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Optimization Study of Dual-Path Logistics Model for Interstellar Material Transport Integrating Space Elevators and Chemical Rockets

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Abstract: Addressing the extreme logistical challenge of transporting 100 million tons of materials across planets for the lunar colony construction mission launching in 2050, this paper establishes a dual-path logistics modeling framework integrating path deconstruction, parameter correction, and multi-objective optimization. The study categorizes transport routes into traditional rocket-based and space elevator-based modes. By introducing a geocorrection factor, it precisely quantifies the impact of different latitude launch sites on rocket payload capacity. Additionally, it derives the lunar soft-landing payload rate for space elevators using the Tsiolkovsky equation. At the optimization decision level, a nonlinear programming model balancing time and cost was established. Utilizing a heuristic algorithm based on a greedy strategy and grid search, the study compared the performance differences among pure rocket, pure elevator, and hybrid transport scenarios. To address real-world random uncertainties, disturbance terms such as equipment failures and maintenance costs were incorporated. The system's robustness was evaluated by constructing a set of near-optimal solutions. Simulation results confirm that the hybrid transport strategy optimally resolves the conflict between rockets' high initial costs and space elevators' limited early-stage capacity, achieving global benefit maximization under specific parameter constraints. This research provides a scientific quantitative basis and decision template for logistics planning in large-scale interstellar colonization.

Keywords: Space elevator; Greedy heuristic algorithm; Dual-path logistics model.

1. Introduction

With the 2050 lunar permanent settlement initiative approaching, transporting 100 million tons of cargo to the lunar surface 380,000 kilometers away presents an unprecedented engineering challenge in human history. This massive migration demands decision-makers strike an optimal balance between mature yet costly and environmentally burdensome chemical rockets and disruptive space elevator systems with low marginal costs. Previous space logistics research has predominantly focused on performance analysis of single transport modes, often overlooking the nonlinear impact of key physical constraints—such as launch site latitude and lunar landing deceleration load damage—on the macro-logistics chain. This section innovates by proposing a phased hybrid logistics framework. It achieves refined modeling of traditional rocket performance through geographic correction factors and carbon tax constraints, while balancing engineering schedule pressures and budget redundancy via asymmetric value assessment mechanisms. The overall research approach begins with modeling the mechanisms of rockets and space elevators separately, then employs time-cost optimization models for multi-scenario solution searches, and finally incorporates random disturbance terms for robustness audits. This aims to reveal the dynamic coordination patterns of heterogeneous transport resources within complex aerospace contexts[1-2].

Multi-Objective Spatio-Temporal Optimization for Interstellar Material Transfer When constructing the transport path model, the study first derived geographical correction factors via the Tsiolkovsky rocket equation. This quantified losses from Earth's rotational linear velocity at launch site latitudes and orbital inclination corrections, enabling dynamic payload adjustments at each station[3]. For cost estimation, the model accounts not only for unit transport prices that exponentially decrease with technological maturity but also incorporates carbon tax costs for CO_2 and particulate emissions. Regarding the space elevator submodel, the study establishes its low-cost transport physical boundaries by calculating the electrical energy work required to overcome Earth's gravitational potential energy and integrating fuel deceleration corrections needed for lunar soft landings. Building upon this foundation, this paper employs a greedy heuristic algorithm to search for optimal solutions within a 50- to 400-year time window. By calculating the Euclidean distance between data points and an ideal reference point, it demonstrates that hybrid transportation schemes significantly outperform any single-mode approach in terms of both project duration reduction and cost control[4].

Robustness and Near-Optimal Strategy Analysis of Transportation Systems Under Random Perturbations Considering the inevitable systemic risks in actual space missions, this study integrates perturbation factor analysis into the optimization framework. The study systematically cataloged risk parameters—including rocket failures, launch pad reconstruction, space elevator cable oscillations, and atomic oxygen corrosion—translating them into correction terms like fixed maintenance costs and payload degradation rates embedded within the objective function. Through secondary optimization of hybrid schemes, the research revealed robust system resilience under perturbations, with cost and time deviations maintained within reasonable bounds. To provide more flexible decision support, the study avoids pursuing a single global optimum. Instead, it constructs a "near-optimal solution set" based on absolute domain radius. This allows decision-makers to flexibly adjust launch frequencies within a time delay of approximately one year or a cost fluctuation of $50 billion, based on future actual policy directions. This ensures the survivability of logistics planning under non-ideal operating conditions[5-6].

