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Decision-Making Models for massive Extraterrestrial Material Transfer Systems Based on Capacity-Constrained Optimization and Reliability Auditing

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ABSTRACT

Addressing the logistical challenges of lunar colony construction, this study proposes a multi-module integrated decision support framework. First, a capacity-schedule-cost model is constructed to optimize the allocation ratio between space elevators and rockets, identifying an "elevator-dominant with rockets as supplementation" strategy as the most cost-effective approach. Second, a Markov reliability model is introduced to quantify effective capacity losses under non-ideal operating conditions, proving that system availability is a high-leverage parameter for long-term scheduling. Additionally, the research establishes a water demand and recycling dynamics model, demonstrating that improving recycling efficiency is the core strategy for reducing long-term logistics burdens. Finally, a full-life-cycle environmental assessment is integrated, and sensitivity analyses identify key parameters influencing planning quality. This framework provides rigorous mathematical tools and management rules for the robust planning of large-scale extraterrestrial logistics systems.

KEYWORDS
heterogeneous transport capacity scheduling, markov reliability model, space logistics, lunar base construction

INTRODUCTION

Establishing a reliable, low-cost, and sustainable interplanetary supply chain represents a core challenge in aerospace systems engineering for achieving large-scale lunar settlement. With the advancement of deep space exploration strategies, lunar bases have gradually shifted from concepts to engineering implementation, facing the extreme challenge of delivering hundreds of millions of tons of materials. In the field of logistics optimization, current research mainly focuses on intelligent algorithms and specific transportation scenarios.

For instance, Lv et al. proposed an intelligent multi-level network optimization method for medical logistics in underground transportation systems [1]. Hongming et al. studied supply chain transportation and route planning under deep reinforcement learning [2]. In terms of specific transport modes, Saleh et al. discussed the implementation of refueling stations in drone-based blood supply transportation [3], Wu et al. proposed a hybrid algorithm for UAV material transportation [4], and Zhang et al. studied trajectory tracking control for emergency supplies transportation robots [5]. Additionally, Zhou et al. analyzed the optimal flow distribution of military supply transportation [6], and Tang et al. explored yaw stability control of unmanned emergency supplies transportation vehicles [7].

Despite these rich results, most studies focus on single-mode transportation or path optimization. An et al. studied the transportation and reserve of emergency medical supplies [8], but did not consider the long-term dynamic demand of extraterrestrial colonies. Research by Guang et al. on autonomous material transportation in construction sites [9] and Döyen et al. on integrated disaster preparedness models [10] lacks discussion on the extreme space environment. In summary, existing logistics optimization research has established a relatively mature methodological framework, primarily exhibiting the following characteristics: In terms of technical approaches, the focus has largely been on leveraging deep reinforcement learning and hybrid intelligent algorithms to address path planning and scheduling challenges in specific scenarios, demonstrating superiority at the algorithmic level. In application scenarios, the focus lies on specific domains such as medical emergency response, military logistics distribution, and underground/construction site transportation on terrestrial environments, emphasizing response speed and robustness in complex terrains or emergency conditions. These achievements provide crucial theoretical foundations for refined management and dynamic scheduling of material transportation. However, most of the above research implicitly assumes relatively well-developed ground infrastructure support in the transportation environment. Furthermore, material demands are typically modeled as short-term or finite-period static tasks. There is a lack of in-depth exploration into: massive material flows across interstellar scales; System reliability degradation under non-ideal operating conditions; Long-term dynamic supply-demand balance within closed ecosystems. As a result, these approaches are difficult to directly transplant into infrastructure construction and long-term survival support missions in extreme extraterrestrial environments.

Prior studies lack systematic attempts to integrate construction timelines, system failure risks, closed-loop life support requirements, and long-term environmental loads into a unified decision framework. While technical feasibility of space elevators or single rocket launch costs has been explored, there is a gap in incorporating non-ideal operating conditions into capacity planning. To address these issues, this study proposes a heterogeneous transport capacity coordination scheduling and reliability assessment system. The innovation lies in employing a modular design to couple physical transport capacity constraints with macroeconomic indicators, deconstructing transport capacity losses under imperfect operations using Markov steady-state distributions, and quantifying key parameters' impact through sensitivity metrics.

MODELS

Capacity–Timeline–Cost Model

Model preparation

We model construction delivery as a long-run flow problem, where mass transportation is viewed as a continuous process. The primary decision variable is the elevator share x , which determines how much mass is allocated to each mode of transport-either elevator or rocket. The model evaluates both methods' capacity and cost over the long term. By considering longrun throughput and cost efficiency, the model seeks to minimize total transportation cost while ensuring that the construction timeline is met[7-8]. It should be noted that while the x=1 case serves as a theoretical benchmark for capacity, the current engineering readiness of space elevator cables (e.g., specific strength requirements) remains a significant technical bottleneck. Thus, x=1 represents a long-term strategic target rather than an immediate operational capability.

The key is to balance the usage of both transport methods to achieve a trade-off between cost and time. The elevator can transport large masses efficiently, but rockets are necessary for high-urgency payloads. This balance ensures that both efficiency and flexibility are incorporated into the planning process.

Model establishment

The model is established using the following relationships. To maintain analytical clarity for long-term strategic planning, we assume simplified linear capacity aggregation. While nonlinear constraints such as launch windows and orbital phase alignments are critical for mission-level scheduling, they are treated as aggregate efficiency factors within our macro-scale framework. First, the combined capacity $Q(x)$ depends on the share of mass allocated to the elevator and rocket:

$$Q(x) = xQ_e + (1-x)Q_r \tag{1}$$

Here, Q_e and Q_r represent the effective annual capacities of the elevator and rocket, respectively, while x represents the fraction of mass allocated to the elevator.

The construction time T is inversely proportional to the combined capacity, as the total mass M divided by the effective capacity determines how long construction will take:

$$T = \frac{M}{Q(x)} \tag{2}$$

Unit costs for the elevator and rocket are denoted by c_e and c_r , respectively. The mixed unit cost $c(x)$ for the chosen allocation x is calculated as:

$$c(x) = xc_e + (1-x)c_r \tag{3}$$

The total transport cost C for delivering the construction mass M is then given by:

$$C = Mc(x) \tag{4}$$

To compare different strategies under a common objective, we introduce a normalized weighted score. This score allows us to compare the cost-time trade-off across different plans:

$$J = w_C \frac{C}{C_{\max}} + w_T \frac{T}{T_{\max}}, w_C + w_T = 1 \tag{5}$$

Here, w_C and w_T are the weights assigned to cost and time, respectively[9]. This score serves as a summary measure, balancing both objectives and facilitating the comparison of different mass allocations between elevator and rocket. Cost contour by elevator share and timeline is shown in figure 1.

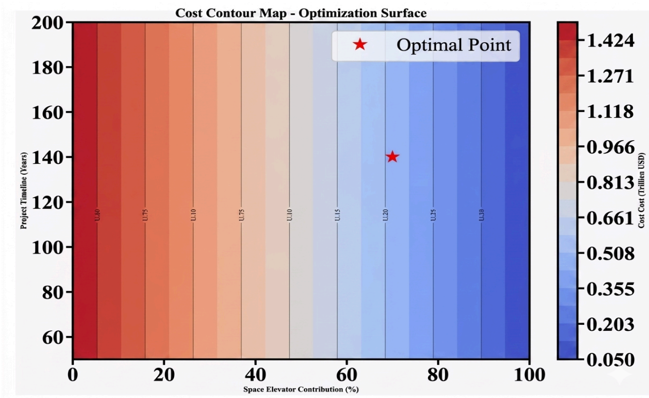

Figure 1. Cost contour by elevator share and timeline

Cost Contour by Elevator Share and Timeline: Total cost decreases sharply as the spaceelevator contribution increases, and the optimum lies in the high-elevator region, indicating an “elevator-dominant with rockets as supplementation” cost-minimizing strategy[10].

Representative scenarios and results

We report representative outcomes to show the relative ranking of different strategies rather than claim a single “true” future value. These representative scenarios vary the elevator share x , which allows us to observe how the allocation affects key metrics like construction time and cost. Table 1 compares three baseline strategies-elevator-only, rocket-only, and hybrid-in terms of capacity, time, and cost.

Table 1. Baseline comparison of construction strategies

Scheme	Capacity (t/yr)	Time (yr)	Cost (B USD)
Elevator only (x = 1)	537,000	187	500
Rocket only (x = 0)	62,500	1,600	15,000
Hybrid (70% / 30%)	394,650	254	4,850

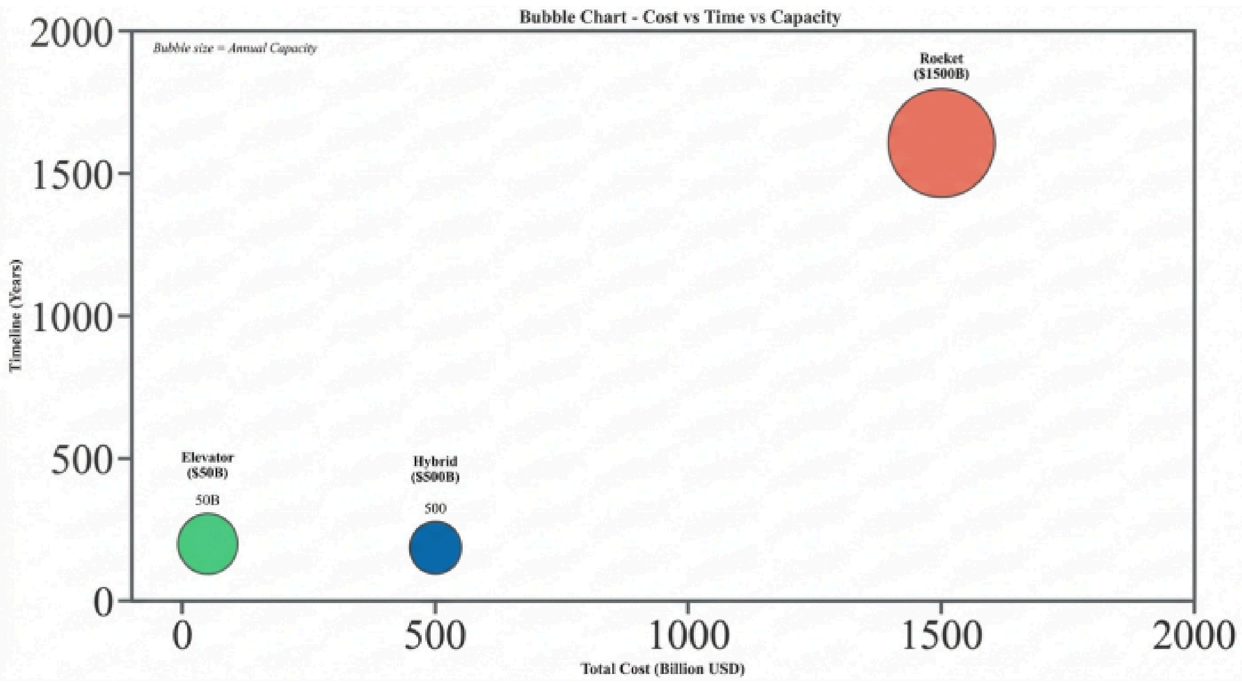

Figure 2. Cost–time–capacity bubble comparison

As show in Figure 2, with bubble size representing annual capacity, the elevator/hybrid solutions deliver higher throughput at substantially lower cost, whereas the rocket option is dominated in both cost and timeline.

Interpretation and planning implications

Equation(2) makes the scale effect explicit: when M is enormous, small throughput differences dominate schedule. This is why rocket-only plans, even if feasible per mission, become infeasible in total duration. The projected 1,600-year duration for the rocket-only strategy is intentionally highlighted to demonstrate that conventional launch technologies are socio-politically unfeasible for millenium-scale colonization, thereby necessitating a paradigm shift in space logistics infrastructure. Equation(4) similarly explains why high rocket unit cost can dominate the overall budget even for moderate rocket fractions [11-13].

Construction Delivery Progress by Strategy (Box Plot): The elevator scenario shows a higher median delivery and lower variability, rockets grow slowly with greater uncertainty, and the hybrid case provides a balanced compromise between stability and speed [14].

Operationally, a simple cargo rule follows: elevators carry high-mass, low-urgency cargo, while rockets are reserved for time-critical or unique payloads. This rule aligns economic efficiency with mission resilience.

Staged commissioning and capacity ramp

Real programs ramp capacity. We capture staging by a piecewise effective capacity:

$$Q_e(t) = \begin{cases} \alpha_1 Q_e, t \in [0, t_1), \\ \alpha_2 Q_e, t \in [t_1, t_2), \\ Q_e, \quad t \geq t_2 \end{cases} \tag{6}$$

with $0 < \alpha_1 < \alpha_2 < 1$. We omit ramp derivations; planners can compute annual delivery year-by-year under the same core equation set[15].

Reliability and Non-Perfect Operations

Availability framework

Imperfect operation is captured by availability A . The key insight is that long-run throughput is reduced approximately in proportion to operational availability. Here A aggregates planned maintenance and unplanned downtime, which is sufficient for long-horizon planning.

$$Q_{eff}(x) = AQ(x) \tag{7}$$

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$$T_{non} = \frac{M}{Q_{eff}(x)} = \frac{T}{A} \tag{8}$$

$$\gamma = \frac{T_{non}}{T} = \frac{1}{A} \tag{9}$$

Equation(9) offers a rule-of-thumb: modest reductions in A produce amplified schedule stretch on already-long timelines.

Markov-state model for availability

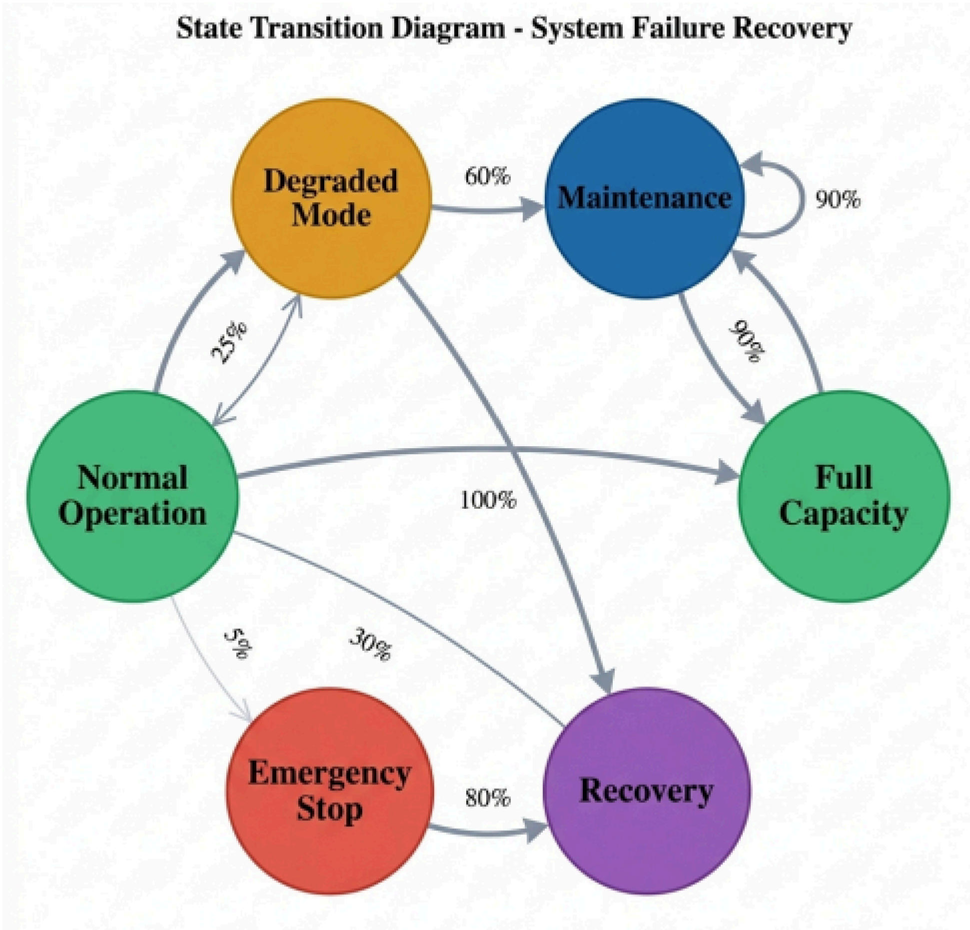

Figure 3. Reliability State Transitions and Recovery Pathways

Reliability State Transitions and Recovery Pathways are shown in figure 3.

We define states (Operational, Degraded, Down). A Markov representation summarizes failure and recovery as steady-state fractions, avoiding event-level simulation while retaining the impact of degraded operation[16-17]. This Markov representation focuses on long-run steady-state fractions. While it does not explicitly simulate cascading failure events, the 'Down' state transitions aggregate the statistical impact of systemic risks on overall system availability.

