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Multi-Objective Decision-Making and Robust Optimization for Large-Scale Earth-Moon Material Transfer Systems in Lunar Base Construction

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ABSTRACT

This paper addresses the bottleneck of transferring 100 million tons of materials for lunar base construction. We establish a closed-loop intelligent decision-making framework that integrates discrete optimization, robustness analysis, and machine learning forecasting. To tackle the coordination challenges of heterogeneous transport modes, a bi-objective mixed-integer programming model combined with a genetic algorithm is proposed, identifying a Pareto-optimal operating point that achieves comprehensive superiority over pure strategies with a completion time of 156.99 years and a cost of $23.62 trillion. Distinct from traditional deterministic studies, this research incorporates robust optimization to reveal structural risk asymmetries, demonstrating that elevator solutions are critically sensitive to schedules while rocket solutions are cost-sensitive, thereby proving the hybrid strategy's superior load-distribution efficacy under extreme scenarios. Furthermore, a data-driven supply scheduling method is developed by coupling ridge regression with high-quantile reliability analysis, which transforms stochastic human water consumption behaviors into reliable, engineering-grade replenishment timelines. Finally, by synthesizing Life Cycle Assessment with TOPSIS, the study quantifies environmental externalities and establishes dynamic decision thresholds, providing rigorous quantitative foundations for the strategic planning of sustainable large-scale deep-space logistics systems.

KEYWORDS
mixed-integer programming, robust decision-making, life cycle assessment

INTRODUCTION

As human deep space exploration transitions from short-term stays to permanent colonization, establishing a logistics system to support a 100,000-person lunar base has become a core bottleneck in space engineering[1]. The task of transferring 100 million tons of materials not only imposes extreme demands on the payload capacity of transport vehicles but also creates complex conflicts among construction timelines, economic costs, and environmental sustainability. Traditional space decision-making relies heavily on empirical rule-setting, struggling to deliver robust execution plans amid complex challenges like maintenance failures, launch losses, and dynamic demand fluctuations. While prior research has achieved breakthroughs in path planning for single transport modes, it generally lacks in-depth analysis of the "elevator-rocket" heterogeneous transport coordination mechanism[2,3]. Few studies integrate long-term construction cycles with subsequent resource resupply and ecological footprint assessments into a unified logical framework. The innovation of this section lies in proposing a closed-loop intelligent decision-making system[4-6]. By integrating discrete optimization, robust planning, and data-driven predictive modeling, it bridges the gap from physical performance simulation to high-dimensional policy trade-offs. The general research approach is as follows: First, establish a baseline for Earth-Moon logistics resource allocation under ideal conditions. