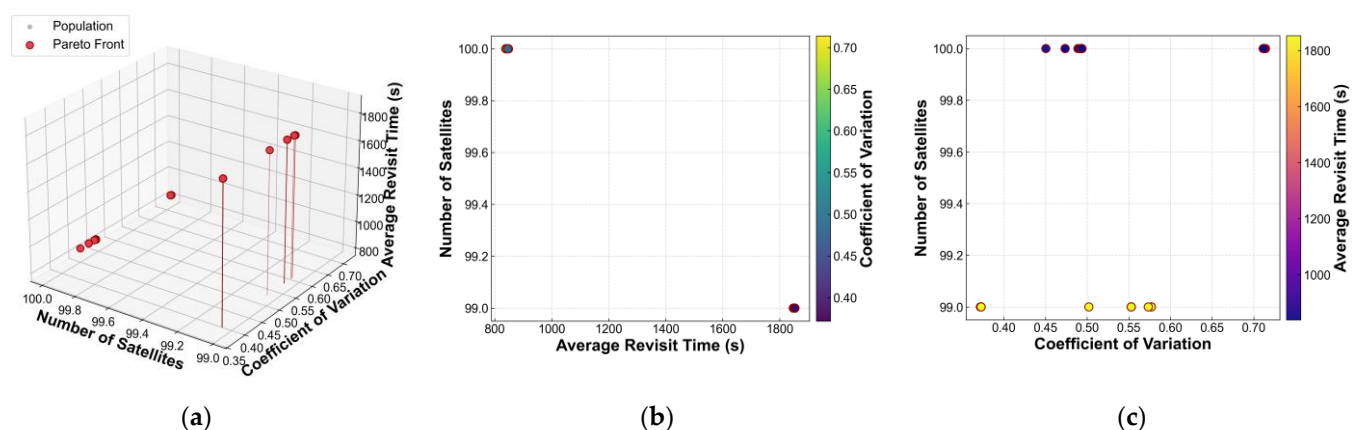


Figure 11. Pareto front solutions of the 50th generation for small-scale constellation optimization: (a) Three-dimensional representation of the Pareto front; (b) Two-dimensional diagram of average revisit time versus constellation size; (c) Two-dimensional diagram of revisit time uniformity versus constellation size.

To further investigate the performance enhancement brought by the coverage uniformity indicator, typical configurations are extracted from the Pareto-optimal front as the experimental group, while a non-Pareto front configuration serves as the control constellation group. Detailed parameters are shown in Table 3. Based on the simulated satellite observation data generated from both groups, track association algorithms are executed [18] to quantitatively evaluate the maritime multi-target tracking capability.

Table 3. Detailed parameters of the constellation.

Solution Type	a	i	P	S	F	Average Revisit Time (s)	Coefficient of Variation
Pareto Frontier Solution	6878	50.49	33	3	5	1858.26	0.38
Non-Pareto Frontier Solution	6878	50.12	11	9	3	1853.99	1.42

Track association algorithm simulations are subsequently carried out under a dynamic scenario with a target vessel density of 50 ships/10⁴ km². According to the simulation results [18], the track association algorithm operating under the Pareto-optimal constellation achieves a 100% matching success rate, enabling all moving ships within the detecting scenario to be correctly identified and tracked. Conversely, the algorithm running under the non-Pareto control constellation yields a reduced matching success rate of 84%, with 8 out of 50 ships failing to be matched successfully. The comparison results are shown in Figures 12 and 13.

This comparative analysis demonstrates a significant performance disparity driven by the spatial uniformity of revisit times within the mission area. Specifically, although both configurations deploy an identical scale of 99 satellites, the non-Pareto solution

suffers from severe regional coverage gaps due to its high coefficient of variation ($CV = 1.42$). In contrast, the Pareto-optimal solution minimizes the variation ($CV = 0.38$), ensuring highly uniform observation timelines. These findings strongly substantiate the necessity and effectiveness of incorporating the coefficient of variation as a critical constraint in constellation optimization frameworks.

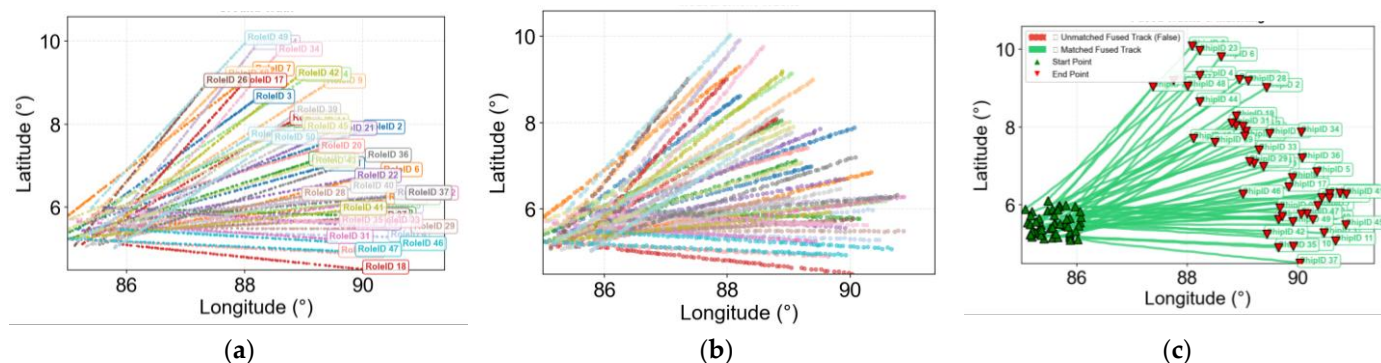


Figure 12. Track association results under the Pareto-optimal constellation: (a) True trajectory; (b) Measured trajectory; (c) Fusion matching relationship.