The Markov steady state is:

$$\pi = \pi P, \sum_i \pi_i = 1 \tag{10}$$

Availability is the probability of being operational or degraded:

$$A = \pi_{op} + \beta \pi_{\deg}, 0 < \beta < 1 \tag{11}$$

The parameter β represents partial throughput when operating in a degraded mode.

Reliability results and narrative

Table 2 shows that availability is a high-leverage KPI: even small losses in A translate into large schedule penalties for century-scale projects.

Table 2. Schedule stretch under availability loss

A	$\gamma = 1/A$	Elevator time (yr)	Hybrid time (yr)
1.0	1.00	187	254
0.9	1.11	208	282
0.8	1.25	234	318
0.7	1.43	267	363
0.5	2.00	374	508

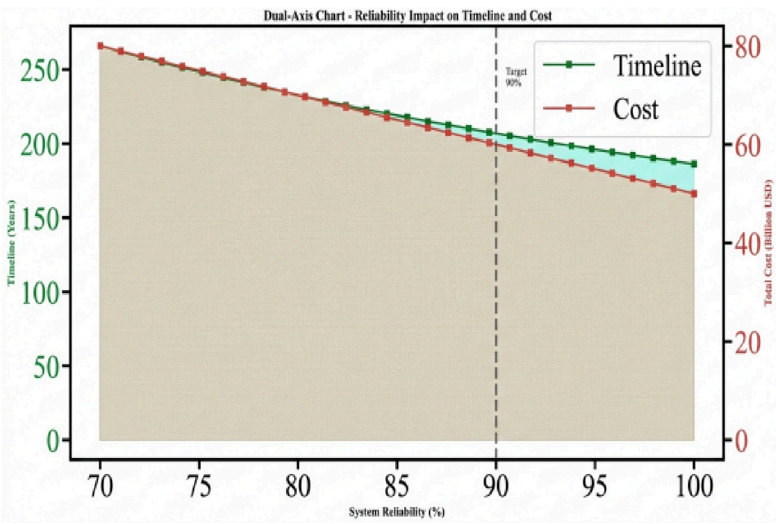

Figure 4. Reliability vs. Timeline and Cost

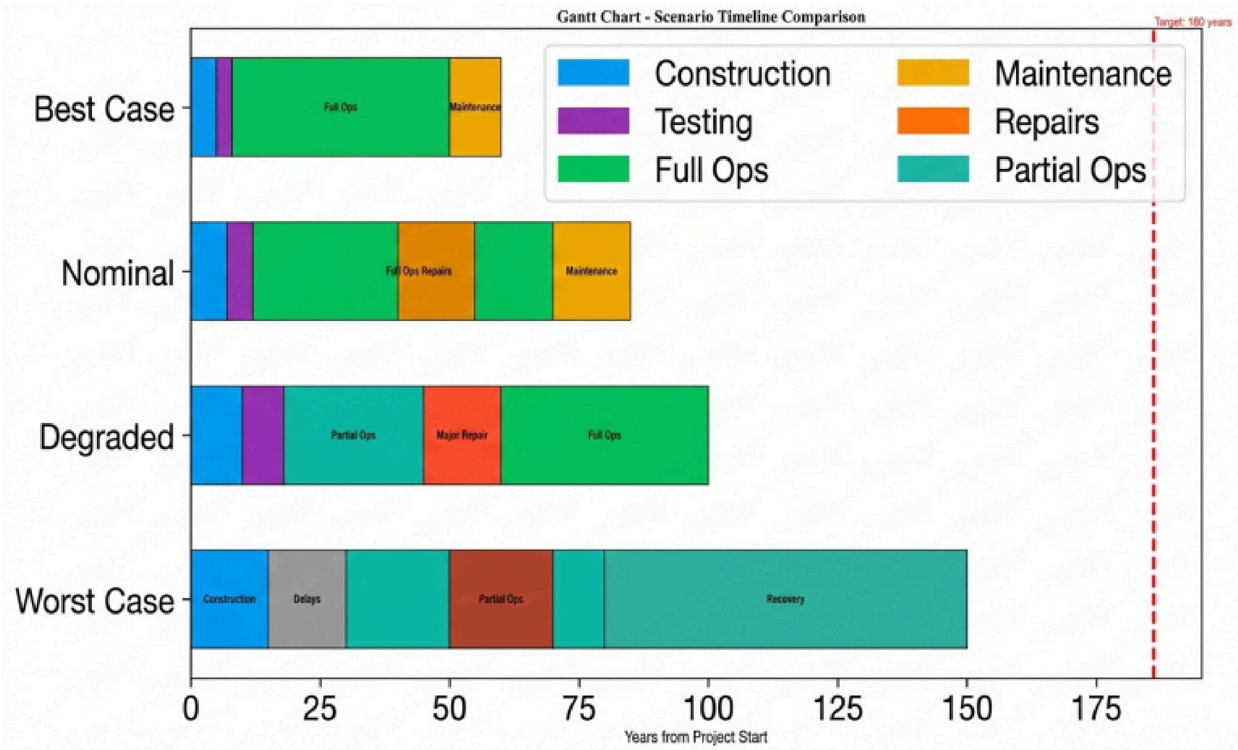

Figure 5. Scenario Timeline Gantt Comparison

Reliability vs. Timeline and Cost (figure 4): Increasing reliability simultaneously reduces both project duration and total cost, implying that investing in redundancy and maintainability yields coupled schedule–budget gains.

Scenario Timeline Gantt Comparison (figure 5): Worst-case completion is primarily extended by delays and recovery phases, motivating explicit contingency buffers and prioritized maintenance/repair scheduling.

