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A Three-Stage Hierarchical Optimization Framework for Operational Imaging Performance in ΔV -Constrained Earth Observation Constellations

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Featured Application

The proposed hierarchical optimization framework can support mission planning and rapid-response configuration of Earth observation satellite constellations operating under propulsion constraints. It is particularly applicable to crisis-monitoring scenarios, border and coastal surveillance, and time-critical environmental assessment missions requiring efficient maneuver allocation and operational response-time evaluation under environmental uncertainty.

Abstract

Earth observation satellite constellations must ensure rapid and reliable coverage of critical areas under propulsion constraints and environmental variability. Existing studies typically treat constellation geometry, maneuver optimization, and operational assessment as separate problems, limiting understanding of the structural origin of performance constraints. This study proposes a three-stage hierarchical optimization framework that separates intrinsic geometric potential, reactive multi-objective maneuver adaptability, and stochastic operational realizability. In Stage 1, a genetic algorithm optimizes constellation geometry with respect to global success rate across multiple areas of interest. In Stage 2, NSGA-II-based maneuver optimization evaluates the trade-off between success rate, time to first access, and total ΔV expenditure. In Stage 3, operational performance is assessed using the Operational Imaging Response Time (OIRT) metric under probabilistic environmental filtering. Simulation results show that constellation geometry is the primary structural determinant of performance within the analyzed configuration range, while maneuver optimization provides moderate but measurable response-time improvements. Environmental filtering reduces achievable coverage relative to purely geometric predictions. The proposed framework establishes a consistent methodology linking constellation synthesis, maneuver planning, and operational response evaluation for time-critical Earth observation missions.



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Keywords: satellite constellation design; multi-objective optimization; orbital maneuver optimization; earth observation; operational imaging response time (OIRT); ΔV constraints; rapid-response imaging

1. Introduction

Earth observation systems (EOSs) constitute a critical component of contemporary environmental monitoring, disaster management, and security-related decision processes.

Satellite imagery supports rapid assessment of floods, earthquakes, landslides, and other large-scale hazards, enabling both civilian and strategic response actions [1–3].

In time-critical scenarios, however, the availability of satellite imagery over a specific Area of Interest (AOI) is not solely determined by the number of deployed satellites. It depends on constellation geometry, orbital configuration, propulsion limitations, and environmental constraints that collectively shape system responsiveness.

Extensive research has addressed constellation geometry and coverage optimization. Classical studies demonstrate that orbital parameters, plane distribution, inclination selection, and phasing strategies significantly influence global coverage and revisit time characteristics [4–10]. In particular, Flower constellation theory [5], route-theory-based constellation synthesis [6–8], and elliptic continuous-coverage designs [9] have established formal relationships between geometry and coverage performance. Revisit-driven multi-target optimization approaches further refined constellation design methodologies [4,10].

Recent advancements in small spacecraft technologies, including documented progress in miniaturized propulsion subsystems and guidance, navigation, and control architectures [11], have enabled increasingly flexible orbital maneuvers. Consequently, numerous approaches to constellation reconfiguration and maneuver cost minimization have been proposed. These include analytical transfer optimization based on Lambert-type formulations [12], fuel-efficient sequencing strategies in multi-spacecraft systems [13], constellation reconfiguration under operational constraints [14–16], and distributed auction-based reassignment algorithms [17].

At the algorithmic level, evolutionary multi-objective optimization methods have been widely applied in orbital maneuver planning. The NSGA-II framework and its theoretical foundations remain central references in multi-objective optimization [18,19], while decomposition-based approaches such as MOEA/D further extend evolutionary optimization capabilities [20]. Recent adaptive and feedback-learning variants of NSGA-II have been applied to responsive multi-satellite observation problems [21]. In parallel, adaptive differential evolution methods have demonstrated improved response-time and fuel-efficiency trade-offs [22], and reinforcement learning techniques have been introduced for scalable constellation operations [23].

In the broader context of genetic optimization, real-coded genetic algorithms (RCGAs) represent an important class of methods for optimization problems involving continuous decision variables. Herrera et al. reviewed the foundations of RCGAs, emphasizing that real-valued representations are particularly natural for parameter optimization problems in continuous domains and discussing the role of selection, crossover, and mutation operators in such algorithms [24]. More recent developments have extended this concept toward adaptive parameter control in real-coded evolutionary search. For example, Beklaryan et al. proposed a real-coded genetic algorithm with fuzzy control (F-RCGA) integrated with system dynamics models, in which fuzzy-control rules are used to adapt algorithmic parameters such as mutation probability, crossover-operator type, and parent-population size [25]. Their optimization experiments demonstrated improved time efficiency compared with other RCGAs and the Monte Carlo method, confirming the relevance of adaptive real-coded genetic approaches for complex continuous optimization problems [25]. These studies indicate that real-coded and adaptive genetic optimization approaches may be particularly relevant for complex design spaces combining continuous parameters with architectural decision variables [24,25]. In the present work, however, the focus is not on developing a new GA variant, but on using a genetic optimization framework as one component of a hierarchical constellation-design and operational-assessment methodology.

Beyond maneuver optimization, geometric inter-satellite relationships and multi-target robustness have been shown to significantly affect constellation performance [26–29].

Scheduling and attitude-planning algorithms for agile constellations confirm that coordinated task allocation substantially increases imaging efficiency [30–32]. Disaster-response scheduling using multi-objective genetic algorithms further emphasizes the integration of coverage rate and completion time metrics in emergency scenarios [3], while mission planning under fuel and time constraints highlights the necessity of explicitly incorporating propulsion limitations into operational decision processes [13].

Despite significant progress in both geometric constellation optimization and maneuver-level responsiveness, these domains are typically treated as separate design problems. Constellation geometry is often optimized independently of reactive maneuver analysis, and operational performance is frequently assessed without explicit structural linkage to intrinsic geometric limitations. Implicitly, many studies assume that maximizing geometric accessibility or revisit frequency directly translates into improved operational responsiveness. This assumption becomes questionable once environmental uncertainty, particularly cloud cover constraints explicitly addressed in pre-launch mission planning datasets [27], is incorporated into the assessment.

Consequently, a structural gap persists between three distinct performance domains:

- Intrinsic geometric potential of a constellation;
- Reactive adaptability achievable under constrained ΔV budgets;
- Stochastic operational realizability under environmental variability.

To the best of the authors' knowledge, the existing literature does not explicitly formulate a hierarchically separated decision architecture that distinguishes and sequentially evaluates these three layers within a single physically consistent framework.

This study does not introduce a novel evolutionary algorithm nor a modified variant of NSGA-II. Instead, its contribution lies in the development and validation of a hierarchical optimization architecture that explicitly separates the following:

1. Intrinsic geometric potential (Stage 1);
2. Reactive multi-objective maneuver adaptability (Stage 2);
3. Stochastic operational realizability evaluated through the Operational Imaging Response Time (OIRT) metric (Stage 3).

By structurally decoupling these layers, the proposed framework enables identification of whether performance limitations originate from orbital geometry, maneuver constraints, or environmental variability. This separation provides a traceable decision pathway from constellation synthesis to operational response-time assessment.

The main objective of this work is, therefore, to formulate and validate a three-stage hierarchical optimization framework for small satellite constellations operating under strict ΔV constraints in crisis-response scenarios. This framework integrates geometric constellation optimization, multi-objective maneuver analysis using NSGA-II, and operational response-time evaluation under probabilistic environmental filtering.

The results demonstrate that constellation geometry constitutes the dominant determinant of system performance, while maneuver optimization provides measurable but secondary improvements. Furthermore, environmental filtering significantly reduces achievable coverage relative to purely geometric predictions, highlighting the necessity of incorporating stochastic operational assessment directly into constellation design processes.

The remainder of this paper is organized as follows. Section 2 presents the methodology. Section 3 reports the simulation results. Section 4 discusses methodological and system-level implications. Section 5 concludes the study.

2. Materials and Methods

This section describes the architecture of the framework and details the mathematical formulations and optimization procedures implemented at each stage.

2.1. Overall Optimization Architecture

The proposed methodology is based on a three-layer optimization architecture integrating the geometric, dynamic, and operational layers of the Earth observation system. This structure enables the separation of constellation design as a long-term planning problem from short-term reactive maneuver adaptation, as well as from the assessment of actual operational effectiveness under environmental conditions.

The first stage (Stage 1) focuses on the global optimization of constellation geometry within a predefined time horizon. Its objective is to maximize the observational potential resulting solely from the orbital configuration.

The second stage (Stage 2) is reactive in nature and involves multi-objective optimization of orbital maneuvers executed in response to a crisis event. At this level, the system's adaptive capability is evaluated under constrained ΔV budgets.

The third stage (Stage 3) introduces the operational layer through the application of the OIRT metric, which incorporates both geometric coverage accumulation and a probabilistic model of environmental conditions.

Such separation prevents the conflation of geometric and dynamic effects and enables unambiguous interpretation of the contribution of each layer to the overall system performance. The general structure of the proposed methodological framework is illustrated in Figure 1.

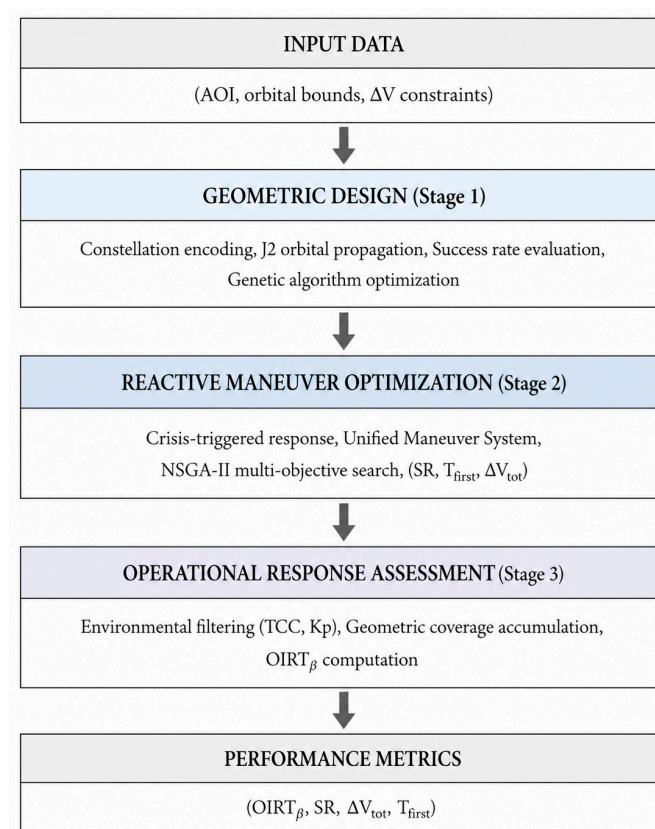


Figure 1. Integrated three-layer optimization architecture combining geometric constellation design (Stage 1), reactive multi-objective maneuver optimization (Stage 2), and operational assessment of observational performance using the OIRT metric (Stage 3).

The detailed pseudocode of the proposed multi-stage optimization framework is provided in Appendix A.

2.2. Stage 1—Constellation Configuration Optimization

Stage 1 focuses on the global optimization of constellation geometry, aiming to maximize intrinsic coverage potential independently of reactive maneuver optimization. This stage defines the decision variables, constraints, and the objective function associated with constellation synthesis.

2.2.1. Stage 1 Optimization Problem

The objective of Stage 1 is to determine a constellation configuration that maximizes its observational potential within a predefined time horizon, considering exclusively the geometric and dynamic properties of orbital motion.

The problem is formulated as a discrete optimization task solved using a genetic algorithm (GA) framework [33]. For clarity, the Stage 1 constellation-geometry optimization can be summarized as the following single-objective problem:

$$\text{Problem } A(\text{Stage } 1) : \max_{g \in \mathcal{G}} F(g) \quad (1)$$

where g denotes the genotype vector describing the constellation configuration, $\mathcal{G}$ represents the set of admissible configurations satisfying the adopted physical and structural constraints, defined over a parameter space containing both discrete and continuous variables ($\mathcal{G} \subset \mathbb{R}^8$), and $F(g)$ is the fitness function quantifying observational performance.

The solution space $\mathcal{G}$ is parameterized using an eight-dimensional genotype representation.

2.2.2. Constellation Representation

Each constellation is represented as an eight-dimensional genotype vector:

$$g = [g_1, g_2, g_3, g_4, g_5, g_6, g_7, g_8] \quad (2)$$

To improve readability, the components of the eight-dimensional genotype vector are summarized in Table 1.