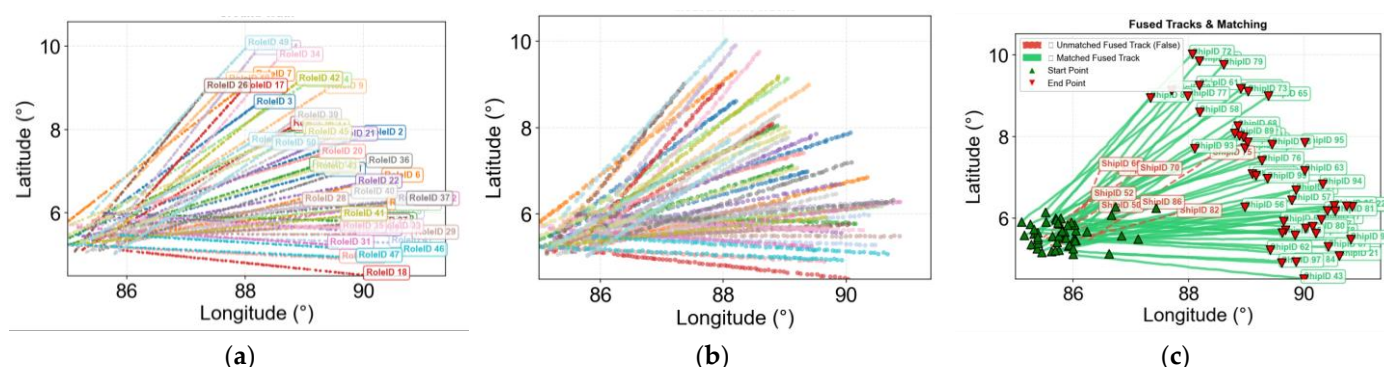


Figure 13. Track association results under the non-Pareto control constellation: (a) True trajectory; (b) Measured trajectory; (c) Fusion matching relationship.

5.2.4. Analysis of Typical Engineering Design

The ultimate output of a multi-objective optimization algorithm is a non-dominated solution set distributed along the Pareto front. In practical aerospace engineering applications, decision-makers are invariably required to screen and select constellation configurations with viable engineering application value from this solution set, based on distinct mission requirements, budgetary constraints, and launch capabilities.

To analyze the engineering utility of the proposed framework, three typical solutions (small-scale economic type, medium-scale balanced type, and large-scale ultimate type) are selected from the 150th-generation Pareto front for evaluation (detailed in Table A2 of Appendix A). The illustration is shown in Figure 14. The specific orbital parameters and performance metrics of the three selected typical constellation design solutions are summarized in Table 4.

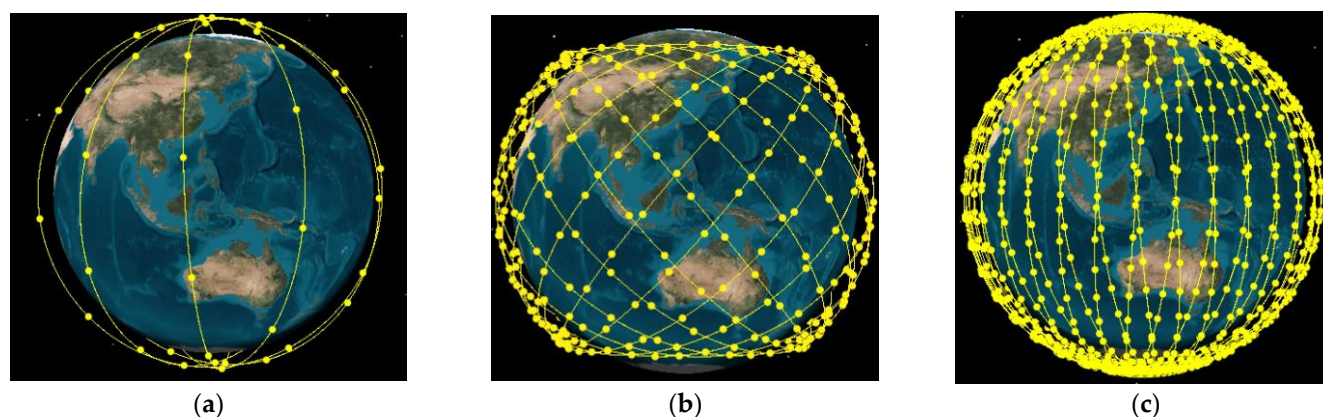


Figure 14. Illustration of three typical constellation design: (a) Small-scale basic type; (b) Medium-scale balanced type; (c) Large-scale ultimate type.

Table 4. Configuration parameters of three typical constellation designs.