The planning implication is direct: investments that raise A by a few points can save decades on long schedules(9), because effective throughput scales roughly with uptime and small downtime reductions compound over multi-century builds. In practice, this justifies early spending on preventive maintenance, spare parts, redundancy in critical subsystems, and clear availability KPIs with monitoring. Hybridization is best treated as insurance against rare but long outages, preserving critical deliveries when the elevator is constrained and avoiding schedule “stall” periods, rather than as a routine channel for bulk flow.

Water Demand, Recycling, and Reserves

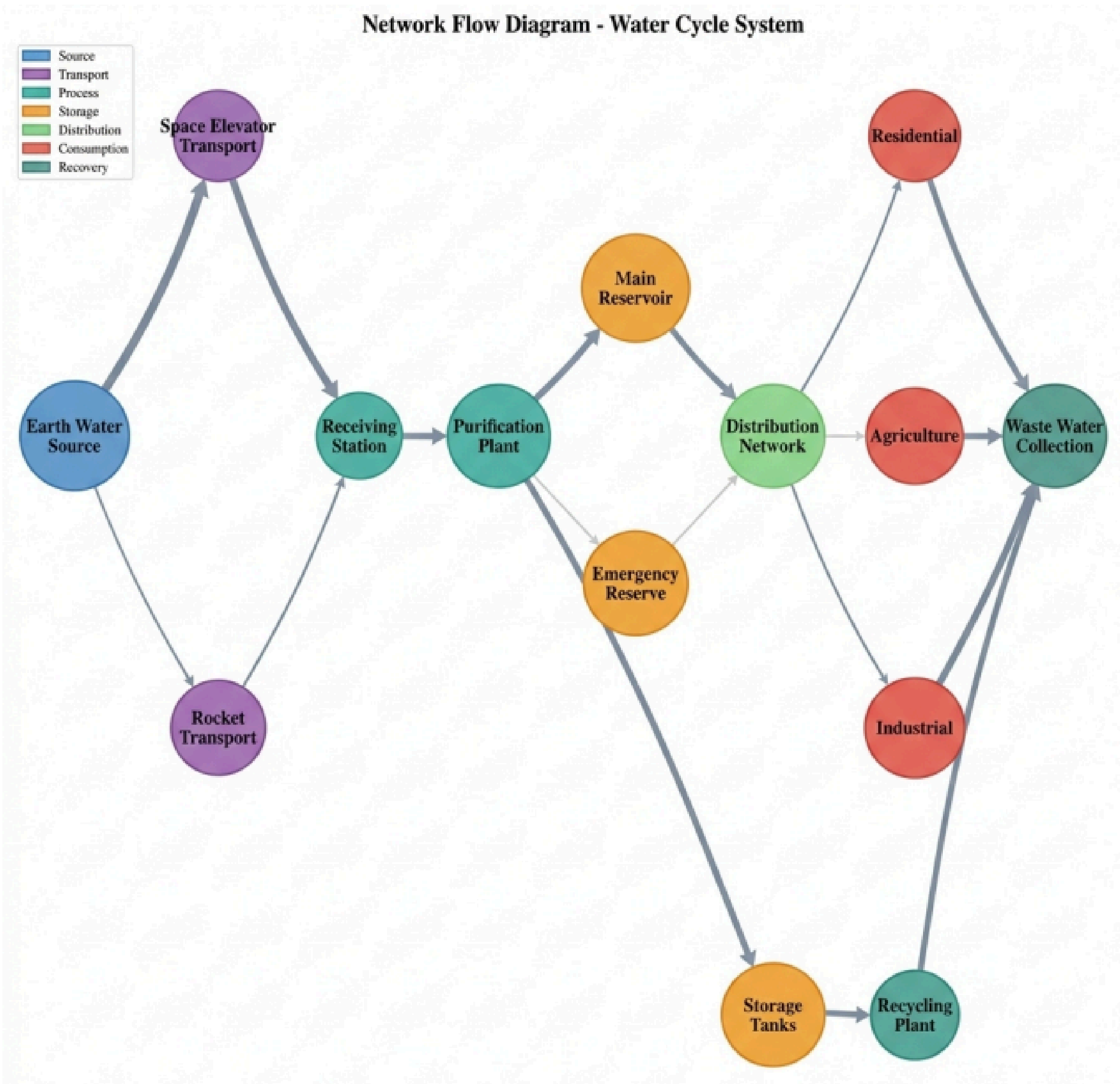

Figure 6. Water Supply and Recycling Flow Network

Water Supply and Recycling Flow Network (figure 6): The end-to-end water network (source–purification–storage–distribution–recycling) identifies critical nodes and bottlenecks, informing redundancy design and emergency reserve allocation.

Water demand model

Water demand is calculated as per-capita consumption multiplied by the population and days in a year. The factor 1000 converts liters to cubic meters and approximates tons of water:

$$W_g = \frac{Np365}{1000} \tag{12}$$

Note that η represents the net recycling efficiency; higher values may implicitly require additional energy or chemical mass overhead, which can be factored into the transport capacity requirements as secondary payloads. where N is the population, and p is per-capita daily water use. Net imported water, W_n , accounts for recycling efficiency η and losses δ :

$$W_n = W_g(1 - \eta + \delta) \tag{13}$$

This shows how recycling and loss rates affect overall demand, with optimization reducing imported water. The annual water logistics cost C_w is based on W_n and follows the same cost structure as construction logistics:

$$C_w = W_n c(x) \tag{14}$$

This directly ties water logistics to the decision variable x , which influences both water and construction cost-efficiency. Water transport cost comparison (elevator vs rocket vs hybrid) is shown in figure 7.