Table 1. Components of the eight-dimensional genotype vector used in Stage 1 constellation optimization.

Gene	Parameter	Admissible Values/Range	Description
g_1	N_{sat} Number of satellites	$\{6, 7, 8, 9\}$	Total number of satellites in the constellation. The selected range for the number of satellites reflects a trade-off between coverage capability and operational cost.
g_2	Orbit type	{SSO97, SSO98, SSO99, SSO_ASC, SSO_DESC, SSO_MIX, LEO76, LEO80, LEO84, LEO88}	All configurations correspond to circular or near-circular LEO orbits. The SSO variants denote Sun-Synchronous Orbits with predefined inclinations of 97°, 98°, and 99°, respectively. The variants SSO_ASC, SSO_DESC, and SSO_MIX represent ascending, descending, and mixed local-time Sun-synchronous configurations. The non-SSO LEO variants correspond to fixed inclinations of 76°, 80°, 84°, and 88°, respectively.
g_3	h Orbital altitude	{400, 450, 500, 550, 600, 650, 700, 750, 800} km	Circular or near-circular orbital altitude, corresponding to a discrete step size of 50 km.
g_4	e Eccentricity	{0.0, 0.01, 0.02}	Orbital eccentricity.

Table 1. Cont.

Gene	Parameter	Admissible Values/Range	Description
g5	N_{plane} Number of orbital planes	{1, 2, 3}	Number of orbital planes used in the constellation.
g6	f RAAN separation scaling factor	[0.75, 1.25]	Scaling factor controlling deviation from uniform inter-plane Right Ascension of the Ascending Node (RAAN) spacing.
g7	Phasing strategy	{EVEN, CLUSTER}	In-plane distribution of satellites. EVEN denotes uniform spacing of satellites in true anomaly within each orbital plane, such that the angular separation between consecutive satellites is given by $\Delta v = \frac{360^\circ}{N_{sat}}$, where N_{sat} is the number of satellites assigned to the plane. CLUSTER denotes a non-uniform configuration in which satellites are grouped within a restricted true-anomaly sector, resulting in locally increased density and larger angular gaps outside the cluster region.
g8	Global RAAN offset	$[0^\circ - 350^\circ]$, step 10°	Global rotation of the constellation in RAAN.

As summarized in Table 1, the genotype combines discrete architectural parameters, such as the number of satellites, orbit family, number of planes, and phasing strategy, with continuous or discretized orbital parameters, such as altitude, eccentricity, RAAN separation scaling, and global RAAN offset. This mixed representation enables simultaneous exploration of constellation topology and orbital geometry within a single GA framework.

The altitude range was limited to 400 – 800 km, which is consistent with the Low Earth Orbit regime analyzed in this study. The RAAN scaling factor allows controlled deviation from uniformly spaced orbital planes, while the phasing strategy determines whether satellites are distributed evenly along the orbit or concentrated within a restricted true-anomaly sector.

The RAAN values of successive orbital planes are defined as follows:

$$\Delta\Omega = f \cdot \frac{360^\circ}{N_{plane}}, \text{ where } \Delta\Omega_k = \Delta\Omega_0 + k \Delta\Omega \quad (3)$$

where $\Delta\Omega_0$ denotes the global RAAN offset (gen g8), and $k \in \{0, \dots, N_{plane} - 1\}$.

In the classical uniformly distributed configuration, the separation between orbital planes is given by $\Delta\Omega = \frac{360^\circ}{N_{plane}}$. The introduction of the scaling factor f modifies this value according to Equation (3), enabling controlled deviation from perfect symmetry. This formulation allows exploration of both uniformly spaced configurations ($f = 1$) and moderately compressed or expanded plane distributions ($\pm 25\%$) without generating geometrically unrealistic arrangements. The range [0.75, 1.25] was selected as a compromise between search space flexibility and preservation of structural stability of the constellation.

2.2.3. Physical and Structural Constraints

The analysis is restricted to Low Earth Orbit (LEO), adopting the following altitude constraint:

$$400 \leq h \leq 800, \text{ where } h = \|\mathbf{r}\| - R_E \quad (4)$$

where h denotes the orbital altitude [km], and R_E is the mean Earth radius [km].

Configurations that do not satisfy this condition are considered physically infeasible and are assigned a fitness value equal to zero.

In addition, a hard constraint on the minimum in-plane satellite separation is imposed. The minimum angular separation corresponds to an along-track distance of 100 km and is expressed as follows:

$$\Delta\theta_{\min} = \frac{360 \cdot d_{\min}}{2\pi(R_E + h)} \quad (5)$$

where $\Delta\theta_{\min}$ is expressed in degrees $^\circ$, $d_{\min} = 100$ [km] denotes the minimum along-track separation distance, and R_E and h correspond to the mean Earth radius and the orbital altitude defined previously.

Any violation of this constraint results in the configuration being deemed infeasible. Solutions that do not satisfy the imposed constraints are assigned the minimum possible fitness value, effectively eliminating them from further evolution.

2.2.4. Dynamic Model and Simulation Parameters

Satellite motion propagation is modeled in the Earth-Centered Inertial (ECI) reference frame, accounting for the Earth's central gravitational field and the perturbation due to the second zonal harmonic of the geopotential, J_2 :

$$\ddot{\mathbf{r}} = -\frac{\mu}{\|\mathbf{r}\|^3}\mathbf{r} + \mathbf{a}_{J_2} \quad (6)$$

where $\ddot{\mathbf{r}}$ is the satellite acceleration in the ECI frame $[\frac{m}{s^2}]$, μ is the Earth's gravitational parameter $[\frac{m^3}{s^2}]$, $\|\mathbf{r}\|$ is the norm of the position vector, and $\mathbf{a}_{J_2}$ denotes the acceleration due to Earth's oblateness. The formulation follows the classical J_2 perturbation model [34].

The simulation is conducted over a 72 h horizon with a propagation time step of 600 s. A geometric access analysis is performed to determine time intervals during which the satellite ground footprint intersects the AOI. The analysis uses sliding time windows of 15 min with a temporal sampling step of 60 s. These parameters provide a balance between dynamical accuracy and computational efficiency.

The model neglects higher-order geopotential harmonics, atmospheric drag, and solar radiation pressure. These simplifications are justified by the relatively short analysis horizon.

For completeness, the potential influence of atmospheric drag at the lowest considered orbital altitude (400 km) was assessed over the 72 h simulation period. Under nominal atmospheric conditions at 400 km altitude, the expected variation in semi-major axis over the 72 h simulation period is on the order of several to tens of meters, resulting in a change in orbital period well below one second. The corresponding cumulative orbital phase drift remains significantly smaller than the adopted 600 s propagation step and the 15 min access window used in the coverage analysis. Therefore, atmospheric drag does not introduce a meaningful modification of access timing within the analyzed horizon and does not affect the relative ranking of constellation configurations.

The position vectors are transformed into the Earth-Centered Earth-Fixed (ECEF) frame to determine sub-satellite geographic coordinates and evaluate ground coverage.

2.2.5. Definition of Observational Success

For each AOI, three operational observation modes are defined in this study and denoted by $m \in \{K, R, C\}$. The mode K represents mosaic imaging (tiling of adjacent ground segments), R represents along-track strip imaging, and C represents cross-track strip imaging. These modes reflect different geometric task-allocation strategies within the considered constellation architecture. The three modes were selected as representative geometric coverage patterns rather than as an exhaustive catalog of sensor acquisition modes.

Success within a time window w is defined as the ability to assign at least N unique imaging scenes to distinct satellites.

$$Success_{m,N}(w) = \begin{cases} 1, & \text{if at least } N \text{ unique scenes can be assigned to distinct satellites in window } w, \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

where m denotes the observation mode, N is the required number of unique scenes, and w is the time window index.

The success rate is defined as the ratio of the number of successful time windows to the total number of analyzed windows:

$$SR_{m,N} = \frac{1}{W} \sum_{w=1}^W Success_{m,N}(w) \quad (8)$$

where W denotes the total number of analyzed time windows.

For each combination of AOI and observation mode, the best achievable success rate was selected under the constraint $N \leq N_{sat}$:

$$SR_{i,m} = \max_{N \leq N_{sat}} SR_{i,m,N} \quad (9)$$

where N_{sat} denotes the number of satellites in the constellation, and i is the index of the AOI.

This approach reflects the effective observational potential of the constellation, given its actual number of satellites.

2.2.6. Fitness Function

The final fitness function is defined as the average value of $SR_{i,m}$ across all analyzed AOIs and observation modes:

$$F = \frac{1}{N_{AOI} \mid \mathcal{M}} \sum_{i=1}^{N_{AOI}} \sum_{m \in \mathcal{M}} SR_{i,m} \quad (10)$$

where N_{AOI} denotes the number of analyzed AOIs ($N_{AOI} = 3$), and $\mathcal{M}$ represents the set of observation modes $\{K, R, C\}$.

The values of SR were computed as normalized ratios within the interval $[0, 1]$. For presentation purposes, percentage scaling was applied exclusively for interpretative clarity. This rescaling does not affect the optimization process, as the genetic algorithm operates on the relative ordering of fitness values.

2.2.7. Numerical Implementation

Numerical computations were performed in Python 3.9 using specialized libraries for orbital propagation, reference frame transformations, and geometric operations.

Constellation configuration optimization was carried out using a genetic algorithm. In the baseline configuration, a population of 20 constellation variants evolved over 8 generations. Tournament selection was applied, combined with a two-point crossover operator and an index-based mutation operator. The best-performing individuals were directly transferred to the subsequent generation using elitism.

To assess the robustness of the optimization process and verify that the identified solution was not an artifact of a limited optimization budget, an extended stability check was performed. In addition to the baseline configuration (20 individuals $\times$ 8 generations), a larger optimization run with 40 individuals evolved over 20 generations was conducted.

The extended configuration resulted in only a marginal improvement in the best fitness value, from 95.21 to 95.83 on the percentage scale. Importantly, the overall constellation architecture remained consistent: both optimization settings converged to a single-plane clustered constellation at 550 km altitude with 7–8 satellites in a near-sun-synchronous orbit. Additional independent runs with different random seeds confirmed convergence to the same high-performance region.

The purpose of this comparison was not to determine globally optimal GA hyperparameters, but to verify the stability of the solution structure under an increased optimization budget. The results indicate that the identified high-performance region is primarily associated with the geometry of the analyzed design space rather than with a single random initialization or premature convergence. A comprehensive GA hyperparameter sensitivity analysis involving systematic variation in crossover and mutation probabilities is beyond the scope of the present study and is identified as a direction for future research.

To ensure reproducibility, a fixed random seed was adopted in all experiments. Each candidate configuration was dynamically propagated over the full 72 h horizon prior to fitness evaluation. The adopted 72 h horizon reflects a realistic operational response timescale in crisis scenarios and enables consistent comparison across configurations. The success rate was computed within the interval $[0, 1]$; percentage scaling was applied exclusively for presentation purposes and did not affect the optimization procedure.

The source code used for orbital propagation, optimization, and OIRT evaluation is available from the corresponding author upon reasonable request.

2.3. Stage 2—Reactive Multi-Objective Maneuver Optimization

Stage 2 addresses reactive orbital maneuvers triggered by a crisis event. Unlike Stage 1, this stage incorporates dynamic constraints and ΔV limitations into a multi-objective optimization framework.

2.3.1. Crisis Scenario Definition

The second stage of the methodology adopts a reactive framework and assumes the occurrence of a crisis event 12 h after the start of the constellation simulation.

Until the operational request is issued ($t_{\text{request}} = 12$ h), satellites are propagated according to the optimized Stage 1 configuration without performing additional maneuvers. From the moment the crisis is declared, impulsive orbital corrections are permitted in order to increase observational effectiveness over designated AOIs.

The crisis analysis is performed for the same compact rectangular AOIs considered in Stage 1, namely, as follows:

- WARSZAWA (latitude: 51.93° – 52.53° , longitude: 20.71° – 21.31°);
- BUSZEHR (latitude: 28.93° – 29.53° , longitude: 50.91° – 51.51°);
- SANKT PETERSBURG (latitude: 59.63° – 60.23° , longitude: 30.03° – 30.63°).

Each AOI spans $\pm 0.3^\circ$ in both latitude and longitude around its central reference coordinate, resulting in compact square regions representing localized crisis targets. In addition to these compact AOIs, two elongated corridor-type regions were introduced to represent geometrically extended crisis scenarios:

- The first corridor represents a north–south oriented vertical strip-PAS_PION (latitude: 51.50° – 54.35° , longitude: 23.20° – 23.90°);
- The second corridor represents an east–west oriented horizontal strip-PAS_POZIOM (latitude: 54.25° – 55.00° , longitude: 18.30° – 22.80°).

Although the AOI set was expanded in Stage 2 by adding two elongated corridor-type regions to the three compact AOIs used in Stage 1, all analyzed AOIs were defined as

fixed geographic regions. Therefore, the framework was evaluated for multiple static AOI geometries, including compact and corridor-shaped regions, but not for mobile target observation scenarios. These corridor-type AOIs were defined to model operational scenarios such as border monitoring or coastal surveillance, where rapid coverage of elongated regions is required. Their inclusion enables evaluation of the constellation's maneuver efficiency under anisotropic spatial demand conditions and tests the robustness of the reactive optimization process against geometrically distinct target structures.

The response evaluation horizon spans 36 h from the crisis declaration time.

2.3.2. Maneuver Genotype Representation

The maneuver scheduling problem is solved using the NSGA-II algorithm [18], in which each individual represents a complete set of maneuver decisions for all satellites in the constellation.

For a constellation consisting of N_{sat} satellites, the decision vector contains five parameters per satellite:

- A maneuver activation flag ($enable \in \{0, 1\}$, where 1 indicates execution of the maneuver and 0 denotes no maneuver);
- The maneuver type identifier;
- The selected decision time window;
- A normalized parameter defining the execution time within the selected window;
- A normalized amplitude parameter defining the magnitude of the orbital change.

A constraint of at most one maneuver per satellite within the analyzed time horizon was imposed. This reflects realistic operational limitations of Earth observation systems and ensures bounded ΔV expenditure.

2.3.3. Orbital Modification Ranges

Four maneuver types were considered: orbital altitude change (ALT), inclination change (INC), right ascension of the ascending node adjustment (RAAN), and phasing maneuver (PHASING). All maneuvers are modeled as instantaneous kinematic modifications of the corresponding orbital elements, without explicit simulation of the detailed thrust profile or impulse sequencing required for physical implementation. This simplified representation enables evaluation of the constellation's reactive potential while maintaining computational tractability.

The decision space is constrained to intervals consistent with realistic propulsion capabilities of small LEO observation satellites. The allowable modification ranges are defined as follows: $\Delta h \in [-20, 20]$ km, $\Delta i \in [-0.5, 0.5]^\circ$, $\Delta \Omega \in [-5, 5]^\circ$, and $\Delta M \in [-45, 45]^\circ$, where Ω denotes the right ascension of the ascending node and M denotes the mean anomaly.

The maneuver amplitude is expressed through linear rescaling of the normalized parameter according to the following:

$$\Delta p = p_{min} + \alpha_{mag}(p_{max} - p_{min}) \quad (11)$$

where $\alpha_{mag} \in [0, 1]$ is the normalized amplitude parameter encoded in the genotype, and p denotes the corresponding orbital element subject to modification.

2.3.4. Maneuver Time Windows

The execution time of each maneuver was constrained to two operational time windows defined relative to the crisis declaration:

- A first window: from 12 to 18 h from the start of the simulation (corresponding to immediate response);
- second window: from 18 to 24 h.

The actual execution time is determined through linear interpolation within the selected window:

$$t_{exec} = t_{min} + \alpha_{time}(t_{max} - t_{min}) \quad (12)$$

where $\alpha_{time} \in [0, 1]$ is the normalized time parameter encoded in the genotype, and t_{min}, t_{max} denote the bounds of the selected decision window.

2.3.5. Maneuver Cost Model

Maneuvers were modeled as instantaneous impulsive velocity changes. The total maneuver cost of the constellation is defined as the sum of the magnitudes of all applied velocity increments:

$$\Delta V_{tot} = \sum_i |\Delta v_i| \quad (13)$$

where Δv_i denotes the velocity impulse magnitude of the i -th maneuver [$\frac{m}{s}$].

The adopted maneuver-cost model is based on an ideal impulsive approximation. It does not explicitly model finite-burn arcs, thrust-direction constraints, thruster duty cycles, attitude-control limitations, or spacecraft-specific propulsion characteristics. This simplification was introduced to isolate the system-level effect of maneuver allocation and orbital-element modification on observational performance within the proposed hierarchical framework. Consequently, the obtained ΔV_{tot} values should be interpreted as comparative maneuver-cost indicators rather than direct low-level propulsion command profiles. The maneuver cost does not constitute a hard constraint but is treated as one of the minimized optimization objectives. This enables analysis of the trade-off between observational effectiveness and propellant expenditure.

2.3.6. Objective Functions and Global Performance Indicators

Stage 2 is formulated as a reactive multi-objective maneuver-optimization problem, denoted here as Problem B. In contrast to Problem A, which maximizes a single constellation-geometry fitness function in Stage 1, Problem B optimizes maneuver decisions for the fixed constellation selected after Stage 1.

The complete maneuver-decision vector is denoted as $\mathbf{u}$, and the admissible decision space is denoted as $\mathcal{U}$. The vector $\mathbf{u}$ includes the maneuver activation flags, maneuver types, execution-time windows, normalized execution-time parameters, and normalized maneuver-amplitude parameters defined in Sections 2.3.2–2.3.4. The corresponding maneuver cost is computed according to the model described in Section 2.3.5.

The Stage 2 optimization problem can be written as follows:

$$\begin{aligned} & \text{Problem B (Stage2 :)} \\ \min_{\mathbf{u} \in \mathcal{U}} F(\mathbf{u}) &= -SR(\mathbf{u}), \frac{T_{first}(\mathbf{u})}{24 \text{ h}}, \Delta V_{tot}(\mathbf{u}) \end{aligned} \quad (14)$$

where SR is the global observational success rate within the interval $[0, 1]$, T_{first} is the global time to first success [h], and ΔV_{tot} is the total maneuver cost [$\frac{m}{s}$].

Time normalization by 24 h allows its expression in units of days. This ensures scale comparability with the remaining objective functions and reflects the natural diurnal operational cycle of Earth observation systems. Response times exceeding 24 h are allowed and result in normalized values greater than one.

The global observational success indicator is defined as follows:

$$SR = \frac{\sum_{j=1}^{N_{AOI}} \sum_{w=1}^{W_j} Success_j(w)}{\sum_{j=1}^{N_{AOI}} W_j} \quad (15)$$

where W_j denotes the number of analyzed time windows for the j -th AOI, $Success_j(w) \in \{0, 1\}$.

This formulation ensures equal weighting of all analyzed crisis AOIs. In Stage 2, the success rate is represented as a normalized ratio within $[0, 1]$, consistent with the NSGA-II framework, where all objective functions are minimized simultaneously.

Maintaining comparable magnitudes among objective functions reduces the risk of dominance in non-dominated sorting and promotes a well-distributed Pareto front.

The time to first success is determined separately for each analyzed AOI:

$$T_{first}^{(AOI_j)} = \min\{t_w \mid Success_j(w) = 1\} \quad (16)$$

The global response time is then defined as follows:

$$T_{first} = \max_{j=1, \dots, N_{AOI}} \left(T_{first}^{(AOI_j)} \right) \quad (17)$$

where t_w denotes the start time of the time window [h].

This formulation enforces the requirement that successful observation must be achieved for all analyzed crisis AOIs. If no success is achieved for a given AOI within the 36 h analysis horizon, the response time for that AOI is assigned the upper bound value of 36 h. Consequently, the global response time T_{first} also assumes this boundary value of 36 h.

2.3.7. NSGA-II Algorithm Parameters

The multi-objective optimization was performed using a population of 20 candidate solutions evolved over 15 generations. Standard crossover and mutation operators appropriate for the NSGA-II algorithm were applied, along with non-dominated sorting and crowding distance-based selection to preserve solution diversity along the Pareto front.

To verify the numerical stability of the obtained Pareto-front structure, an extended stability check was performed using a population of 40 candidate solutions evolved over 30 generations. Increasing the population size and the number of generations did not alter the overall structure of the Pareto front or the location of the knee-point solution. Multiple independent runs with different random seeds also confirmed consistent Pareto-front geometry and knee-point localization.

The objective of this comparison was to verify the robustness of the Stage 2 trade-off structure rather than to identify globally optimal NSGA-II hyperparameters. A comprehensive sensitivity analysis involving systematic variation in crossover probability, mutation probability, population size, and generation count was not performed and remains a direction for future work.

To ensure reproducibility of the experiments, a fixed random seed was used. The evaluation of candidate solutions was parallelized to improve computational efficiency.

2.4. Stage 3—Operational Imaging Response Time (OIRT)

Stage 3 is performed for the Pareto-optimal solutions obtained in Stage 2 and constitutes the operational evaluation layer of dynamically optimized maneuver configurations.

The OIRT metric is introduced to quantify the time required to achieve a specified coverage threshold β of AOIs, while accounting for variability in environmental conditions.

In contrast to traditional revisit time metrics or deterministic time-to-first-observation measures, the proposed metric has a stochastic character and integrates three key components:

- Access geometry resulting from maneuver optimization (Stage 2);
- Precise geometric accumulation of unique ground coverage with elimination of scene overlaps;
- Probabilistic modeling of operational availability based on cloud cover and geomagnetic activity.

2.4.1. Probabilistic Environmental Filtering

The operational usability of each access window is modeled probabilistically based on two long-term climatological datasets: Total Cloud Cover (TCC) derived from ERA5 reanalysis data and the planetary geomagnetic activity index (Kp).

The cloud cover data are based on ERA5 reanalysis products averaged over a 10-year period (2014–2023). The dataset provides monthly and hourly climatological values of Total Cloud Cover (TCC) expressed in percent [%], representing the mean fraction of sky covered by clouds. The adopted values correspond to statistical averages and do not represent deterministic forecasts or operational weather data.

Geomagnetic activity is represented by the planetary Kp index obtained from the official dataset provided by the GFZ Helmholtz Centre for Geosciences (Niemegk) and distributed via NOAA SWPC, covering the period 2014–2023. The Kp index is defined on a quasi-logarithmic discrete scale from 0 to 9 and represents global geomagnetic disturbance levels. The values used in the model correspond to climatological averages aggregated by month and 3 h UTC interval.

For a given month m and UTC hour h , the probability of satisfying the cloud cover condition is defined as follows:

$$P_{clear} = \max\left(0, 1 - \frac{TCC_{m,h}}{100}\right) \quad (18)$$

Similarly, the probability of safe geomagnetic conditions is defined as follows:

$$P_{safe} = \max\left(0, 1 - \frac{Kp_{m,h}}{9}\right) \quad (19)$$

where $TCC_{m,h} \in [0, 100]$ is expressed as a percentage value, and $Kp_{m,h} \in [0, 9]$ is the geomagnetic activity index. Linear normalization provides a continuous probabilistic interpretation of environmental severity without introducing deterministic thresholding. The operator $\max(0, \cdot)$ ensures that the resulting probabilities remain within the admissible interval $[0, 1]$.

For each access window, two independent Bernoulli trials are performed corresponding to probabilities P_{clear} and P_{safe} . Cloud cover and geomagnetic activity were treated as statistically independent phenomena due to the absence of a documented physical coupling affecting optical acquisition probability at the considered timescale. Scene acceptance requires simultaneous success of both trials. A geometrically feasible observation is, therefore, not deterministically invalidated by environmental conditions but probabilistically weighted, allowing realistic modeling of seasonal atmospheric variability and geomagnetic activity effects.

The adopted environmental model is climatological rather than event-driven and does not modify orbital propagation or geometry. Instead, it statistically modulates the effective usability of observation opportunities in Stage 3.

All climatological datasets used in this study (ERA5 reanalysis cloud cover and Kp geomagnetic index) are publicly available from their respective official repositories.

2.4.2. Tile-Based Geometric Coverage Accumulation

Coverage accumulation is performed at the tile level in chronological order based on the start time of each access window. For every operationally accepted access window (i.e., after environmental filtering), the following steps are executed:

- Polygons representing individual observation tiles are constructed;
- Each tile is intersected with the AOI boundary;
- A scene is formed as the geometric union of all valid tiles within that window;
- coverage is accumulated over time through successive geometric union operations:

$$A_{covered}(t) = Area\left(\bigcup_{t_i \leq t} (S_i \cap AOI)\right) \quad (20)$$

where S_i denotes the geometric footprint of the i -th accepted sensor scene and AOI is the analyzed AOI.