Solution Type	Constellation Size	Semi-major Axis (km)	Inclination (°)	Number of Planes P	Satellites per Plane S	Phase Factor F	Average Revisit Time (s)	Revisit Time Uniformity
Solution 1: Small-Scale Economic	50	6976.44	86.95	5	10	2	1724.11	1.37
Solution 2: Medium-Scale Balanced	425	6977.63	50.01	17	25	9	169.17	0.80
Solution 3: Large-Scale Ultimate	1248	6976.61	85.03	32	39	2	72.84	0.53

(1) Solution 1: Small-Scale Economic Type

This solution is suitable for the initial phase of engineering construction or scenarios where the budget is highly constrained. It represents an ultra-low-cost configuration that forms a valid Walker constellation using only 50 satellites, serving as the minimum-scale solution on the Pareto front. Its mean revisit time reaches 1724.11 s, which successfully fulfills baseline requirements for wide-area survey missions that do not demand high timeliness. Furthermore, its uniformity indicator of 1.37 exhibits high robust stability among ultra-small-scale constellations, proving that the geometric layout of this configuration is rationally engineered.

(2) Solution 2: Medium-Scale Balanced Type

Functioning as the primary constellation architecture for next-generation maritime moving target detection, this configuration offers exceptional cost-effectiveness. Positioned at the critical knee point region of the Pareto front, this solution establishes a dense network of 17 orbital planes with 25 satellites per plane, allowing the average revisit time to be drastically compressed to 169.17 s, which completely satisfies the operational requirements of multi-target maritime tracking. The most prominent advantage of this design lies in its uniformity metric, which drops to an optimal 0.80. This indicates that the Walker configuration achieves a high degree of spatial-temporal symmetry, meaning that the revisit time fluctuations across different global maritime regions and time steps are minimized. Consequently, it guarantees highly stable and continuous observation intervals for continuous track association.

(3) Solution 3: Large-Scale Ultimate Type

This solution represents a large-scale space-based system configuration tailored for the detection of dense moving targets in maritime zones. Utilizing a massive network of 32 planes with 39 satellites per plane, the mean revisit time is pushed down to a mere

72.84 s. Notably, compared to even larger front solutions detailed in the appendix (e.g., the 2000-satellite configuration), solution 3 utilizes only about 62% of the total satellite assets while securing an equivalent, minute-level operational efficiency.

From a broader system-engineering perspective, scaling the deployment from 425 to 1248 satellites (an addition of nearly 823 satellites) optimizes the revisit time by approximately 96.33 s. Conversely, further expanding from 1248 to 2000 satellites yields a marginal benefit of only 36.89 s. This analysis explicitly reveals the highly non-linear relationship between satellite investment scale and system capability at the engineering decision-making level, providing data-driven support for cost–benefit justifications during project initialization and trade studies.

6. Conclusions

To address the challenge where traditional geometry-coverage-oriented constellation designs fail to adapt to the tracking requirements of non-uniformly distributed maritime moving targets, a mission-driven, constraint-guided, space-ground integrated multi-objective optimization framework for large-scale constellations is proposed in this paper. The primary conclusions and contributions achieved herein are summarized as follows:

The established model characterizes the coupling relations among the constellation revisit period, payload localization accuracy, target maneuverability, and trackable target density. This model is then converted into a mathematical constraint that, together with the constellation size and revisit uniformity objectives, enables the NSGA-II algorithm to achieve Pareto-optimal trade-offs among tracking performance, coverage uniformity, and system cost within the Walker-Delta configuration space.

Simulation results validate the engineering effectiveness of the proposed framework. The relationship between satellite scale and mean revisit time follows a pattern of diminishing marginal utility, while the correlation between satellite scale and revisit uniformity exhibits a funnel-shaped distribution, indicating that the uniformity of small-scale constellations is highly sensitive to structural configuration and can be significantly enhanced through algorithmic optimization. By incorporating the coefficient of variation of revisit time as an independent optimization objective, the framework effectively identifies constellation solutions with superior coverage balance, leading to a marked improvement in track association success rates.

It should be noted that the current work focuses specifically on circular-scanning radar as the representative observation modality. Nevertheless, the proposed optimization framework is architecturally extensible and not inherently restricted to this sensor type. Adapting the framework to accommodate other sensing modalities—such as synthetic aperture radar (SAR), optical sensors, or passive radio-frequency (RF) systems—by reformulating the corresponding measurement models and error propagation mechanisms represents a promising direction for future research. In addition, future work may also consider incorporating non-uniform target distribution patterns and dynamic coverage requirements into the constellation optimization framework to further enhance its adaptability to complex and time-varying maritime scenarios.

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Appendix A

Detailed data of Simulation Section 5.2.1.

Table A1. Statistical data of average indicators per generation over 150 iterations.