2. The Dual-Path Logistics Model

We categorize the cargo transportation pathways into two types: Rocket Transport (R) and the Space Elevator (SE). In the R pathway, cargo is loaded into rocket capsules and launched directly from a launch site to the Moon. In the SE pathway, cargo is first elevated to Galactic Harbour and subsequently transported to the Moon via rockets or alternative vehicles[7]. Drawing upon relevant literature, we propose the following estimations and corrections for the engineering parameters of both pathways:

2.1. Rocket Sub-model

The rocket baseline payload $\mathrm{M_{unit}} = 150$ ton, and fuel mass $\mathrm{M_{fuel}} = 1400$ ton.

The transport cost per unit mass for rockets is $\mathrm{P(t)} = \mathrm{P_0} \cdot \exp(-0.02\mathrm{t})$, $\mathrm{P_0} = 1500\ \mathrm{USD/kg}$, which decays exponentially over time due to technological iterations. The fixed expenditure per rocket launch is $\mathrm{P_{launch}} = 10{,}000{,}000\ \mathrm{USD}$.

Due to the varying geographical locations of launch sites, we introduce a geographical correction factor $\phi_{\mathrm{geo,i}}$ to adjust the effective payload of a single rocket for each launch site (located at latitude L). In accordance with the Tsiolkovsky rocket equation, we provide the following calculation formula:

$$\phi_{\mathrm{geo,i}} = \exp\left(-\frac{\mathrm{V_{eq}}(1-\cos\mathrm{L}) + 2\mathrm{V_{orb}} \cdot \sin\left(\frac{\max\{0,|\mathrm{L}|-\mathrm{i_{gt}}\}}{2}\right)}{\mathrm{V_e}}\right) \tag{1}$$

$\mathrm{V_{eq}} = 465\ \mathrm{m/s}$: represents the Earth's linear rotation velocity; $\mathrm{V_{orb}} = 7800\ \mathrm{m/s}$ denotes the velocity in Low Earth Orbit (LEO); $\mathrm{i_{igt}} = 28.5°$ is the angle between the Moon's orbital plane and the equatorial plane; $\mathrm{V_c} = 4410\ \mathrm{m/s}$ represents the effective exhaust velocity of the rocket engine. The first term accounts for rotation velocity loss due to high latitude, while the second term accounts for orbital maneuver loss[8-10].

When calculating this correction factor, we opted to use an empirical formula (using French Guiana, near the equator, as the baseline) instead of complex physical formula calculations to accelerate model solution speed. In fact, this empirical formula aligns closely with the theoretical principles numerically.

$$\phi_{\mathrm{geo,i}} = \begin{cases} 0.001 \cdot (\mathrm{L} - 5.2) & \mathrm{L} \le 28.5 \\ 0.02 \cdot (\mathrm{L} - 28.5) + 0.0233 & \mathrm{L} > 28.5 \end{cases} \tag{2}$$

Additionally, we considered the costs and impacts incurred by a "carbon tax." This focuses primarily on carbon dioxide and soot produced by the combustion of rocket LOX/Kerosene engines; these pollutants are directly proportional to fuel mass. We adopt the concept of a carbon dioxide emission tax to measure the impact of these pollutants, where soot is converted to carbon dioxide equivalents at a specific ratio ($\beta = 1000$)). We finally present:

$$\mathrm{C_{Env}} = \mathrm{C_{carbon}} \cdot \textstyle\sum_{\mathrm{t}}^{\mathrm{T}} \sum_{\mathrm{i}=1}^{10} \mathrm{N_{i,t}} \cdot \mathrm{M_{fuel}} \cdot \left(\mathrm{E_{CO_2}} + \beta \cdot \mathrm{E_{Soot}}\right) \tag{3}$$

Where $\mathrm{C_{carbon}} = 150\ \mathrm{USD/t}$ is the carbon dioxide treatment cost, and $\mathrm{E_{CO_2}} = 3.15$, $\mathrm{E_{Soot}} = 0.025$ is the conversion ratio of pollutants (tons) per ton of fuel.