To ensure accurate surface area computation on the curved Earth surface, all polygons are locally projected onto an azimuthal equidistant projection centered on the AOI. The projection is used exclusively for area calculation, while access geometry is evaluated in the Earth-Centered Earth-Fixed (ECEF) frame. The resulting areas are expressed in square kilometers [km²].

The coverage ratio is defined as follows:

$$\beta(t) = \frac{A_{covered}(t)}{A_{AOI}} \quad (21)$$

where A_{AOI} is the total area of the analyzed region. The cumulative union operator ensures that overlapping observations do not artificially inflate the coverage estimate.

2.4.3. Definition of the OIRT Metric

For predefined coverage thresholds $\beta \in \{0.2, 0.4, 0.6, 0.8, 0.9, 1.0\}$, the time at which a given coverage level is achieved is defined as follows:

$$t_\beta = \inf\{t \geq t_{request} \mid \beta(t) \geq \beta\} \quad (22)$$

where $t_{request}$ is the time of the operational request, and β is the required operational coverage threshold.

The OIRT is then defined as follows:

$$OIRT_\beta = t_\beta - t_{request} \quad (23)$$

If a given coverage threshold is not reached within the analyzed time horizon, the realization is considered unsuccessful for that specific value of β . In the statistical analysis, realizations that do not achieve the required threshold are treated as failure cases with an infinite response time. Mean OIRT values were computed only over successful realizations, while $P(success)$ was reported separately. This approach enables consistent estimation of the probability of success as well as robust analysis of the response time distribution.

2.4.4. Seasonal Monte Carlo Analysis

Due to the probabilistic nature of the environmental filtering, the OIRT metric is evaluated using a Monte Carlo approach. For each month of the year:

- Access logs are temporally shifted to the analyzed calendar month;
- The operational request time is set to the first day of the month at 08:00 UTC. The fixed request time ensures comparability across months and isolates environmental variability from request-time randomness;
- $N = 20$ independent simulation realizations are performed.

The value $N = 20$ was selected as a compromise between estimation stability and computational cost. Convergence analysis indicated stabilization of the mean OIRT estimator for $N \geq 15$. The relative change in the mean OIRT between $N = 15$ and $N = 20$ remained below 2%, confirming estimator stability.

For each coverage threshold β , the following statistical measures are determined:

- Mean OIRT value;
- Standard deviation;
- Probability of achieving the coverage threshold;
- Empirical cumulative distribution function of the response time $P(OIRT_{\beta} < t)$;
- Percentile intervals (5–95%).

This approach enables simultaneous assessment of the expected operational performance and the system's robustness to seasonal environmental variability.

In contrast to traditional revisit time metrics, OIRT is a threshold-based and accumulative measure that integrates environmental filtering with the temporal evolution of geometric coverage.

3. Results

This section presents the simulation results obtained for each optimization stage. The analysis is structured according to the three-layer framework, beginning with global constellation geometry optimization.

3.1. Stage 1—Global Optimization of Constellation Geometry

The first stage addressed the global optimization of constellation geometry using a genetic algorithm (GA). The objective was to maximize the global observational success rate SR under geometric constraints only, without incorporating reactive maneuvers or environmental filtering.

The optimization was performed for constellations composed of 6–9 satellites. The design space included variations in orbital type, altitude, eccentricity, phasing strategy, and plane configuration. The fitness function was defined as the global success rate averaged across all analyzed AOIs.

3.1.1. Genetic Algorithm Convergence and Stability

For clarity of interpretation, fitness values in this section are presented on a percentage scale (0–100), while normalized values in the range $[0, 1]$ were used during the optimization process.

The baseline GA configuration (population size 20, eight generations) yielded a best fitness value of 95.21. The maximum fitness increased from 78.58 in generation 0 to 88.32 in generation 1, reaching 93.04 in generation 2. From generations 2 to 7, the maximum value remained stable at 93.04, with a final improvement to 95.21 achieved in generation 8. Fitness was calculated according to Equation (10), while Figure 2 presents the evolution of maximum and average fitness values across successive generations on a percentage scale.

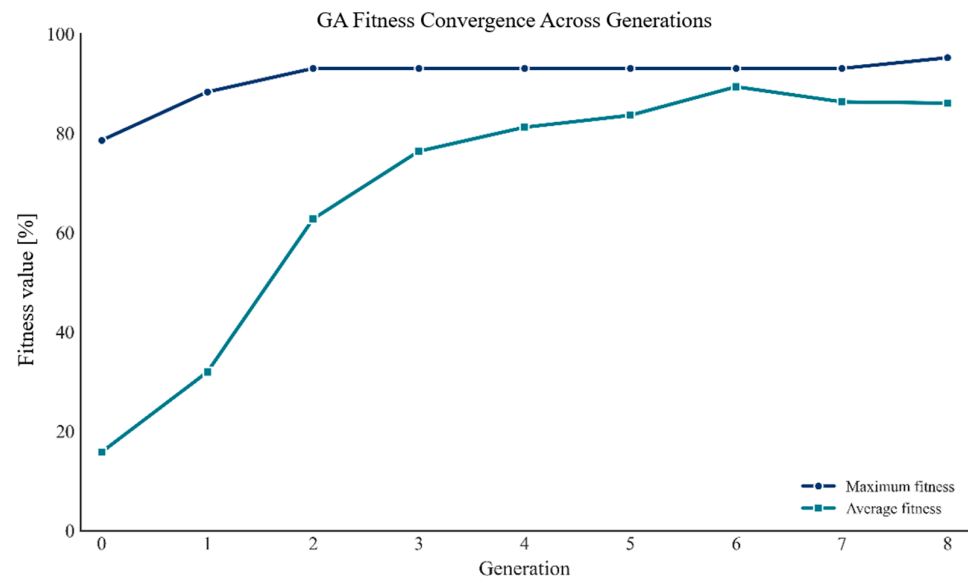


Figure 2. Evolution of maximum and average GA fitness values across successive generations. The horizontal axis represents the generation number, while the vertical axis represents the fitness value expressed on a percentage scale (0–100). Fitness was calculated according to Equation (10).

As shown in Figure 2, rapid convergence is observed within the first three generations, followed by a stabilization phase. Across all 180 fitness evaluations performed in the baseline configuration, including generation 0, global mean fitness was 68.16, with a standard deviation of 33.73. The overall distribution of fitness values is shown in Figure 3.

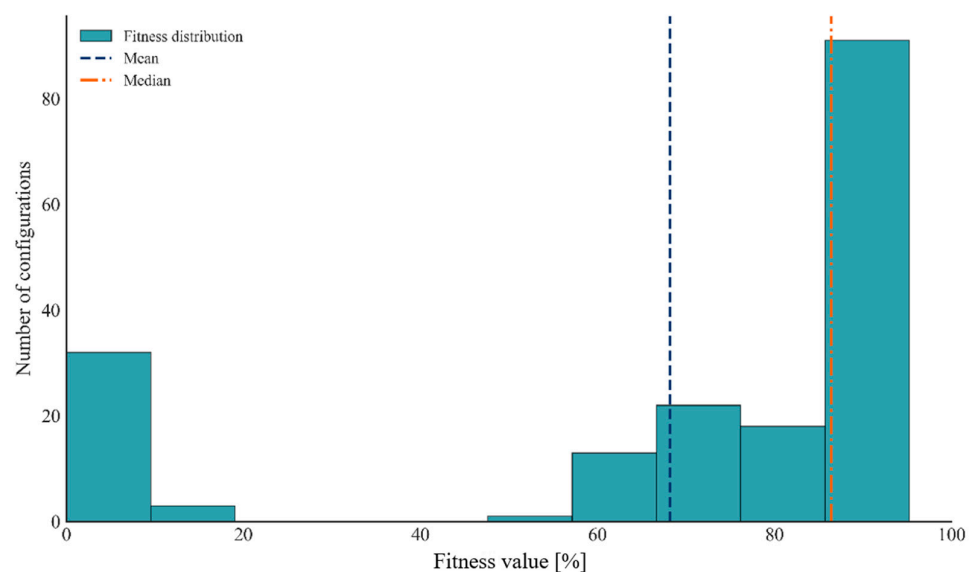


Figure 3. Distribution of fitness values across all 180 evaluated constellation configurations in the baseline GA run, including generation 0. Fitness values are expressed on a percentage scale. The dashed and dotted lines denote the mean and median values, respectively.

In parallel, the average population fitness increased from 15.82 in generation 0 to 89.36 in generation 6 and remained above 86.00 during the final optimization phase. The minimal standard deviation of 5.74 observed in generation 6 indicates strong population concentration within a narrow region of high-quality solutions.

To verify convergence robustness, an extended configuration (*population size* = 40, *generations* = 20) was executed. The best fitness value obtained in this case was 95.83. The extended run improved the best fitness by 0.62 percentage points, corresponding to

less than 1% relative improvement over the baseline result. The structural characteristics of the best-performing constellation were preserved across both runs, indicating stable convergence behavior and limited sensitivity to the optimization budget.

3.1.2. Optimal Constellation Structure

The best-performing architectures identified in Stage 1 correspond to single-plane clustered constellations. Among the analyzed orbital families, SSO_ASC and SSO99 variants achieved the highest fitness values, with peak performance observed at an altitude of 550 km.

The top-ranked configurations are summarized in Table 2, which presents the principal orbital parameters and corresponding success rates.

Table 2. Top-ranked constellation configurations identified in Stage 1.

Rank	Fitness	Orbit Type	Altitude [km]	Inclination [°]	Number of Satellites	Number of Planes	Phasing
1	95.21	SSO_ASC	550	97.756	8	1	CLUSTER
2	93.04	SSO_ASC	550	97.760	8	1	CLUSTER
3	88.56	SSO99	550	99.000	7	1	CLUSTER
4	85.78	SSO_MIX	550	98.822	8	1	CLUSTER
5	83.81	SSO99	550	99.000	7	1	CLUSTER
6	65.23	LEO80	550	80.000	6	1	CLUSTER

Across the leading solutions, several structural patterns can be observed. All top configurations employ a single orbital plane combined with a clustered phasing strategy. The number of satellites varies between 7 and 8 for the highest-ranking variants, while inclination values remain consistent with the selected orbit family (SSO_ASC or SSO99). The distribution of fitness values as a function of constellation size is presented in Figure 4 using boxplots, where each box corresponds to one satellite-count group.

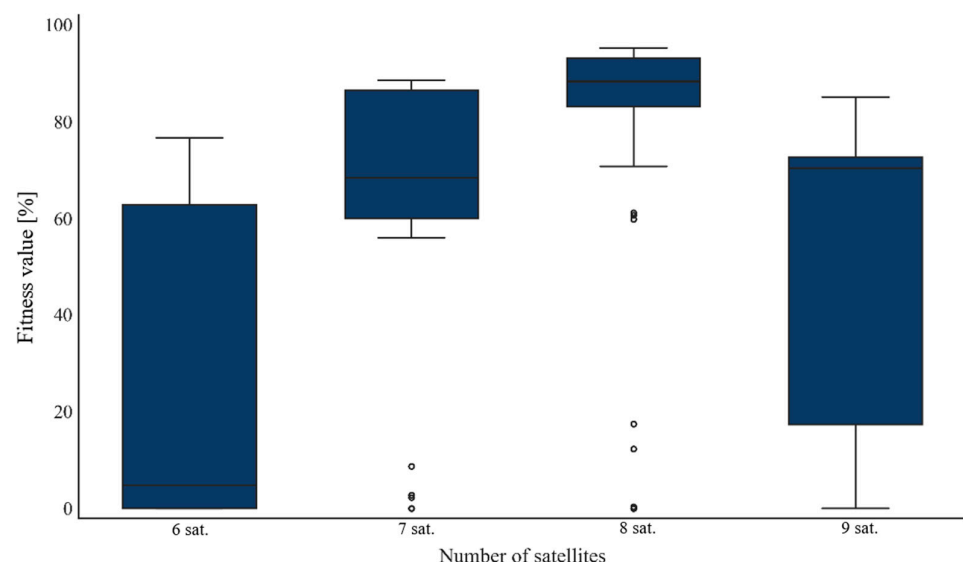


Figure 4. Distribution of fitness values as a function of the number of satellites across all evaluated constellation configurations in Stage 1. Each box corresponds to a constellation size group indicated on the horizontal axis. Boxes represent the interquartile range (IQR), the central horizontal line denotes the median, whiskers indicate the non-outlier range, and individual points denote outliers. Fitness values are expressed on a percentage scale.

The distribution of fitness values as a function of orbital altitude is shown in Figure 5 using boxplots, where each box corresponds to one altitude group. The highest median fitness values are observed at 550 km.