Iteration	Hypervolume	Average Constellation Size	Average Revisit Time	Average Coefficient of Variation	The Standard Deviation of HV	The Relative Standard Deviation
0	11,976,649.9	821	187.8832	1.108712136	383,914.4	0.032055
1	12,202,057.2	854	165.4495	0.700795312	288,649.5	0.023656
2	12,392,963.7	801	187.952	0.700439398	158,542.8	0.012793
3	12,506,678.4	782	197.3795	0.687243997	141,988	0.011353
4	12,539,339.1	784	194.4691	0.66816847	138,436.7	0.01104
5	12,555,209.6	789	189.6154	0.65794629	136,352.6	0.01086
6	12,588,073.9	771	192.4674	0.653979196	140,092.7	0.011129
7	12,608,421.6	767	195.8373	0.653422611	143,798.8	0.011405
8	12,630,498.5	766	197.5103	0.652015558	124,198.3	0.009833
9	12,642,032.4	760	201.938	0.656849758	121,599.4	0.009619
10	12,671,211.7	754	207.124	0.662063954	112,358.1	0.008867
11	12,694,319.8	757	209.0387	0.663620029	102,215.1	0.008052
12	12,702,797.8	759	208.0035	0.666339287	101,742.4	0.008009
13	12,720,771.5	766	212.6055	0.677729943	96,601.6	0.007594
14	12,758,395.9	772	212.7116	0.681917373	82,909.3	0.006498
15	12,763,279.4	766	215.1791	0.684844864	81,614.62	0.006394
16	12,771,109.1	764	219.5667	0.69330611	80,845.49	0.00633
17	12,776,622.1	781	216.7808	0.699025969	82,990.79	0.006496
18	12,791,421	777	218.6963	0.705310846	80,581.03	0.0063
19	12,794,912	774	219.4326	0.706293743	80,418.13	0.006285
20	12,797,076.8	776	220.6325	0.713091931	81,889.73	0.006399
21	12,812,809.6	781	218.9856	0.717866572	76,303.24	0.005955
22	12,815,281.7	778	221.7577	0.720695854	74,736.91	0.005832
23	12,818,008.3	773	224.4035	0.725319165	74,193.76	0.005788
24	12,821,501.6	773	226.3657	0.72946954	74,104.53	0.00578
25	12,830,434.8	768	227.1112	0.736022418	77,416.9	0.006034
26	12,854,490.1	771	225.6084	0.740081679	60,325.08	0.004693
27	12,870,855.3	772	230.1404	0.745590278	47,238.26	0.00367
28	12,886,702.7	755	235.5487	0.750059974	39,790.92	0.003088
29	12,894,851.7	761	235.2082	0.749872268	41,559.91	0.003223
30	12,895,963.4	754	236.6059	0.751169451	40,899.11	0.003171
31	12,910,020.4	754	238.6874	0.753588462	28,113.29	0.002178
32	12,911,739.1	751	239.6437	0.76065027	29,191.02	0.002261
33	12,914,348.5	744	243.4611	0.764530891	28,562.33	0.002212
34	12,915,287.8	748	244.0308	0.770082454	29,595.7	0.002292

35	12,916,591.5	748	242.6656	0.770301167	27,679.68	0.002143
36	12,919,440.8	749	245.3056	0.775414533	25,720.14	0.001991
37	12,920,162.1	752	245.3369	0.778459193	25,552.06	0.001978
38	12,923,988.8	748	247.5527	0.77979383	27,913.91	0.00216
39	12,924,463.5	736	249.4234	0.78614237	27,929.58	0.002161
40	12,923,595.2	736	250.1617	0.789857104	28,140.05	0.002177
41	12,928,215.2	743	250.2296	0.788411201	29,364.47	0.002271
42	12,928,329	739	255.6466	0.789901405	28,305.09	0.002189
43	12,930,140.5	738	255.3736	0.791794922	28,609.31	0.002213
44	12,937,150.7	737	257.4658	0.79408625	34,164.29	0.002641
45	12,941,071.3	735	260.5584	0.793872428	35,574.27	0.002749
46	12,941,316.6	729	265.3258	0.797628307	35,591.32	0.00275
47	12,943,632.2	735	262.1014	0.799955111	38,029.59	0.002938
48	12,949,977.8	732	263.5621	0.796304924	36,999.9	0.002857
49	12,950,351.2	728	265.5315	0.793631967	37,837.49	0.002922
50	12,951,503.5	717	267.0234	0.79568206	37,513.62	0.002896
51	12,950,653.9	723	265.9384	0.798620114	36,567.26	0.002824
52	12,951,295.6	717	269.0312	0.804427063	36,946.78	0.002853
53	12,952,567.3	714	271.8063	0.802521744	35,406.41	0.002734
54	12,953,282	703	274.7409	0.802138634	35,857.8	0.002768
55	12,953,236.8	711	274.4098	0.804043017	36,682.5	0.002832
56	12,953,676.1	709	275.2231	0.803094204	37,144.13	0.002867
57	12,956,174.3	717	275.0457	0.803545403	37,012.45	0.002857
58	12,955,942.4	712	276.3028	0.798885985	36,898.24	0.002848
59	12,957,813.6	711	277.4752	0.793881303	38,394.15	0.002963
60	12,958,727.3	711	279.6646	0.798323912	40,174.66	0.0031
61	12,957,545.9	712	280.0565	0.800673472	39,679.86	0.003062
62	12,958,370.2	717	280.7092	0.800087189	40,309.37	0.003111
63	12,962,770.2	721	279.4962	0.803434273	44,988.55	0.003471
64	12,964,254.6	717	281.6952	0.806288207	46,722.31	0.003604
65	12,967,159.2	712	282.616	0.804097111	45,350.74	0.003497
66	12,965,200.4	714	284.0023	0.808698456	45,463.04	0.003507
67	12,965,798.9	708	286.3948	0.802027902	45,130.39	0.003481
68	12,968,404.7	712	285.8264	0.800978755	45,671.56	0.003522
69	12,967,984.8	720	284.1153	0.804086131	44,732.2	0.003449
70	12,966,610.1	708	288.5867	0.80571972	45,546.53	0.003513
71	12,970,064.9	691	289.5794	0.802870215	46,386.75	0.003576
72	12,971,143.5	706	289.6272	0.802924577	45,699.67	0.003523
73	12,971,912.8	704	290.631	0.804488848	44,685.5	0.003445
74	12,972,010.3	704	292.078	0.804539102	44,593.98	0.003438
75	12,972,790	701	293.2178	0.800294688	43,810.01	0.003377
76	12,973,471.5	703	293.3116	0.804800033	44,407.85	0.003423
77	12,971,861.2	702	293.5889	0.803457949	43,840.01	0.00338
78	12,977,265.4	710	292.0573	0.807769348	44,195.52	0.003406
79	12,976,947.5	707	295.8307	0.808536662	43,388.27	0.003343
80	12,974,734.5	702	300.8162	0.811487285	44,407.52	0.003423
81	12,976,050.5	704	301.3689	0.811884741	45,010.33	0.003469
82	12,975,692.4	707	302.2797	0.811209107	44,220.01	0.003408
83	12,977,198.4	704	304.06	0.808769687	45,869.51	0.003535
84	12,977,450.5	695	308.4065	0.813350945	45,600.99	0.003514
85	12,979,585.7	698	306.7826	0.808102053	46,818.52	0.003607
86	12,978,580.8	702	308.1993	0.808387177	46,689.42	0.003597
87	12,978,810.8	704	309.59	0.8100924	45,704.52	0.003521