2.2. Space Elevator Sub-model

With a total of three units, the annual transport capacity for a single unit upper limit is defined as $\mathrm{m_{SE,annual}} = 179{,}000\ \mathrm{t/year}$. Furthermore, we must introduce a landing correction factor. Launching a vehicle from the top of the space elevator to descend onto the lunar surface requires carrying fuel for deceleration. This correction factor is defined as the ratio of effective payload to actual payload. Following the Tsiolkovsky rocket equation, we provide its calculation formula:

$$\eta_{\mathrm{land}} = \exp\left(-\frac{\Delta\mathrm{V_{landing}}}{\mathrm{I_{sp}} \cdot \mathrm{g}}\right) \approx 0.6 \tag{4}$$

$\Delta\mathrm{V_{landing}} = 2400\ \mathrm{m/s}$ is the lunar surface escape velocity the velocity requiring deceleration; $\mathrm{I_{sp}} = 450\ \mathrm{s}$ represents the specific impulse of the rocket engine; $\mathrm{g} = 9.8\ \mathrm{m/s^2}$ is the recommended value for gravitational acceleration.(Based on the information provided in the problem, the R pathway does not need to account for this term.)

For its cost, we believe it can be estimated based on electricity consumption, where power consumption correlates with the work done by the SE carrying cargo against Earth's gravity. We present the following formula:

$$\mathrm{m_{eff}} = \mathrm{m_{total}} \cdot \eta_{\mathrm{land}},\ \mathrm{COST} = \mathrm{c_{ops}} \cdot \mathrm{m_{eff}} \tag{5}$$

Where $\alpha = 0.3$ is the mechanical efficiency of the space elevator; $\mathrm{C_{elec}} = 0.2\ \mathrm{USD/kw \cdot h}$ is the estimated electricity cost at the SE; $\mathrm{R} = 6371\ \mathrm{km}$, $\mathrm{r} = 106371\ \mathrm{km}$ represent the Earth's radius and the distance from the Galactic Harbours to the Earth's center, respectively; and $\mathrm{P_{SE}} = 80\ \mathrm{USD/kg}$ is the transport price from the Galactic Harbours to the Moon, which is significantly lower compared to direct rocket transport. We provide the final calculation formula:

$$\mathrm{c_{ops}} = \frac{\frac{1}{\alpha} \cdot \mathrm{GM_{earth}} \cdot \left(\frac{1}{\mathrm{R}} - \frac{1}{\mathrm{r}}\right) \cdot \mathrm{C_{elec}} + \mathrm{P_{SE}} \cdot \eta_{\mathrm{land}}}{\eta_{\mathrm{land}}} \approx 100\ \mathrm{USD/kg} \tag{6}$$

2.3. Time-Cost Optimization Model

First, consider the core constraint of transport mass:

$$\mathrm{M_{goal}} \le \textstyle\sum_{\mathrm{t}}^{\mathrm{T}} \mathrm{m_{SE,t}} + \sum_{\mathrm{t}}^{\mathrm{T}} \sum_{\mathrm{i}=1}^{10} \mathrm{N_{i,t}} \cdot \mathrm{M_{unit}} \cdot \phi_{\mathrm{geo,i}} \tag{7}$$

The second constraint condition is established through a launch limit. For rocket launch sites, it is crucial to determine an annual launch upper limit to control the total rocket launch volume within a reasonable range.

$$0 \le N_{i,t} \le 300\ (\forall i, t) \tag{8}$$

The decision variables are: $N_{i,t}$, $m_{SE,t}$. We select the minimization of total cost as the local optimum for processing, while time is determined by the algorithm.