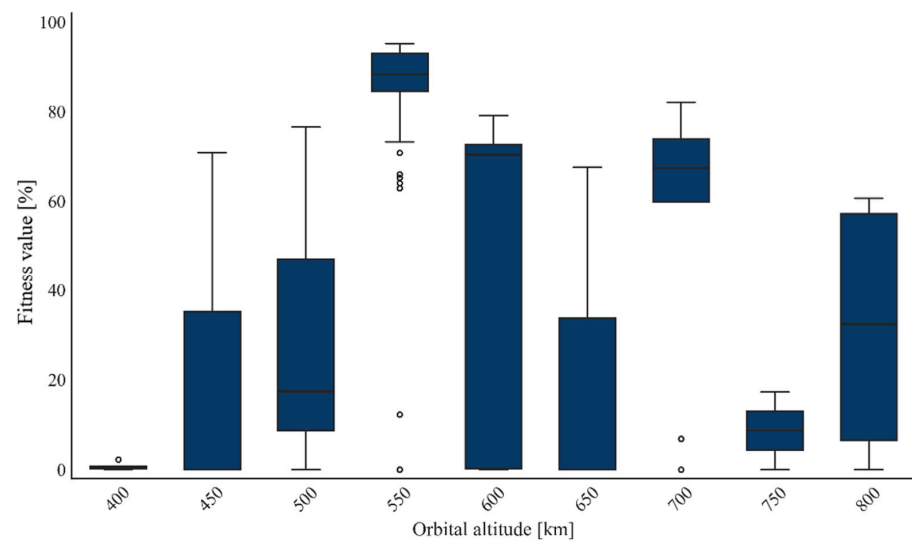


Figure 5. Distribution of fitness values as a function of orbital altitude across all evaluated constellation configurations in Stage 1. Each box corresponds to an orbital altitude group indicated on the horizontal axis. Boxes represent the interquartile range (IQR), the central horizontal line denotes the median, whiskers indicate the non-outlier range, and individual points denote outliers. Fitness values are expressed on a percentage scale.

Although fitness values decrease gradually across the ranking, the general architectural layout remains unchanged. Differences between the highest-ranked variants are primarily associated with minor adjustments in satellite count or orbit type rather than fundamental modifications of constellation structure.

3.1.3. Benchmark Comparison

To assess the effectiveness of the GA-based optimization, a benchmark comparison was conducted against two reference strategies:

1. A random sampling baseline consisting of 100 randomly generated constellations;
2. A classical Walker-like symmetric configuration employing uniform RAAN spacing and EVEN phasing.

The best GA solution achieved a global success rate of 95.83, while the baseline GA configuration (20×8) achieved 95.21.

For the random sampling baseline, the mean success rate was 14.01, with a standard deviation of 25.59. The maximum success rate observed among the 100 random constellations reached 83.54, indicating that high-performing architectures may occur sporadically, but without structural consistency.

The classical symmetric Walker configuration yielded a global success rate of 0.0 under the adopted crisis-AOI definition. This indicates that, despite its geometric regularity, the evenly distributed architecture fails to simultaneously satisfy the global success condition across all analyzed AOIs.

The comparison is illustrated in Figure 6, which shows the relative performance of both GA configurations, the random baseline (mean and maximum), and the symmetric Walker reference. The GA-optimized constellation clearly approaches the upper performance bound of the explored design space, while classical symmetric deployment does not provide viable coverage under the adopted global-success criterion.

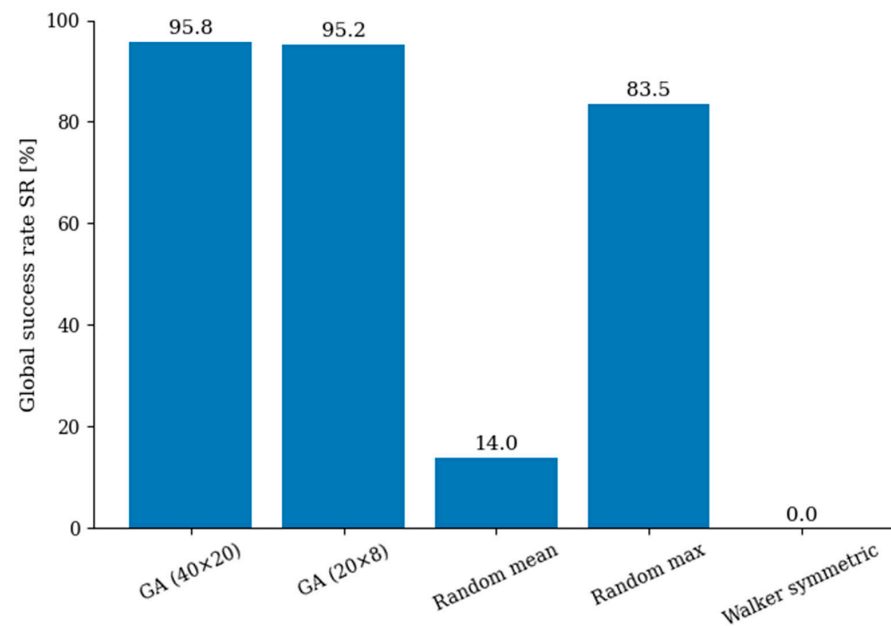


Figure 6. Comparison of global success rates obtained from GA optimization (two parameter settings), random sampling baseline (mean and maximum over 100 samples), and a classical symmetric Walker configuration.

3.2. Stage 2—Reactive Optimization of Orbital Maneuvers

In Stage 2, the static constellation geometries obtained in Stage 1 were subjected to reactive maneuver optimization under a constrained total maneuver budget ΔV . The optimization problem was formulated as a multi-objective task minimizing the negative success rate, the normalized time to first success, and the total maneuver cost ΔV .

Pareto-optimal fronts were obtained for three representative constellation configurations: SSO_ASC (eight satellites), SSO99 (seven satellites), and LEO80 (six satellites).

3.2.1. Structure of the Pareto Front

For each constellation, a set of Pareto-optimal solutions was obtained in the $(\Delta V, SR)$ space, where SR denotes the observational success rate. The resulting Pareto fronts are shown in Figure 7.

Table 3. Objective-function values and aggregated maneuver-decision characteristics for representative Pareto solutions marked in Figure 7.

Constellation	Representative Solution	Candidate ID	$\Delta V_{tot}[\frac{m}{s}]$	SR	$T_{first}[h]$	Active Maneuvers	Maneuver Composition
SSO_ASC	Baseline	0	0.000	0.150	1.333	0	none
	Knee	11	0.025	0.171	1.333	3	ALT (3)
	Maximum-SR	10	4.888	0.201	1.333	7	PHASING (3), RAAN (2), ALT (2)
SSO99	Baseline	0	0.000	0.150	1.333	0	none
	Knee	18	3.808	0.204	1.333	5	PHASING (3), ALT (2)
	Maximum-SR	2	10.075	0.377	1.333	6	PHASING (6)
LEO80	Baseline	0	0.000	0.137	3.000	0	none
	Knee	7	3.711	0.169	2.833	5	ALT (2), PHASING (2), RAAN (1)
	Maximum-SR	2	7.218	0.347	2.833	5	PHASING (4), ALT (1)

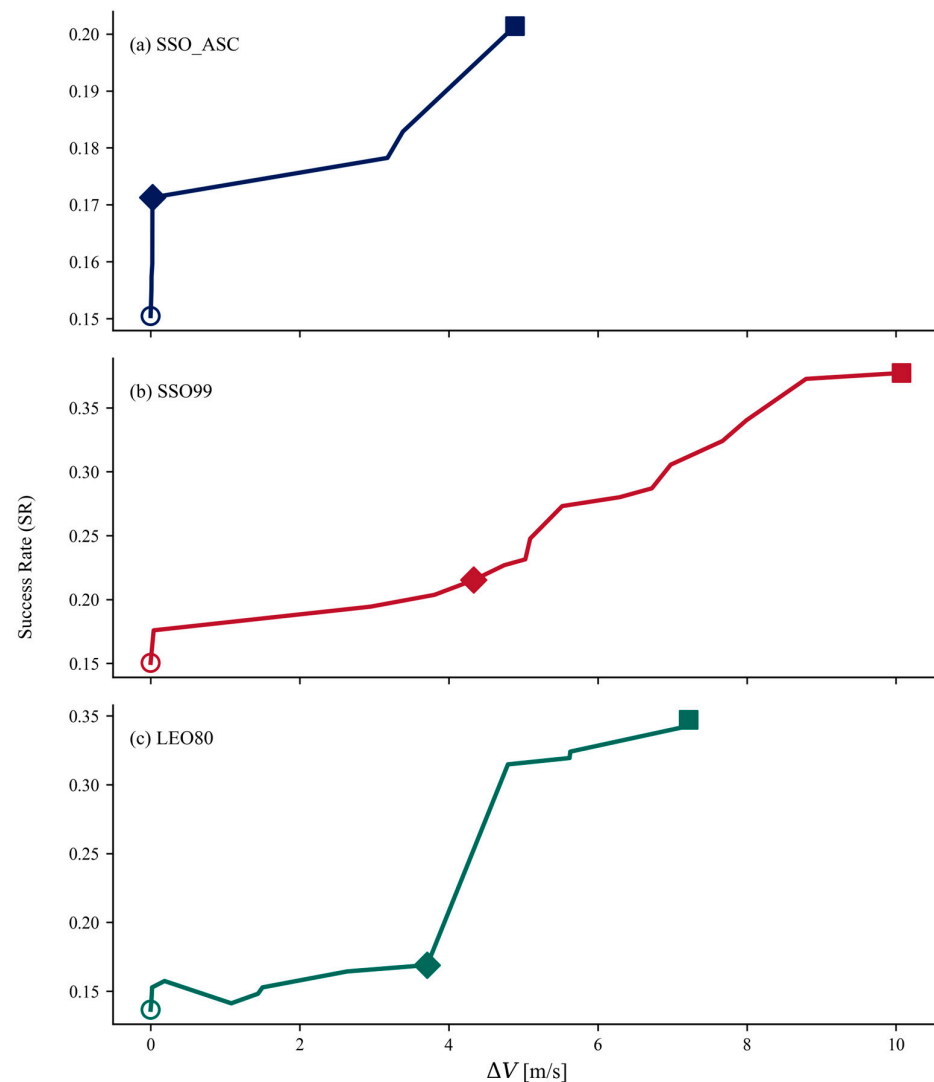


Figure 7. Pareto fronts in the ΔV – SR space for three reference constellations: (a) SSO_ASC, (b) SSO99, and (c) LEO80. The baseline configuration (open circle), the knee point (diamond), and the maximum-SR solution (square) are indicated as representative Pareto solutions. The corresponding objective-function values and aggregated maneuver-decision characteristics are summarized in Table 3. Each panel uses an individual SR axis scale to emphasize non-linear characteristics.

To improve the interpretability of the Pareto fronts, the representative solutions marked in Figure 7 were additionally summarized in Table 3. These solutions correspond to the baseline or no-maneuver case, the geometric knee point, and the maximum-SR solution. Instead of numbering all Pareto-optimal individuals, which would reduce the readability of Figure 7, the selected points capture the main trade-off structure between maneuver cost and observational improvement. The table reports the corresponding objective-function values and aggregated maneuver-decision characteristics, including the number of active maneuvers and the maneuver-type composition.

The table reports aggregated maneuver-decision characteristics rather than the full satellite-level genotype, because listing all per-satellite decision variables for all Pareto-optimal individuals would substantially reduce readability. The comparison shows that the baseline solutions correspond to the no-maneuver case and, therefore, provide the lowest SR values. The knee solutions introduce a limited number of maneuver activations and provide intermediate improvements in SR with moderate ΔV expenditure. The maximum-SR solutions require larger maneuver budgets and, in most cases, a higher level of maneuver

activation. Across the representative Pareto solutions, PHASING maneuvers dominate the high-SR region, whereas ALT maneuvers are mainly present in low- and intermediate- ΔV solutions. RAAN corrections appear only sporadically. This indicates that the attainable improvement in SR is driven primarily by along-track redistribution of satellites and moderate altitude adjustments rather than by systematic plane-change maneuvers.

In all cases, a monotonic increase in the observational success rate SR was observed with increasing maneuver budget ΔV . However, the magnitude of attainable improvement differed substantially between architectures:

- For SSO_ASC, the success rate increased from 0.150 to 0.201, corresponding to a total improvement of $\Delta SR_{\text{total}} = 0.051$;
- For SSO99, the success rate increased from 0.150 to 0.377, yielding $\Delta SR_{\text{total}} = 0.227$;
- For LEO80, the success rate increased from 0.137 to 0.347, corresponding to $\Delta SR_{\text{total}} = 0.211$.