88	12,983,973	704	311.6492	0.807582841	42,905.8	0.003305
89	12,984,129.8	695	314.8343	0.805441198	42,425.68	0.003268
90	12,985,706.8	703	311.0838	0.804127932	38,416.35	0.002958
91	12,987,623.5	691	314.5989	0.806469981	37,672.81	0.002901
92	12,986,680.3	697	314.6907	0.807704396	37,424.15	0.002882
93	12,987,371	698	316.2411	0.806568976	38,342.79	0.002952
94	12,986,670.2	689	320.6514	0.807663086	36,871.77	0.002839
95	12,985,505.1	696	321.8938	0.812228785	36,013.27	0.002773
96	12,986,176.9	696	320.6653	0.812267197	32,629.77	0.002513
97	12,987,708.8	694	322.4609	0.810060505	33,319.91	0.002565
98	12,988,992.2	690	321.6978	0.810855622	32,348.7	0.00249
99	12,986,962.8	691	320.6974	0.815716365	32,535.27	0.002505
100	12,987,514.9	685	322.4813	0.818188372	31,667.34	0.002438
101	12,989,225.1	694	323.2682	0.817610134	31,923.52	0.002458
102	12,988,038.1	692	320.9926	0.818974912	33,333.8	0.002567
103	12,988,732.9	691	322.9393	0.817632879	30,505.75	0.002349
104	12,987,546.4	691	325.4763	0.815578411	30,190.88	0.002325
105	12,987,443.6	688	323.8836	0.814759161	30,000.22	0.00231
106	12,989,829.8	690	324.4902	0.817313392	28,151.76	0.002167
107	12,991,788.3	695	325.6155	0.820285314	26,472.36	0.002038
108	12,992,596.3	690	328.5551	0.816997035	26,683.74	0.002054
109	12,991,852.6	686	330.5679	0.815650323	26,690.53	0.002054
110	12,991,428.8	693	329.1841	0.820385092	27,509.42	0.002118
111	12,990,964.9	694	330.0964	0.819292671	28,412.49	0.002187
112	12,990,472.1	690	332.5155	0.819538956	28,034.54	0.002158
113	12,989,425.8	694	333.1829	0.818365644	29,061.92	0.002237
114	12,991,391.9	692	335.4694	0.818692635	29,379.54	0.002261
115	12,991,840	687	340.3932	0.825352059	27,167.23	0.002091
116	12,992,704.9	684	341.2946	0.820587241	27,123.73	0.002088
117	12,991,157.1	673	342.1607	0.820088209	27,806.45	0.00214
118	12,991,179.2	685	342.1459	0.818255759	27,828.31	0.002142
119	12,991,646.3	683	342.7699	0.81798225	28,712.69	0.00221
120	12,994,891.6	690	342.2395	0.811138461	27,842.16	0.002143
121	12,993,624.3	687	346.8626	0.816678707	27,187.42	0.002092
122	12,992,466.4	680	354.0461	0.822673129	29,506.47	0.002271
123	12,993,273.7	679	352.4578	0.820042459	28,336.16	0.002181
124	12,989,930.3	681	351.3966	0.821392774	30,302.84	0.002333
125	12,990,887.8	676	351.9232	0.819320647	30,940.62	0.002382
126	12,990,643.6	686	350.376	0.817735092	30,254.89	0.002329
127	12,990,909.2	683	355.0675	0.822132894	31,141.95	0.002397
128	12,990,457.4	677	356.1818	0.821205147	29,171.22	0.002246
129	12,990,557.5	682	353.1576	0.820706862	30,476.1	0.002346
130	12,991,603	683	352.307	0.822291561	30,100.23	0.002317
131	12,993,482.4	673	356.1458	0.824426187	28,629.57	0.002203
132	12,992,190.5	676	356.3948	0.824145065	31,151.13	0.002398
133	12,992,063.9	680	358.4472	0.825433549	31,397.35	0.002417
134	12,992,746.6	672	360.2491	0.82616964	30,783.58	0.002369
135	12,991,135.4	678	358.8268	0.823244395	31,711.31	0.002441
136	12,991,781	678	358.6723	0.824215798	31,355.78	0.002414
137	12,990,989.7	671	361.7554	0.827167363	31,064.84	0.002391
138	12,991,182.5	674	363.5692	0.827999985	30,803.96	0.002371
139	12,992,078.9	674	362.6809	0.824179932	28,544.42	0.002197
140	12,991,560.3	666	365.0076	0.823500675	29,304.78	0.002256