$$C = C_{Rocket} + C_{SE} + C_{Env} \tag{9}$$

Considering that both rockets and space elevators operate under ideal conditions, we can provide the cost calculations for both at this stage:

$$\begin{gathered} C_{Rocket} = \sum_t^T \sum_{i=1}^{10} N_{i,t} \cdot (P(t) \cdot M_{unit} + P_{launch}) \\ C_{SE} = \sum_t^T \frac{m_{SE,t}}{\eta_{land}} \cdot c_{SE} \end{gathered} \tag{10}$$

For SE, we note that its cost is far lower than the R pathway ($c_{SE} \ll P_0$). Therefore, we believe the space elevator should be the primary transport mode and utilized to its maximum capacity:

$$m_{SE,t} = \begin{cases} 0 & \text{non}-\text{operational} \\ 3 \cdot m_{SE,annual} \cdot \eta_{land} & \text{operational} \end{cases} \tag{11}$$

For rockets, since their unit transport price decreases exponentially, we are more inclined to utilize rockets in later years when prices are lower.

We now consider optimization calculations under three schemes:

Pure Rocket Scheme; 2. Pure Space Elevator Scheme; 3. Hybrid Scheme.

Scheme 1:

We adopt a reverse allocation method. First, we set a completion deadline, then use a greedy algorithm from back to front to prioritize task allocation to high-efficiency launch sites, aiming to maximize the benefit of the decreasing unit cost. We choose to set the completion timeline between 50 and 400 years, performing an allocation calculation every 10 years. If completion is not possible within the timeline, we skip to the next timeline.

Scheme 2:

For the space elevator, time and cost are calculated directly.

Scheme 3:

The space elevator cost is extremely low and should be utilized continuously. For the deficit, we adopt the following strategy: before the unit transport price decays to a certain proportion, we maintain a low launch frequency and only launch from primary high-efficiency launch sites; subsequently, when the unit transport price becomes acceptable, we launch at full capacity to recover the waiting time. For the latter allocation, we employ a greedy algorithm similar to Scheme 1, prioritizing the assignment of transport tasks to launch sites with high efficiency. To this end, we define two control parameters, p and q: p is used to limit the number of launches when the unit price is excessively high, while q is used to determine if the unit price is within an acceptable range.

$$N_{i,t} \begin{cases} = 0 & \exp(-0.02t) > q\text{and}\phi_{geo,i} \le 0.8 \\ \le 300 \cdot p & \exp(-0.02t) > q\text{and}\phi_{geo,i} > 0.8 \\ \le 300 & \exp(-0.02t) \le q \end{cases} \tag{12}$$

Subsequently, we perform a grid search on p and q. The search range and step size are:

$$\begin{cases} p \in [0,0.20]\Delta p = 0.01 \\ q \in [0.30,0.90]\Delta q = 0.03 \end{cases} \tag{13}$$

The final optimization calculation results are as figure 1:

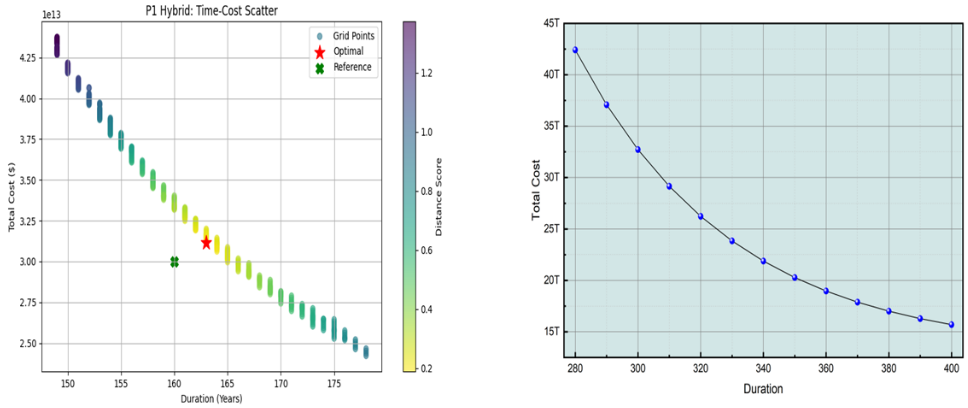

Figure 1 Time-cost scatter diagram of hybrid scheme for problem 1

Multi-objective Optimization Evaluation Criteria for Hybrid Scheme:

Through literature review, analysis, and analogical deduction, we believe the ideal financial budget for this project is 30T USD, with a completion time of 160 years (this is a fairly ideal and rigorous standard).