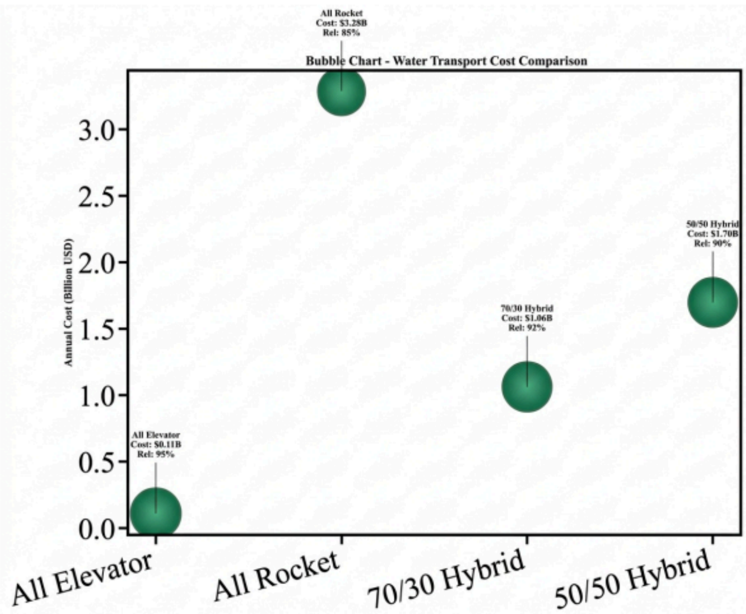

Figure 7. Water transport cost comparison (elevator vs rocket vs hybrid)

Water Transport Cost Comparison (Elevator vs Rocket vs Hybrid): The all-elevator option achieves the lowest annual cost with the highest reliability, the all-rocket option is most expensive and least reliable, and hybrids provide controlled trade-offs supporting "elevator baseline + rocket emergency" logistics.

Reserve sizing

To ensure water availability during disruptions, we define the daily gross demand $D = W_g/365$. If the colony requires τ days of autonomy, the reserve mass R is calculated as:

$$R = \tau \frac{W_n}{365} \tag{15}$$

This reserve sizing approach ensures that the colony can maintain a consistent water supply during unforeseen interruptions, such as equipment failure or operational delays.

Water results and operational policy

Table 3. One-year water logistics (representative)

Item	Value	Unit
Population N	100,000	person
Per-capita use p	50	L/(person day)
Gross demand W g	1,825,000	t/yr
Net import W n (η = 0 . 90 , δ = 0 . 02)	219,000	t/yr
Net import W n (η = 0 . 95 , δ = 0 . 02)	127,750	t/yr
30-day reserve R (η = 0 . 95)	10,500	t

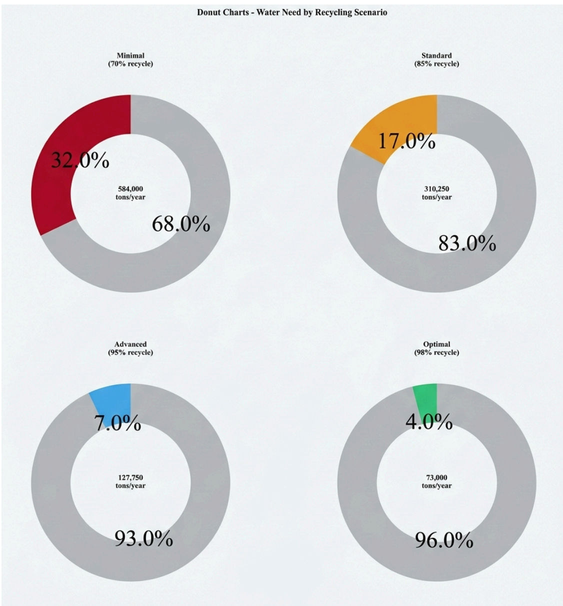

Figure 8. Water Import Reduction by Recycling Scenario

One-year water logistics are shown in table 3. Water Import Reduction by Recycling Scenario (figure 8): Higher recycling efficiency markedly reduces the net imported water requirement, confirming that improving n is the primary lever for lowering long-term water logistics and dependence on external supply.

Equation(13) highlights that improving recycling efficiency is the most effective way to reduce recurring mass imports, which is central to long-term sustainability. Even small gains in η can noticeably reduce W_n , thereby lowering both recurring transport cost and the net-demandbased reserve requirement.

In operational terms, this makes recycling performance a first-order KPI rather than a secondary efficiency detail. Maintaining high η requires stable power, routine monitoring, and timely maintenance, since degradation over long durations can accumulate into substantial additional imports. Thus, design choices that improve robustness and ease of repair can be justified directly through reduced logistics burden.

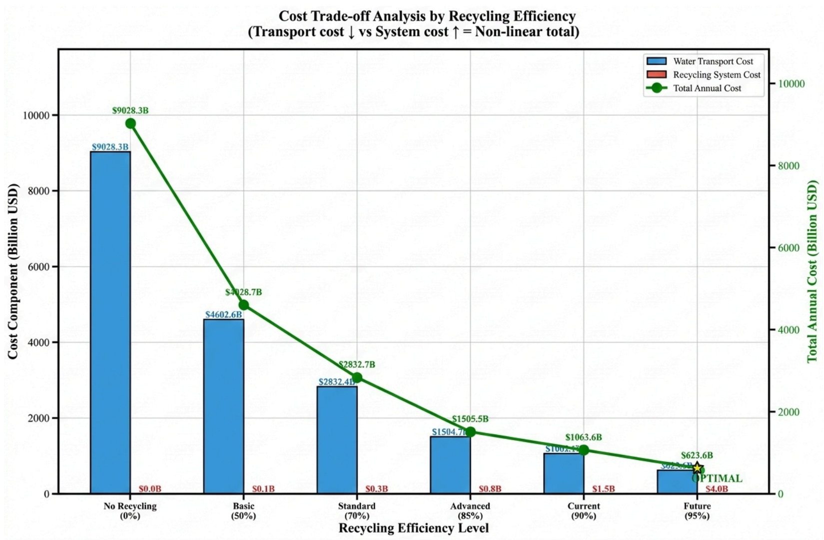

Figure 9. Annual Cost Trade-off vs. Recycling Efficiency

Annual Cost Trade-off vs. Recycling Efficiency (figure 9): As recycling technology improves, both annual water demand and the corresponding transport cost decline together, indicating recycling upgrades simultaneously improve operational feasibility and budget.