141	12,989,949.8	679	358.9437	0.822150722	28,915.04	0.002226
142	12,988,335.6	682	356.6058	0.823449804	28,724.5	0.002212
143	12,988,859.5	672	359.1236	0.823165439	27,664.1	0.00213
144	12,988,554.4	668	364.4199	0.823470331	26,658.03	0.002052
145	12,989,368.2	680	360.0869	0.822925633	27,454.98	0.002114
146	12,989,429.5	678	360.657	0.824653917	29,140.51	0.002243
147	12,987,989.3	677	363.2407	0.826885304	27,080.18	0.002085
148	12,987,327.7	670	368.8454	0.823903917	28,352.36	0.002183
149	12,989,661	669	367.1587	0.823600057	30,010.57	0.00231
150	12,989,008.1	678	366.5757	0.829470156	29,746.24	0.00229

Detailed data of Simulation Section 5.2.1.

Table A2. Detailed analysis of 150th-generation pareto frontier.

Population Size	a	i	P	S	F	Average Revisit Time (s)	Coefficient of Vari- ation	Constellation Size
1	6976.44	86.95	5	10	2	1724.11	1.37	50
2	6976.59	89.42	5	10	4	1799.83	1.36	50
3	6977.96	86.38	5	10	4	1771.47	1.36	50
4	6977.46	87.19	5	10	4	1761.76	1.36	50
5	6977.96	83.63	5	10	0	1731.67	1.37	50
6	6977.86	83.85	5	11	4	1571.70	1.45	55
7	6977.23	89.73	5	11	4	1635.65	1.44	55
8	6977.99	87.52	5	11	4	1606.95	1.44	55
9	6976.42	88.97	5	11	1	1594.65	1.44	55
10	6977.96	88.53	5	11	4	1623.49	1.44	55
11	6977.99	89.77	5	11	4	1632.35	1.44	55
12	6977.49	88.47	5	11	1	1580.42	1.44	55
13	6975.21	89.98	7	10	6	1304.25	1.10	70
14	6976.60	88.47	7	10	4	1277.60	1.10	70
15	6976.61	87.49	7	10	2	1296.38	1.10	70
16	6977.99	90.00	7	11	6	1158.36	1.16	77
17	6977.86	88.47	7	11	0	1177.61	1.16	77
18	6878.00	50.00	8	10	0	1011.54	1.21	78
19	6975.98	50.00	8	10	7	855.23	1.10	80
20	6977.96	50.01	8	11	7	781.06	1.16	88
21	6976.30	85.37	9	10	8	984.35	0.85	90
22	6977.95	50.00	8	12	7	714.93	1.22	96
23	6977.89	50.00	8	12	6	717.22	1.20	96
24	6978.00	85.64	9	11	5	880.42	0.88	99
25	6977.93	51.50	10	10	4	717.83	0.81	100
26	6977.62	50.01	8	13	4	658.03	1.26	104
27	6977.23	88.02	11	10	6	817.66	0.59	110
28	6977.14	50.00	11	10	2	634.25	1.39	110
29	6977.14	50.00	11	10	3	638.19	1.37	110
30	6977.87	50.01	8	14	8	613.68	1.32	112
31	6977.83	50.00	8	15	1	573.02	1.35	120
32	6976.74	50.01	12	10	3	593.65	0.70	120
33	6977.83	89.75	11	11	8	737.94	0.63	121
34	6977.96	86.13	11	11	5	736.52	0.65	121
35	6978.00	50.01	8	16	2	542.39	1.41	128
36	6977.66	87.36	13	10	1	690.83	0.41	130
37	6977.23	89.45	13	10	3	696.68	0.36	130