We evaluate by calculating the Euclidean distance between data points and reference points, selecting the data point with the lowest score as the optimal solution. Euclidean distance effectively reflects the comprehensive impact of multiple indicators and is sensitive to single deviations. Furthermore, its property as a strictly convex function ensures convergence to a unique global optimum. The specific rules in this model are as follows:

Reference point data and distance normalization conditions:

$$C_0 = 30\text{TUSD}, T_0 = 160\text{yearand} N_C = 10\text{TUSD}, N_T = 20\text{year} \tag{14}$$

For this project, we only consider penalties incurred by cost overruns and time delays. We adopt a one-sided penalty function to correct the distance.

$$\begin{cases} \Delta C = \frac{C-C_0}{N_C} \\ \Delta T = \frac{T-T_0}{N_T} \end{cases}, \Delta C' = \begin{cases} 0 & \Delta C \le 0 \\ \Delta C & \Delta C > 0 \end{cases}, \Delta T' = \begin{cases} 0 & \Delta T \le 0 \\ \Delta T & \Delta T > 0 \end{cases} \tag{15}$$

In summary, the final score is:

$$S = \sqrt{(\Delta C')^2 + (\Delta T')^2} \tag{16}$$

Optimal Solution Strategy: $p = 0.03$, $q = 0.51$, $C = 31.1\text{TUSD}$, $T = 163\text{year}$

Conclusion:

Both the pure rocket and pure SE schemes are undesirable; the duration is too long, rendering them meaningless. Adopting a hybrid scheme to strengthen transport capacity is a wise move. This scheme considers both time and monetary costs, yielding the best comprehensive effect. The final completion time and cost of the optimal solution strategy are quite close to the reference points. The values of the two parameters also corroborate our view: reasonably limiting the number of launches during the early high-price period and decisively launching at full capacity when prices are low is the optimal choice in terms of engineering and economics.

2.4. Time Cost Optimization Model with Disturbance Factors

In this model, we incorporate the impact of perturbations, such as malfunctions in rockets and space elevators, on the system.

To address this, we introduce correction terms into the original formulas to account for expenditures related to malfunctions and maintenance. Following a literature review, the relevant parameters are presented in the table 1.

Table 1 relevant parameters

Symbol	Meaning	Value
C_{fixed}	Fixed annual maintenance cost per launch site	50M USD
C_{rebuild}	Launch pad reconstruction cost	300M USD
capex $_{SE}$	Total construction cost of three space elevators	250B USD
c_{maint}	Maintenance cost as a percentage of total cost (SE)	2%
a	Mass loss rate of R pathway	3%
b	Mass loss rate of SE	10%

Specifically, we focus on the unavailability rate (b) of the space elevator. Since the various factors are usually independent, the system's availability (A) is the product of the availability of each component

$$A = (1 - b_{\text{maint}}) \times (1 - b_{\text{dynamic}}) \times (1 - b_{\text{risk}}) \tag{17}$$

Then the total loss rate b is:

$$b = 1 - A \approx b_{\text{maint}} + b_{\text{dynamic}} + b_{\text{risk}} \approx 0.1 \tag{18}$$

For Rocket:

$$C_{\text{Rocket}} = \sum_t^T \sum_{i=1}^{10} N_{i,t}(P(t)M_{\text{unit}} + P_{\text{launch}}) + \sum_t^T 10C_{\text{fixed}} + \sum_{i=1}^{10} \left\lfloor \frac{N_{i,\text{total}}}{100} \right\rfloor C_{\text{rebuild}} \tag{19}$$

The second and third terms serve as correction terms, representing the maintenance costs for the ten launch sites and the mandatory reconstruction costs for the launch pads incurred after every 100 launches, respectively.