Therefore, the colony should prioritize recycling systems as critical infrastructure. Investing in redundancy, spare parts, and rapid repair capabilities will be key to maintaining water security, especially in the face of unexpected operational setbacks or equipment failures.

Practically, this means modular, fail-operational recycling units with critical spares (filters, pumps, valves) stocked on-site, and explicit repair-time targets as an operations KPI. A simple contingency rule that prioritizes essential uses during disruptions further protects safety while limiting imported mass growth, while non-essential demand can be curtailed temporarily to preserve reserves.

Water Use Priority Allocation (Radar): the radar profile highlights a clear priority hierarchy for scarce-water operations-hygiene and agriculture rank highest, sanitation follows as a secondary essential load, while cooking and drinking sit at mid-level and industrial use is comparatively lower. This pattern provides a practical rationing and dispatch rule under disruption: protect health-critical services first, sustain food production next, then allocate remaining capacity to lower-priority demands, with the emergency reserve used only to bridge short outages and stabilize recovery.

Environmental Impact Model

Emissions accounting

Total CO_2 emissions are modeled by emission factors, where e_e and e_r represent per-ton life-cycle emission intensities for elevator and rocket transport, respectively:

$$E = M[xe_e + (1-x)e_r] \tag{16}$$

This accounting links environmental impact directly to the allocation decision x , making it straightforward to evaluate mitigation strategies such as shifting bulk flow toward the elevator.

We also include a composite index for other impacts (e.g., non- CO_2 pollutants, local disturbance, and resource footprints) by normalizing each indicator to a common scale:

$$I_{env} = \sum_{k=1}^{K} w_k \frac{E_k}{E_{k,max}}, \sum_{k=1}^{K} w_k = 1 \tag{17}$$

A policy cap can be represented as:

$$E \leq E_{cap} \tag{18}$$

This framework allows for flexible policy design, enabling both cap-based regulation and cost-effective mitigation strategies.

Environmental results and mitigation

Table 4. Environmental comparison (illustrative)

Scheme	CO 2 (Mt)	Index I env	Mitigation leverage
Elevator only	50	0.10	Clean electricity reduces e e
Hybrid (70/30)	635	0.45	Reduce rocket fraction; carbon pricing
Rocket only	2000	0.90	Limited by propellant chemistry

Environmental comparison is shown in table 4. Mitigation Options: Cost vs. CO_2 Reduction: The cost–reduction scatter reveals a Paretolike trade-off, supporting prioritizing high-abatement, low-cost options such as clean power for elevator operations.

Environmental Impacts: Rocket vs. Space Elevator: Rockets dominate elevators across $CO_2/NOx/noise$ and other impacts, justifying a policy of "elevator for bulk, rockets for urgent/critical payloads". The key mitigation is structural: reduce rocket share for bulk transport. Additional mitigation is to decarbonize elevator power so that e_e becomes small. An explicit cap(18)would naturally exclude rocket-dominant strategies for megaton transport.

Optional Multi-Criteria Decision Layer

When decision makers must explicitly trade cost, schedule, reliability, and environment, a simple MCDA layer formalizes ranking. We provide governing equations only.

$$D_i^+ = \sqrt{\sum_k w_k (v_{ik} - v_k^+)^2}, D_i^- = \sqrt{\sum_k w_k (v_{ik} - v_k^-)^2} \tag{19}$$

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{20}$$

Parallel Coordinates: Multi-Metric Scenario Comparison (CO_2–Cost–Time–NOx–Sustainability): multi-criteria comparison: Multi-metric profiles show elevator/optimized plans outperform overall while hybrids balance risk and responsiveness, guiding strategy selection via integrated time–cost–environment KPIs.

Implementation Detail: Cargo Policy and Risk Register

Default bulk cargo (structures, containers/feedstock, routine water) goes by elevator for steady throughput and low marginal cost, while rockets are reserved for time-critical items (medical, critical spares) and payloads with special integration constraints; hybrid switching is triggered only by pre-defined thresholds (e.g., prolonged elevator degradation or backlog of critical cargo).

Key risks include tether dynamics and climber failures, mitigated by damping/telemetry, conservative operating envelopes, redundancy, and predictive maintenance; operational constraints (power interruption, port bottlenecks) are mitigated by storage/microgrid capability, drills, parallel handling, and KPI monitoring; external shocks (debris, station-keeping anomalies) rely on tracking/avoidance and controlled shutdown protocols; water risks (recycling shortfall, contamination) require redundant treatment, spares, and emergency-import triggers, while cyber risk is reduced by segmentation and offline fallback.

ERROR ANALYSIS AND SENSITIVITY ANALYSIS

Uncertainty mainly enters through unit costs ((c_e, c_r)), capacities ((Q_e, Q_r)), and availability A . In practice, these parameters are scenario-dependent: unit costs vary with energy prices, learning curves, and financing assumptions; effective capacities vary with scheduling efficiency, maintenance cycles, and port/harbour handling limits; and availability aggregates both random failures and planned downtime. Because the core equations are algebraic and monotone, the direction of influence is clear and the resulting sensitivities are straightforward to interpret for decision support. We therefore focus on identifying high-leverage parameters that most strongly change schedule, cost, and operational risk, rather than attempting to overfit uncertain numerical values. The Monte Carlo simulations (Figure 10) provide a stochastic robustness check beyond static sensitivity, capturing how cumulative uncertainties in cost and capacity affect the probability distribution of completion timelines. Monte carlo completion time distributions (elevator vs. rocket vs. hybrid) are shown in figure 10.