38	6977.94	50.01	11	12	6	526.67	1.50	132
39	6977.94	50.01	11	12	10	531.21	1.48	132
40	6977.99	51.62	12	11	5	552.29	0.71	132
41	6977.23	89.50	13	11	5	626.27	0.37	143
42	6977.90	50.04	8	18	7	477.99	1.49	144
43	6977.96	85.97	15	10	5	602.95	0.28	150
44	6977.75	50.03	14	11	1	460.26	0.76	154
45	6977.07	89.97	13	12	5	582.51	0.40	156
46	6977.99	50.00	10	16	9	441.85	1.00	160
47	6977.13	89.19	17	10	16	534.59	0.26	170
48	6977.98	51.18	16	11	11	413.67	0.67	176
49	6955.69	88.02	15	12	14	521.82	0.28	180
50	6977.23	89.74	13	14	12	497.77	0.43	182
51	6977.94	88.02	17	11	16	489.46	0.26	187
52	6976.78	89.59	19	10	4	478.04	0.34	190
53	6977.99	50.00	18	11	17	361.09	0.67	198
54	6977.93	50.39	10	20	1	356.64	1.13	200
55	6971.91	52.45	20	10	16	372.69	0.52	200
56	6974.72	89.94	17	12	10	448.26	0.24	204
57	6977.04	50.00	13	16	3	338.72	1.23	208
58	6977.03	50.02	19	11	12	342.20	0.51	209
59	6977.99	89.25	15	14	11	431.60	0.20	210
60	6978.00	50.01	18	12	11	330.20	0.67	216
61	6977.99	50.00	10	22	9	322.84	1.18	220
62	6977.96	50.00	13	17	12	320.98	1.30	221
63	6977.99	89.74	15	15	14	402.18	0.18	225
64	6976.37	50.01	12	19	7	313.79	0.89	228
65	6977.16	86.14	21	11	16	394.52	0.39	231
66	6977.06	50.00	13	18	8	303.54	1.31	234
67	6971.69	89.21	17	14	14	387.84	0.21	238
68	6977.60	50.01	25	10	10	287.45	0.31	250
69	6977.11	50.01	17	15	15	280.41	0.79	255
70	6978.00	50.02	10	26	7	272.04	1.26	260
71	6978.00	50.01	13	21	12	259.12	1.39	273
72	6977.99	50.00	10	28	8	253.68	1.32	280
73	6977.98	89.99	15	19	8	317.37	0.19	285
74	6977.99	50.02	12	24	9	247.38	0.99	288
75	6969.45	56.38	27	11	26	265.04	0.54	297
76	6977.98	50.00	13	23	12	236.88	1.46	299
77	6978.00	50.01	15	20	12	235.54	0.98	300
78	6970.47	56.15	28	11	12	255.15	0.44	308
79	6978.00	50.00	21	15	8	226.18	0.47	315
80	6977.96	50.00	10	32	9	221.88	1.42	320
81	6977.03	50.02	25	13	11	220.14	0.62	325
82	6977.98	50.01	15	22	14	213.37	1.01	330
83	6977.94	50.75	10	35	3	204.82	1.48	350
84	6946.47	90.00	17	21	9	267.86	0.16	357
85	6976.83	87.75	15	24	1	250.58	0.29	360
86	6978.00	50.00	15	24	14	195.89	1.03	360
87	6977.26	50.00	26	14	2	196.66	0.61	364
88	6977.93	50.73	12	31	11	193.54	1.10	372
89	6978.00	50.00	15	25	14	188.05	1.07	375
90	6977.79	50.01	27	14	8	189.82	0.42	378

91	6977.65	50.09	21	19	10	179.61	0.61	399
92	6977.90	50.03	17	24	1	176.27	0.84	408
93	6958.91	88.79	19	22	13	223.37	0.32	418
94	6977.63	50.01	17	25	9	169.17	0.80	425
95	6977.29	50.00	12	36	1	164.96	1.18	432
96	6977.99	50.01	15	29	0	162.07	1.12	435
97	6955.48	90.00	19	23	3	215.22	0.32	437
98	6977.54	50.01	26	17	11	162.17	0.46	442
99	6977.97	50.22	14	32	5	158.98	1.05	448
100	6977.70	50.02	19	24	2	156.42	0.69	456
101	6977.98	50.02	31	15	10	154.33	0.80	465
102	6978.00	50.01	15	32	9	146.83	1.15	480
103	6977.99	50.01	12	41	11	144.92	1.25	492
104	6977.07	90.00	17	29	5	184.03	0.25	493
105	6977.97	89.66	15	33	5	183.12	0.21	495
106	6977.12	50.06	21	24	3	142.36	0.63	504
107	6977.04	50.00	14	37	13	137.06	1.14	518
108	6969.27	86.43	21	25	20	175.37	0.43	525
109	6941.67	90.00	17	31	14	182.45	0.15	527
110	6977.98	50.03	19	28	13	134.24	0.68	532
111	6977.04	50.00	14	39	13	129.97	1.17	546
112	6977.97	89.92	15	37	12	163.44	0.23	555
113	6977.96	50.00	15	38	10	123.60	1.23	570
114	6952.70	70.78	26	22	25	158.83	0.56	572
115	6977.99	50.00	15	39	14	120.37	1.24	585
116	6978.00	50.00	49	12	48	121.60	0.92	588
117	6975.95	89.34	19	32	16	149.48	0.37	608
118	6977.97	50.01	15	41	14	114.69	1.27	615
119	6942.38	89.29	17	37	14	153.24	0.17	629
120	6977.70	50.00	15	42	14	111.86	1.28	630
121	6977.88	50.00	17	38	16	111.32	0.92	646
122	6976.27	50.00	17	39	13	108.77	0.93	663
123	6977.29	50.00	27	25	11	106.11	0.74	675
124	6923.12	53.20	33	21	32	118.00	0.58	693
125	6977.99	50.00	15	47	10	99.95	1.33	705
126	6977.97	50.01	15	48	3	97.81	1.35	720
127	6977.07	50.00	46	16	3	97.30	0.67	736
128	6977.98	50.00	16	48	15	93.27	1.04	768
129	6977.68	88.82	19	41	3	116.40	0.38	779
130	6977.96	62.07	50	16	12	98.86	0.66	800
131	6977.99	50.00	48	17	10	87.77	0.58	816
132	6977.99	50.01	49	17	14	85.95	0.57	833
133	6964.99	51.22	22	38	14	88.90	0.56	836
134	6978.00	50.01	25	34	24	84.17	0.55	850
135	6889.45	52.03	31	28	1	98.61	0.54	868
136	6977.90	50.01	33	27	13	80.26	0.82	891
137	6977.96	50.00	21	43	10	79.21	0.70	903
138	6978.00	50.05	40	23	9	77.82	0.71	920
139	6978.00	50.05	39	24	9	76.55	0.61	936
140	6977.98	50.19	23	42	2	74.32	0.49	966
141	6977.99	50.00	26	38	11	72.43	0.60	988
142	6903.39	58.75	31	32	1	91.05	0.45	992
143	6977.98	50.00	37	27	11	71.62	0.80	999