The Pareto front of SSO_ASC is relatively short and exhibits limited variability across the explored maneuver range. In contrast, SSO99 and LEO80 display extended fronts characterized by a pronounced growth phase followed by gradual saturation at higher ΔV values.

3.2.2. Limited Variability of the Time-to-First-Success Criterion

The relationship between the maneuver budget ΔV and the time to first success T_{first} was evaluated for all Pareto-optimal solutions obtained in Stage 2. The resulting dependencies are shown in Figure 8.

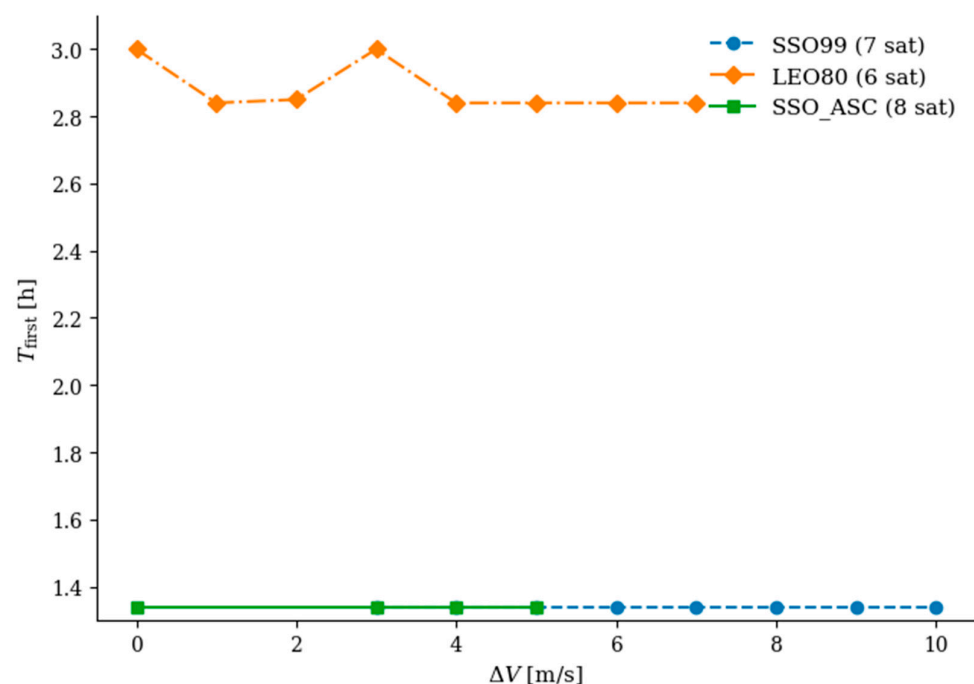


Figure 8. Dependence of the time to first success T_{first} on the total maneuver budget ΔV for the three analyzed constellation configurations.

Across the entire explored maneuver range, T_{first} remains nearly constant for all constellation architectures. The total variation does not exceed approximately 0.17 h for the LEO80 configuration and is negligible for the SSO-based configurations.

Compared to the dispersion observed in the success rate SR along the Pareto fronts, the variability of T_{first} is minimal.

This behavior can be explained by the orbital geometry of the first access opportunity. The time to first success (T_{first}) is primarily determined by the initial relative phasing of the satellites with respect to the AOIs, the orientation of the orbital plane, and the alignment of the ground track with the target regions at the time of the crisis request. Within the short response horizon considered in this study, small reactive maneuvers mainly modify the distribution and frequency of subsequent access opportunities rather than substantially shifting the earliest feasible overpass. In particular, altitude and phasing corrections can improve cumulative coverage and increase the number of successful windows, but their effect on the first dominant access window remains limited when the initial constellation geometry already provides an early candidate access. This explains why T_{first} exhibits only minor fluctuations, whereas the success rate (SR) changes more visibly along the Pareto front.

3.2.3. Availability Improvement Thresholds

For each constellation, the maneuver budgets ΔV required to achieve 50% and 90% of the total attainable improvement in observational success rate were determined. These thresholds characterize the progression of improvement along the Pareto front.

1. For SSO_ASC:
 - $\Delta V_{50} = 3.18 \frac{m}{s}$;
 - $\Delta V_{90} = 4.89 \frac{m}{s}$;
2. For SSO99:
 - $\Delta V_{50} = 5.52 \frac{m}{s}$;
 - $\Delta V_{90} = 8.79 \frac{m}{s}$;
3. For LEO80:
 - $\Delta V_{50} = 4.79 \frac{m}{s}$;
 - $\Delta V_{90} = 7.21 \frac{m}{s}$.

The geometric knee point of each Pareto front was also identified:

- SSO_ASC: $0.03 \frac{m}{s}$;
- SSO99: $3.81 \frac{m}{s}$;
- LEO80: $3.71 \frac{m}{s}$.

The complete set of values is summarized in Table 4.

Table 4. Maneuver budget required to achieve partial saturation of the total observational improvement.

Constellation	$SR_{baseline}$	SR_{max}	ΔSR_{total}	$\Delta V_{50} [\frac{m}{s}]$	$\Delta V_{90} [\frac{m}{s}]$	Knee $[\frac{m}{s}]$
SSO_ASC	0.150	0.201	0.051	3.18	4.89	0.03
SSO99	0.150	0.377	0.227	5.52	8.79	3.81
LEO80	0.137	0.347	0.211	4.79	7.21	3.71

3.2.4. Sensitivity and Structural Characteristics of Pareto-Optimal Solutions

The local sensitivity of the success rate SR with respect to ΔV was evaluated along the Pareto front. The maximum observed slopes were as follows:

- 7.37 for SSO_ASC;
- 0.62 for SSO99;
- 1.12 for LEO80.

Further analysis of maneuver composition, including the representative Pareto solutions summarized in Table 3, indicates that phasing corrections (PHASING) and altitude ad-

justments (ALT) dominate among Pareto-optimal solutions. RAAN and inclination-related corrections occur only sporadically and contribute marginally to the overall performance variation. This confirms that most of the attainable improvement in *SR* is associated with along-track redistribution of satellites and moderate altitude-related changes rather than systematic modifications of the orbital-plane geometry.

3.3. Stage 3—Operational Imaging Response Time (OIRT)

Stage 3 evaluates constellation performance under environmental uncertainty by incorporating probabilistic filtering effects (cloud cover and geomagnetic activity) into the geometric coverage obtained in Stages 1 and 2. The resulting performance metric is the OIRT.

If the coverage threshold β is not reached within the analyzed time horizon, the OIRT value is considered undefined.

The analysis was conducted for the following:

- Three constellation configurations (baseline, knee solution, and maximum-*SR* solution);
- Two crisis AOIs (PAS_PION and PAS_POZIOM). The crisis AOIs correspond to the vertical and horizontal corridor-type regions defined in Section 2.3.1, characterized by north–south and east–west oriented rectangular geometries, respectively;
- Twelve calendar months;
- Coverage thresholds $\beta \in \{0.2, 0.4, 0.6, 0.8, 0.9, 1.0\}$;
- Twenty Monte Carlo realizations per month.

Subsequent subsections present the statistical characteristics of OIRT, including coverage-threshold dependence, seasonal variability, and reliability metrics.

3.3.1. Dependence of OIRT on the Coverage Threshold β

Within the range of operationally achievable coverage thresholds, the OIRT increases monotonically with increasing β . Although the thresholds $\beta \in \{0.6, 0.8, 0.9\}$ were evaluated, Figure 9 presents only those thresholds that were reached in at least one Monte Carlo realization. This avoids plotting undefined OIRT values for threshold levels that were not operationally attainable within the analyzed response horizon. Consequently, PAS_PION is shown for $\beta = 0.6$, whereas PAS_POZIOM is shown for $\beta = 0.8$.

In the seasonal model, the maximum operationally achievable coverage levels were as follows:

- PAS_PION: $\beta_{max}^{Stage3} = 0.6$;
- PAS_POZIOM: $\beta_{max}^{Stage3} = 0.8$.

For PAS_PION, only $\beta = 0.6$ is operationally attainable; curves for higher thresholds are omitted because the coverage condition was not satisfied in any realization.

For PAS_POZIOM at $\beta = 0.8$ in the knee configuration, the following values were obtained:

- Minimum OIRT: 5.42 h;
- Maximum OIRT: 6.93 h;
- Global mean: 6.06 h;
- Maximum inter-configuration difference: approximately 1.45 h.

The knee configuration is reported here as a representative compromise solution capturing the majority of attainable improvement without entering the diminishing-return regime of high ΔV expenditure.

A comparison of maximum achievable coverage levels between Stage 2 (geometric analysis) and Stage 3 (environmental filtering) is provided in Table 5.

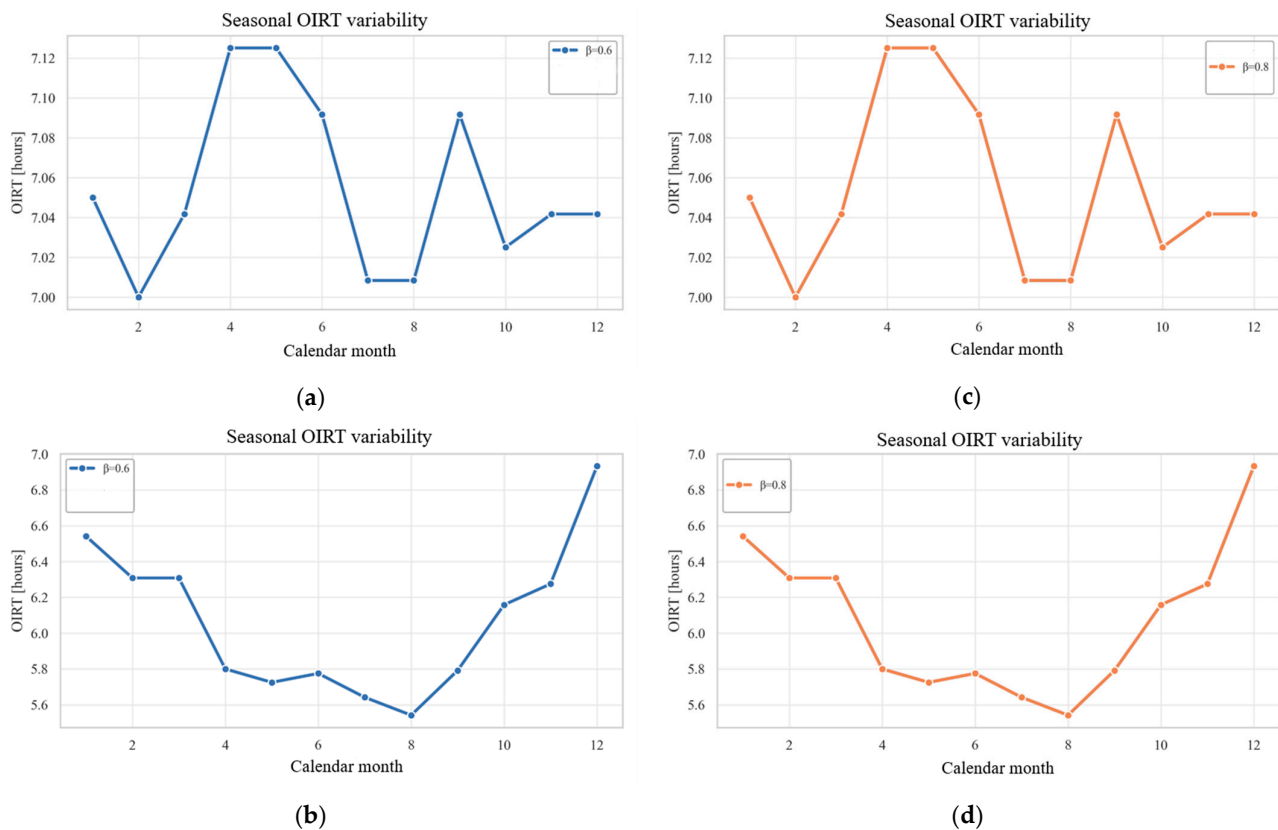


Figure 9. Seasonal variability of the OIRT for operationally attainable coverage thresholds as a function of calendar month: (a) PAS_PION, comparative lower-SR configuration; (b) PAS_PION, knee configuration; (c) PAS_POZIOM, comparative lower-SR configuration; (d) PAS_POZIOM, knee configuration. Only thresholds reached in at least one Monte Carlo realization are shown; missing β curves indicate that the corresponding coverage threshold was not achieved within the analyzed response horizon.