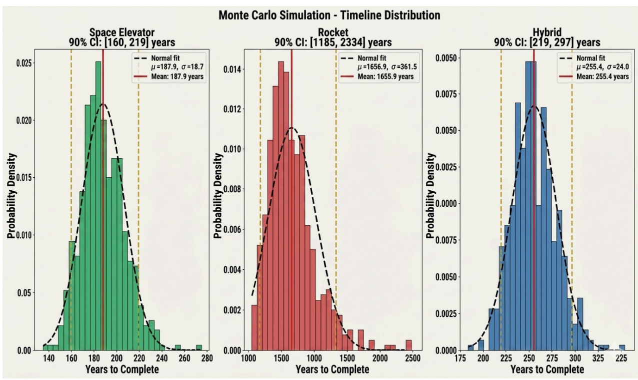

Figure 10. Monte carlo completion time distributions (elevator vs. rocket vs. hybrid)

Monte Carlo Completion Time Distributions (Elevator vs. Rocket vs. Hybrid): The Monte Carlo experiment perturbs the key inputs within plausible bounds and recomputes outcomes, illustrating how long-horizon plans amplify small differences in throughput and reliability.

For example, from Equation(2), $\partial T/\partial Q=-M/Q^2$, meaning the schedule penalty of losing capacity is convex: the same absolute capacity loss causes a much larger time increase when Q is already low. From Equation(9), the elasticity of non-perfect schedule with respect to availability is $\partial lnT_{non}/\partial lnA=-1$, showing that availability improvements translate nearly one-for-one into schedule protection in relative terms. This justifies treating availability as an engineering KPI with explicit targets, rather than an after-the-fact performance metric.

We define normalized sensitivity indices for a parameter θ affecting output Y :

$$S_{Y,\theta}=\frac{\theta}{Y}\frac{\partial Y}{\partial\theta} \tag{21}$$

These indices support comparing parameters with different units on a common scale, and they can be evaluated locally around a baseline or used qualitatively to rank levers. For the schedule, key indices are:

$$S_{T,Q}=-1,S_{T,A}=-1 \tag{22}$$

under the simplified model where $T\propto 1/Q$ and $T_{non}\propto 1/A$. The interpretation is that a 1% increase in capacity or availability yields approximately a 1% decrease in the corresponding completion time metric. For water imports, from Equation(13):

$$S_{W_n,\eta}=-\frac{\eta}{1-\eta+\delta} \tag{23}$$

This expression indicates that as η approaches 1, the marginal value of further recycling improvements can become very large, especially when losses δ are controlled.

Table 5. Qualitative sensitivity ranking

Parameter	Primary output	Sensitivity
Availability A	Schedule T non	High

Table 5. Qualitative sensitivity ranking

Parameter	Primary output	Sensitivity
Elevator capacity Q e	Schedule T	High
Recycling efficiency η	Imported water W n	High
Rocket unit cost c r	Total cost C	Medium
Loss fraction δ	Imported water W n	Low–Medium

Note: The ‘Medium’ sensitivity for rocket unit cost is specific to the ‘elevator-dominant’ optimal strategy. In scenarios where rocket reliance remains high, this parameter would naturally exhibit higher leverage on the total budget.

Qualitative sensitivity ranking is shown in table 5. Overall, the analysis suggests prioritizing investments that increase effective throughput and availability, and treating recycling performance as an operational cornerstone for reducing recurring logistics load. In particular, improvements that raise long-run capacity or reduce downtime have compounding benefits over multi-decade horizons, because schedule delay accumulates year after year in a throughput-limited program. For water logistics, sustained high recycling efficiency not only reduces annual import mass but also relaxes reserve requirements and lowers exposure to short-term transport disruptions.

Parameters with medium sensitivity are still important for budgeting and risk management, but they are less likely to overturn the main strategic ranking unless they shift by large factors. As a result, they are best handled through conservative ranges and scenario checks rather than being treated as primary design drivers.

CONCLUSIONS

By constructing an integrated model encompassing transport capacity scheduling, reliability auditing, resource assurance, and environmental impact assessment, this study systematically demonstrates the significant advantages of a coordinated system centered on space elevators as the primary logistics conduit for large-scale extraterrestrial settlement construction. This approach notably shortens construction timelines and reduces costs. The research not only quantifies the multiplier effect of system availability on long-term planning but also identifies water recycling efficiency as a key lever for reducing recurring operational burdens. However, the current model retains limitations, such as highly abstracted parameterization in describing orbital mechanics and cable dynamics, cost projections highly susceptible to external economic assumptions, and simplified dynamic nonlinear simulations during capacity ramp-up phases. Future research will focus on extending this framework to Mars or asteroid logistics scheduling, incorporating rolling planning mechanisms based on real-time sensor data, and exploring integration with digital twin technology to achieve higher-precision fault prediction and automated decision support.

Author Contributions

Conceptualization – Kaiwei Yang; methodology – Xinyuan Mei; formal analysis – Xinyuan Mei; investigation – Kaiwei Yang; resources – Xinyuan Mei,Kaiwei Yang; writing-original draft preparation – Xinyuan Mei; writing-review and editing – Xinyuan Mei,Kaiwei Yang; visualization – Xinyuan Mei; supervision – Xinyuan Mei. All authors have read and agreed to the published version of the manuscript. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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