144	6977.96	50.00	33	31	14	69.94	0.80	1023
145	6978.00	50.02	22	47	19	69.20	0.58	1034
146	6977.98	50.02	22	48	7	67.78	0.59	1056
147	6977.99	50.00	28	38	8	67.26	0.63	1064
148	6977.95	50.01	45	24	16	66.20	0.78	1080
149	6977.95	50.01	46	24	9	64.76	0.59	1104
150	6977.98	50.01	49	23	17	63.54	0.58	1127
151	6978.00	50.01	44	26	21	62.60	0.87	1144
152	6978.00	50.01	48	24	33	62.06	1.08	1152
153	6977.93	50.01	43	27	21	61.57	0.87	1161
154	6977.98	50.00	27	44	9	60.24	0.66	1188
155	6978.00	50.01	43	28	20	59.40	0.87	1204
156	6977.93	50.01	25	49	13	58.43	0.68	1225
157	6977.93	50.00	46	27	26	57.56	1.00	1242
158	6976.61	85.03	32	39	2	72.84	0.53	1248
159	6977.99	50.01	34	37	2	56.84	0.76	1258
160	6978.00	50.02	46	28	35	55.53	0.83	1288
161	6977.98	50.00	29	45	9	54.80	0.72	1305
162	6977.93	50.01	46	29	26	53.65	0.97	1334
163	6959.67	52.68	30	45	29	56.64	0.62	1350
164	6977.93	50.02	36	38	35	52.31	0.75	1368
165	6977.96	50.00	33	42	14	51.61	0.68	1386
166	6977.93	50.02	35	40	34	51.10	0.71	1400
167	6977.98	50.00	33	43	25	50.41	0.66	1419
168	6977.96	50.01	36	40	7	49.70	0.79	1440
169	6977.94	50.01	39	37	12	49.58	0.89	1443
170	6977.99	50.00	33	44	18	49.26	0.73	1452
171	6977.99	50.04	49	30	10	48.69	0.78	1470
172	6977.31	50.43	33	45	5	48.58	0.75	1485
173	6977.99	50.00	50	30	11	47.68	0.65	1500
174	6977.95	50.01	41	37	35	47.19	0.70	1517
175	6977.99	50.01	48	32	18	46.57	0.80	1536
176	6977.99	50.02	50	31	24	46.14	0.97	1550
177	6978.00	50.02	39	40	29	45.92	0.83	1560
178	6977.98	50.00	33	48	18	45.12	0.69	1584
179	6977.97	50.02	49	33	5	44.27	0.77	1617
180	6977.96	51.35	48	34	7	44.70	0.70	1632
181	6977.97	50.00	50	33	22	43.38	0.95	1650
182	6977.96	50.01	48	35	10	42.58	0.86	1680
183	6977.93	50.01	46	37	30	42.03	0.82	1702
184	6977.96	50.01	42	41	13	41.56	0.85	1722
185	6977.93	50.00	48	36	22	41.41	0.93	1728
186	6917.92	63.50	37	47	3	52.85	0.59	1739
187	6977.93	50.04	44	40	17	40.66	0.83	1760
188	6978.00	50.00	47	38	6	40.07	0.71	1786
189	6977.95	50.01	50	36	7	39.76	0.88	1800
190	6977.99	50.01	49	37	28	39.44	0.91	1813
191	6977.95	50.00	48	38	2	39.22	0.74	1824
192	6977.90	50.00	49	38	19	38.42	0.88	1862
193	6977.99	50.00	48	39	18	38.23	0.84	1872
194	6978.00	50.03	46	41	0	37.96	0.87	1886
195	6977.97	50.01	49	39	31	37.43	0.83	1911
196	6977.67	50.00	46	42	37	37.05	0.79	1932

197	6978.00	50.00	46	42	17	37.01	0.85	1932
198	6977.97	50.00	50	39	21	36.67	0.95	1950
199	6977.95	50.00	46	43	37	36.15	0.77	1978
200	6977.97	50.01	50	40	6	35.59	0.73	2000

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