Table 5. Maximum achievable coverage levels in Stage 2 and Stage 3.

AOI	Stage 2 Max β	Stage 3 Max β
PAS_PION	~ 0.86	0.60
PAS_POZIOM	~ 0.92	0.80

The corresponding relative reductions in maximum achievable coverage are approximately 30% for PAS_PION and 13% for PAS_POZIOM.

3.3.2. Seasonal Variability of OIRT

Seasonal variability of the OIRT was analyzed for the operationally attainable case, i.e., PAS_POZIOM at the coverage threshold $\beta = 0.8$. Monthly mean OIRT values together with 5–95 percentile intervals are presented in Figure 10 for two representative constellation configurations.

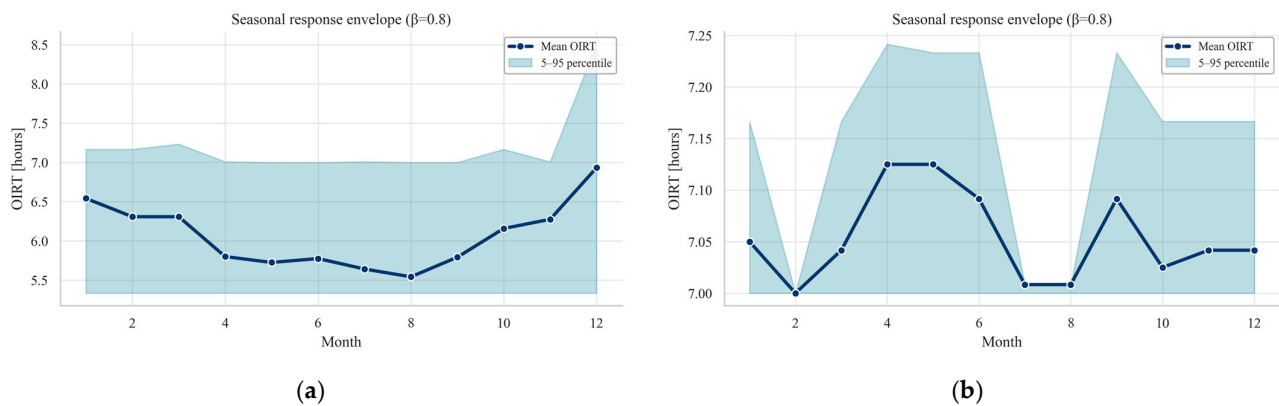


Figure 10. Seasonal variability of the OIRT for the operationally attainable case (PAS_POZIOM, $\beta = 0.8$) as a function of calendar month: (a) max-SR configuration identified in Stage 2; (b) comparative lower-SR Pareto configuration. Shaded areas represent the 5–95 percentile interval.

For PAS_PION, the threshold $\beta = 0.8$ was not reached in any Monte Carlo realization under the adopted seasonal model. Consequently, seasonal variability analysis is not applicable for this AOI at the considered threshold.

For PAS_POZIOM, clear seasonal variability is observed. For the configuration achieving the highest geometric success rate (max-SR solution identified in Stage 2), the following values were obtained:

- Minimum OIRT ≈ 5.55 h (August);
- Maximum OIRT ≈ 6.95 h (December);
- Seasonal amplitude exceeding 1.4 h.

The 5–95 percentile interval remains moderate throughout the year, although broader dispersion is visible in selected months characterized by increased environmental variability.

In contrast, the comparative configuration with lower geometric performance exhibits substantially reduced seasonal variability:

- Mean OIRT range ≈ 7.00 – 7.12 h;
- seasonal amplitude < 0.15 h.

While the lower-performance configuration demonstrates greater temporal stability, it remains systematically slower across all months. The higher-performance configuration, although more sensitive to seasonal environmental fluctuations, provides significantly shorter response times during favorable periods.

These results indicate that seasonal variability does not alter the relative ranking of configurations. Instead, it modulates the absolute response times while preserving the geometry-driven performance hierarchy established in earlier optimization stages.

3.3.3. Reliability of the Response Time

Cumulative distribution functions (CDFs) were used to estimate the probability of achieving the operational coverage threshold $\beta = 0.8$ within time t .

For PAS_POZIOM, the threshold $\beta = 0.8$ is operationally attainable, enabling estimation of the response time distribution for both analyzed configurations (Figure 11).

For the configuration achieving the highest geometric success rate, most Monte Carlo realizations reach $\beta = 0.8$ approximately 6.5 h before the request time.

For the comparative configuration with lower geometric performance, the response-time distribution is shifted toward longer times, with threshold attainment typically occurring in the 6.8–7.0 h range.

The response-time difference between configurations is approximately 1.4–1.5 h.

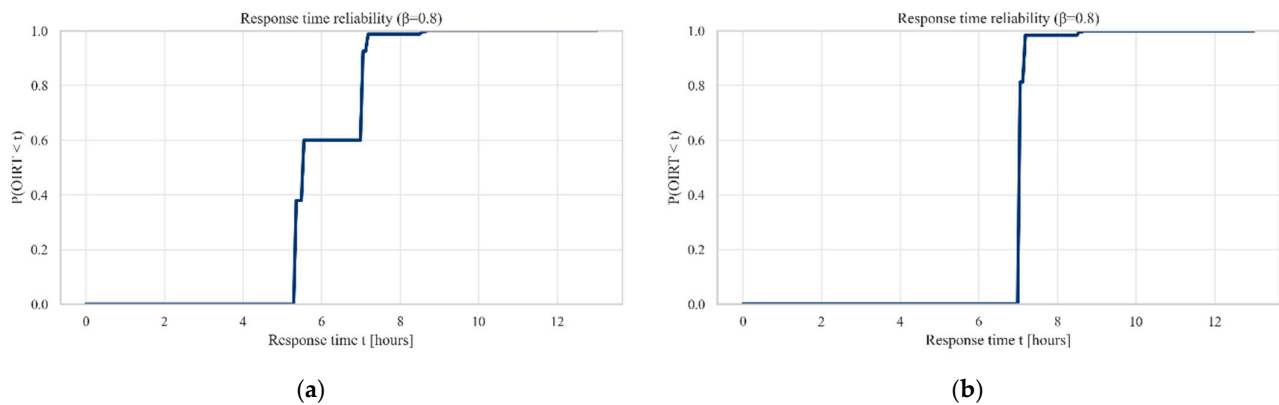


Figure 11. Cumulative probability of reaching 80% coverage ($\beta = 0.8$) as a function of response time for PAS_POZIOM: (a) max-SR configuration identified in Stage 2; (b) comparative lower-SR Pareto configuration.

For PAS_PION, the threshold $\beta = 0.8$ was not reached in any Monte Carlo realization under the seasonal model. Consequently, estimation of the response-time distribution is not possible for this case.

3.3.4. Effect of Maneuver Optimization Under Environmental Filtering

To assess the influence of reactive maneuvers under environmental constraints, OIRT values were compared for three constellation variants:

- Baseline configuration;
- Compromise (knee) solution;
- Maximum-SR solution.

The analysis was performed for the operational threshold $\beta = 0.8$, attainable only for PAS_POZIOM in the seasonal model. Table 6 presents the global OIRT metrics averaged over calendar months and Monte Carlo realizations.

Table 6. Global OIRT metrics for $\beta = 0.8$ (PAS_POZIOM), averaged across months and Monte Carlo realizations.

Constellation	Variant	$OIRT_{mean}$ [h]	Δ vs. Baseline [h]	$P(success)$
SSO_ASC	Baseline	7.38	—	1.00
	Knee	6.92	−0.46	1.00
	Max-SR	6.39	−0.99	1.00
SSO99	Baseline	7.34	—	1.00
	Knee	6.88	−0.46	1.00
	Max-SR	6.41	−0.93	1.00

For both constellations, maneuver optimization reduces the mean response time by up to approximately 1 h relative to the baseline configuration.

The probability of achieving the threshold remains equal to 1.0 for all analyzed variants.

4. Discussion

The results obtained in the three-stage framework allow interpretation of constellation performance across geometric, dynamic, and operational layers. The analysis demonstrates that static geometry, maneuver-based reconfiguration, and environmental uncertainty influence system behavior in structurally different ways.

4.1. Geometric Optimization and Structure of the Design Space

Stage 1 indicates that the admissible orbital parameter space contains a clearly identifiable high-performance region characterized by the following:

- Single-plane architectures;
- Clustered phasing;
- Altitudes around 550 km;
- Sun-synchronous inclination regimes.

The rapid convergence of the genetic algorithm and the stabilization of fitness values across generations suggest that this region represents a structurally stable optimum rather than a stochastic artifact of the search process.

This observation is consistent with previous analytical studies demonstrating that sun-synchronous clustered architectures have been shown to provide a favorable compromise between revisit frequency and longitudinal coverage distribution [5–8].

The benchmark comparison further demonstrates that symmetric Walker-type configurations, although geometrically regular, may fail under crisis-driven, spatially separated AOI conditions. Similar observations have been reported in constellation design studies where anisotropic target distributions reduce the effectiveness of uniformly distributed architectures. The present results support this perspective by showing that geometric symmetry alone does not guarantee mission-specific coverage performance.

Rather than maximizing overpass frequency, the fitness function favors balanced spatiotemporal coverage across multiple AOIs. This finding reinforces the hypothesis that constellation performance is strongly dependent on the spatial structure of mission requirements. Within the analyzed parameterization and satellite-number range, constellation geometry emerges as the dominant structural driver of crisis-response capability.

4.2. Geometry-Dependent Responsiveness to Maneuver Optimization

Stage 2 reveals that responsiveness to reactive maneuvers is strongly conditioned by baseline geometry.

Three behavioral regimes can be distinguished:

- A low-reactivity regime (SSO_ASC), where the geometry is already close to the static optimum and additional ΔV expenditure yields limited improvement;
- A highly reconfigurable regime (SSO99), characterized by substantial success-rate growth and a clear non-linear activation region;
- A threshold-activated regime (LEO80), where measurable improvement occurs only after crossing a moderate ΔV threshold.

The invariance of the time-to-first-success criterion across the Pareto fronts is particularly noteworthy. It indicates that the first dominant access window is governed primarily by the initial orbital phase distribution, orbital plane orientation, and ground-track alignment with the AOIs at the crisis request time. Reactive maneuvers modify cumulative availability by increasing the number of successful access windows, but they do not substantially alter the timing of the earliest feasible overpass within the short response horizon.

This observation aligns with previous studies on constellation reconfiguration, which report diminishing returns when baseline geometry is already near-optimal. In such cases, maneuvers refine coverage distribution rather than fundamentally altering temporal access structure.

Consequently, the multi-objective optimization effectively reduces to a two-dimensional trade-off between ΔV and success rate SR for the analyzed scenario.

These findings partially support the working hypothesis that artificial-intelligence-based multi-objective optimization can enhance maneuver planning efficiency; however, the magnitude of improvement is strongly geometry-dependent.

4.3. Transition from Geometric Potential to Operational Performance

Stage 3 introduces environmental filtering, transforming geometric availability into operational response time (OIRT).

A central outcome of this stage is the non-linear relationship between geometric success rate and operational response time. Although configurations with higher SR generally exhibit lower OIRT, the relationship is not proportional. This discrepancy reflects the conceptual difference between the following:

- SR, which measures geometric access frequency;
- OIRT, which measures the time required to accumulate a specified coverage threshold under uncertainty.

Similar discrepancies between geometric access metrics and effective acquisition probability have been reported in cloud-constrained Earth observation analyses [27].

The reduction in maximum achievable coverage levels between Stage 2 and Stage 3 (approximately 30% for PAS_PION and 13% for PAS_POZIOM) highlights the importance of incorporating environmental variability into constellation evaluation. Similar reductions in effective coverage under atmospheric filtering have been observed in Earth observation mission analyses where cloud statistics significantly constrain optical imaging availability.

These results indicate that purely geometric optimization may systematically overestimate real-world responsiveness if environmental constraints are not explicitly considered.

4.4. Operational Significance of Maneuver Optimization

Under environmental filtering, reactive maneuvers reduce OIRT by up to approximately one hour for the operationally attainable threshold $\beta = 0.8$. However, the probability of reaching the threshold remains unchanged across baseline and optimized configurations.

Thus, maneuver optimization primarily shifts the response-time distribution toward shorter values without altering structural attainability.