For SE:

$$C_{SE} = \sum_t^T \frac{m_{SE,t}}{\eta_{\text{land}}} \cdot c_{SE} + \sum_t^T \text{capex}_{SE} \cdot c_{\text{maint}} \tag{20}$$

The second correction term represents maintenance costs quantified based on construction costs. Regarding the mass constraints, the corrected formulation is derived as follows:

$$M_{\text{goal}} \le \sum_t^T m_{SE,t}(1 - b) + \sum_t^T \sum_{i=1}^{10} N_{i,t} M_{\text{unit}} \phi_{\text{geo},i}(1 - a) \tag{21}$$

Only the Hybrid Scheme possesses practical utility. Consequently, we proceed directly to optimize this specific scheme, employing the methodology consistent with Scheme 2.

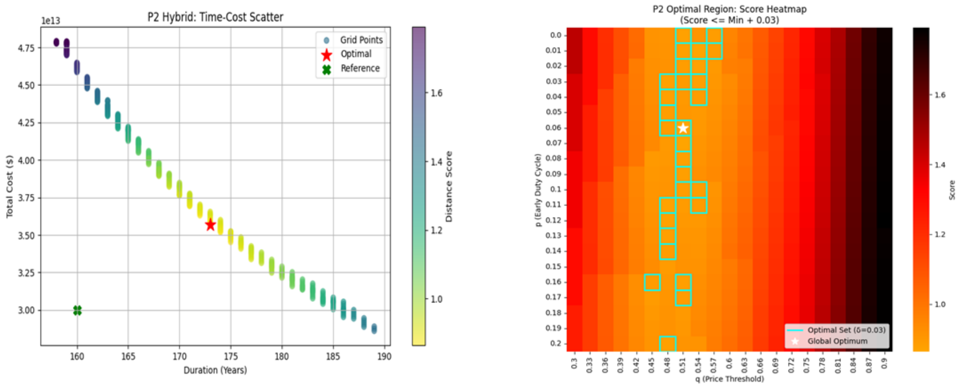

Figure 2 Time-cost scatter diagram and score heat map of hybrid scheme

Time-cost scatter diagram and score heat map of hybrid scheme are shown in figure 2. Optimal solution strategy: $p = 0.06$, $q = 0.51$, $C = 35.7\text{TUSD}$, $T = 173\text{year}$

To provide more robust and flexible decision support, we do not merely seek a unique Global Optimum, but rather construct a "Near-Optimal Solution Set".

We defined the Euclidean distance $S(p, q)$ of each scheme to the ideal reference point in the normalized objective space. An absolute neighborhood radius $\delta = 0.03$ is set to filter all solutions satisfying the following condition, thereby constituting the optimal solution set Ω:

$$\Omega = \{(p, q) | S(p, q) - S_{\min} \leq \delta\} \tag{22}$$

In this framework, $\delta = 0.03$ implies that we allow a scheme to deviate in the worse direction by no more than approximately 1 Year in duration, or 0.5T USD in cost. The modified logic allows for the inclusion of Aggressive Strategies or Conservative Strategies. As long as the degradation in the inferior dimension does not breach the δ threshold, these distinct strategies are retained as alternatives, providing a richer strategic menu for adapting to future choices. Specifically, in this case, the optimal range for the task is $\Omega \in [0,0.2] \times [0.45,0.57]$, which determines the boundaries of rational and acceptable strategies.

3. Conclusions

This paper systematically explores optimal material transfer strategies for lunar colony construction by developing a dual-radius logistics model with physical constraint modifications, confirming the superior efficacy of a phased hybrid transport architecture in addressing extreme payload demands. The research not only quantifies the contribution of geographic location to launch costs but also demonstrates the system's high stability under random perturbations through the construction of a near-optimal solution set. However, current research has limitations, such as assuming basic economic parameters remain constant over a 170-year cycle, ignoring random processes like inflation or market volatility, and employing linear simplifications in simulating environmental degradation. Future research should focus on incorporating stochastic differential equations to model financial market volatility and developing nonlinear ecological damage functions to capture threshold effects in ecosystems under extreme launch frequencies. This will further enhance the scientific rigor and predictive capability of the interstellar logistics decision-making framework.

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