In time-critical scenarios, a reduction of approximately 13–14% in response time may be operationally relevant, particularly in rapid-response imaging scenarios where imaging latency directly affects decision cycles. Nevertheless, the improvement remains moderate relative to the total response horizon. These findings suggest that propellant expenditure should be evaluated against quantifiable temporal gains rather than assumed performance enhancement.

4.5. Seasonal Variability and Structural Robustness

Seasonal variability affects absolute OIRT values but does not modify configuration ranking. Even under environmental filtering, the ranking of configurations remains geometry-driven. The optimized geometry exhibits seasonal acceleration windows with moderate dispersion, whereas less favorable configurations show reduced seasonal amplitude but consistently longer response times.

This suggests that orbital phasing interacts with seasonal environmental patterns, yet baseline geometry remains the dominant structural determinant of system responsiveness within the analyzed mission profile.

The results, therefore, indicate that while seasonal variability introduces stochastic dispersion, it does not overturn the geometric hierarchy established in earlier optimization stages.

4.6. Broader Implications for Constellation Design

The combined results of all three stages support several broader conclusions:

- Constellation geometry emerges as the dominant structural driver of crisis-response capability within the analyzed configuration range;
- Reactive maneuvers provide measurable but limited acceleration, particularly for geometries already near static optimality;
- Geometric availability metrics alone are insufficient for evaluating time-critical mission performance;
- Operational response-time metrics should be integrated into optimization frameworks at early design stages;
- Environmental uncertainty significantly reduces achievable coverage thresholds and must be incorporated into realistic system assessment.

The proposed three-stage methodology (geometry → maneuvers → operational filtering) offers a systematic approach to bridging abstract geometric optimization and realistic mission-response evaluation.

4.7. Advantages over Alternative Assessment Strategies

The proposed framework should not be interpreted as a new evolutionary algorithm, but rather as a structured decision methodology that integrates several well-established optimization and assessment components into a hierarchical workflow. Its main advantage is the explicit separation of three performance layers that are often analyzed jointly or only partially in alternative approaches: geometric constellation potential, reactive maneuver adaptability, and operational realizability under environmental constraints.

The numerical results illustrate the practical benefit of this separation. In Stage 1, the GA-optimized constellation achieved a global success rate of 95.83, compared with a mean value of 14.01 for the random sampling baseline and 0.0 for the classical symmetric Walker-like configuration under the adopted global success criterion. In Stage 2, reactive maneuver optimization produced different levels of improvement depending on the initial constellation geometry: the total attainable increase in success rate was 0.051 for SSO_ASC, 0.227 for SSO99, and 0.211 for LEO80. In Stage 3, environmental filtering further reduced the maximum achievable coverage thresholds from approximately 0.86 to 0.60 for PAS_PION and from approximately 0.92 to 0.80 for PAS_POZIOM. These values show that each layer reveals a different performance-limiting mechanism that would be difficult to identify using a single-stage or purely geometric assessment.

Compared with purely geometric constellation optimization, the proposed approach provides an additional diagnostic layer by verifying whether the high intrinsic coverage potential of a constellation can be translated into improved operational performance after a crisis request. A configuration with high geometric fitness in Stage 1 does not necessarily provide the best reactive behavior once maneuver limitations, timing constraints, and AOI-specific accessibility are considered. The Stage 2 analysis, therefore, allows the user to distinguish between architectures that are geometrically efficient and those that are also maneuver-responsive.

Compared with single-objective or weighted-sum maneuver optimization, the multi-objective formulation used in Stage 2 preserves the trade-off between success rate, response time, and total ΔV expenditure. This is particularly important in crisis-response scenarios, where the best operational decision may depend on whether the priority is maximum coverage, minimum response time, or fuel preservation. A single-objective formulation would require these preferences to be fixed a priori, whereas the Pareto-front representation exposes the range of feasible compromises and enables post-optimization selection of representative solutions such as the knee point.

Compared with approaches that stop at deterministic access or coverage analysis, the Stage 3 OIRT-based assessment incorporates probabilistic environmental filtering. This makes it possible to quantify the degradation between geometric availability and operationally achievable imaging performance. As shown by the reduction in attainable coverage thresholds after environmental filtering, purely geometric analysis may overestimate operational responsiveness when cloud cover and space-weather constraints are not considered.

The benefit of the proposed approach is, therefore, not limited to improving a single metric. Rather, it provides a traceable decision pathway from constellation synthesis through maneuver trade-off analysis to operational response-time assessment. This allows performance losses to be attributed to their dominant source: insufficient constellation geometry, limited maneuver effectiveness, or environmental filtering. Such attribution would be difficult in a non-hierarchical method or in an approach based only on a single optimization stage.

4.8. Limitations and Future Research Directions

Several limitations of the present study should be acknowledged.

First, the constellation size was restricted to 6–9 satellites within a predefined orbital parameterization. Larger-scale or heterogeneous constellations may exhibit different responsiveness regimes.

Although GA convergence was verified using an increased optimization budget and additional random seeds, a full hyperparameter sensitivity analysis, including systematic variation in crossover and mutation probabilities, was not performed. A similar limitation applies to the NSGA-II configuration used in Stage 2, where the Pareto-front stability was verified using an increased population size, a greater number of generations, and additional random seeds, but a complete sensitivity comparison across different parameter combinations was not conducted. Such analyses would be valuable for assessing the numerical sensitivity of both optimization stages and are planned as future work.

The simulation horizon was limited to 72 h, reflecting the crisis-response focus of the study. Therefore, the conclusions should be interpreted within the analyzed short-term operational response horizon. Long-term orbital evolution, cumulative perturbation effects, repeated maneuver cycles, and station-keeping requirements remain outside the scope of the present work and are identified as future validation directions.

Second, the maneuver model adopted in Stage 2 assumes ideal impulsive velocity increments and does not explicitly account for finite-burn effects, low-thrust propulsion dynamics, thrust-direction constraints, or spacecraft-specific propulsion characteristics. Therefore, the reported ΔV values should be interpreted as comparative system-level maneuver-cost indicators. Incorporating satellite-specific thrust models and finite-burn dynamics is an important direction for future engineering-level validation.

The observation model was limited to three representative geometric coverage patterns: mosaic imaging, along-track strip imaging, and cross-track strip imaging. These patterns capture the main spatial coverage strategies considered in this study, but they do not exhaust the full range of sensor-specific acquisition modes used in Earth observation missions. Extending the framework to additional imaging modes, such as spotlight, stripmap, sliding spotlight, staring, wide-swath, stereo, or multi-angle imaging, would require corresponding extensions of the sensor-footprint model and success-function definition.

The framework was evaluated for several fixed AOI geometries, including compact AOIs and elongated corridor-type regions. However, mobile target observation scenarios were not considered in the present study and remain outside its scope. Future work may verify the applicability of the framework to time-varying observation tasks.

Third, the environmental model was based on probabilistic filtering rather than fully dynamic cloud-field prediction. Coupling constellation optimization with predictive environmental modeling could refine operational performance estimates.

Fourth, maneuver optimization was performed as a post-geometric correction stage. Future work may integrate OIRT directly into the evolutionary optimization objective, enabling joint geometric-operational optimization.

Additional research may explore the following:

- Direct OIRT-based optimization;
- Dynamic AOIs/moving targets;
- Integration of predictive environmental modeling;
- Propellant allocation scheduling strategies.

Such extensions would further generalize the presented framework and enable broader applicability to diverse Earth observation mission profiles.

5. Conclusions

This study developed and validated a hierarchical three-stage optimization framework for Earth observation satellite constellations operating under maneuver constraints and environmental uncertainty. The proposed methodology establishes a structured transition from geometric constellation synthesis to reactive maneuver refinement and finally to operational response-time evaluation using the OIRT metric.

The framework integrates three complementary decision layers:

- Geometric constellation optimization (Stage 1);
- Multi-objective reactive maneuver adaptation using NSGA-II (Stage 2);
- Operational performance assessment based on probabilistic environmental filtering and tile-based coverage accumulation (Stage 3).

This layered structure enables quantitative traceability between architectural design decisions and mission-level operational performance.

The principal findings of the study can be summarized as follows:

1. **Reactive maneuver optimization provides measurable but moderate operational gains.**
Under constrained ΔV budgets, maneuvers reduce response time by up to approximately 1 h (13–14%) for operationally attainable coverage thresholds. Maneuvers, therefore, act as corrective refinements rather than primary performance drivers.
2. **Geometric accessibility does not translate linearly into operational responsiveness.**
A clear non-linearity exists between geometric metrics such as success rate (SR) and the operational OIRT metric. High geometric accessibility does not guarantee proportional reduction in response time once environmental variability is considered.
3. **Environmental filtering significantly constrains achievable operational coverage.**
Incorporating Total Cloud Cover (TCC) and geomagnetic activity (Kp) reduces achievable coverage levels by up to approximately 30% for selected AOIs, demonstrating that purely geometric evaluations may overestimate real-world responsiveness.
4. **The OIRT metric provides a decision-oriented performance indicator aligned with time-critical mission requirements.**

By combining cumulative coverage thresholds with stochastic environmental effects, OIRT enables direct evaluation of mission-relevant response capability.

5. **The three-stage architecture enhances interpretability and extensibility of constellation optimization.**

Separating geometric, dynamic, and operational layers improves transparency of performance drivers and facilitates adaptation to alternative mission profiles, environmental models, and sensor configurations.

Overall, the proposed framework establishes a consistent methodology for linking constellation design with operational performance assessment. Integrating geometric optimization, maneuver constraints, and environmental variability within a unified evaluation structure provides a robust foundation for the development of time-sensitive Earth observation systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AOI	Area of Interest
CDF	Cumulative Distribution Function
GA	Genetic Algorithm
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OIRT	Operational Imaging Response Time
SR	Success Rate
TCC	Total Cloud Cover
ΔV	Total Maneuver Budget

Appendix A

Algorithm A1. Pseudocode of the Multi-Stage Optimization Framework
Input:
AOI definitions
Orbital parameter bounds
ΔV constraints
Environmental datasets (TCC, Kp)

Algorithm A1. *Cont.***Stage 1—Geometric Constellation Optimization**

```

1: Initialize candidate solution set  $P_0$ 
2: for generation  $g = 1$  to  $G_1$  do
3:   for each decision vector  $x \in P_g$  do
4:     Propagate orbital dynamics (J2 model)
5:     Evaluate Success( $w, m, N$ )
6:     Aggregate SR across AOIs and modes
7:     Compute fitness  $F(x)$  as average best SR
8:   end for
9:   Apply selection, recombination, and mutation operators
10:  Form next solution set  $P_{g+1}$ 
11: end for
12: Select top-K constellation configurations  $C^*$ 

```

Stage 2—Multi-Objective Maneuver Optimization

```

13: for each constellation  $C \in C^*$  do
14:   Initialize maneuver solution set  $Q_0$ 
15:   for generation  $g = 1$  to  $G_2$  do
16:     for each maneuver schedule  $M \in Q_g$  do
17:       Apply maneuver model
18:       Propagate updated orbital states
19:       Evaluate objective functions:
20:          $f_1 =$  -success rate
21:          $f_2 =$  time to first success ( $T_{\text{first}}$ )
22:          $f_3 =$  total maneuver cost ( $\Delta V_{\text{tot}}$ )
23:     end for
24:     Perform non-dominated sorting
25:     Apply selection based on Pareto dominance and density metric
26:     Form next solution set  $Q_{g+1}$ 
27:   end for
28:   Extract Pareto-optimal maneuver sets  $M^*$ 
29: end for

```

Stage 3—Operational Response Assessment (OIRT)

```

30: for each solution pair  $(C, M^*)$  do
31:   for each month do
32:     for each Monte Carlo realization do
33:       Apply probabilistic environmental filtering
34:       Accumulate geometric coverage  $A_{\text{covered}}(t)$ 
35:       Compute coverage ratio  $\beta(t)$ 
36:       Determine first time  $t_\beta$  such that  $\beta(t) \geq \beta$ 
37:       If threshold not reached within horizon  $\rightarrow$  mark failure
38:     end for
39:     Compute statistical estimators over realizations:
40:       mean(OIRT_ $\beta$ ),
41:       standard deviation,
42:        $P(\text{success})$ ,
43:       percentile intervals

```

Algorithm A1. *Cont.*

37: end for

38: end for

Output:

 Optimized constellation configurations C^* Pareto-optimal maneuver strategies M^*

Operational response metrics:

 OIRT- β distributions,

success probability,

seasonal variability indicators

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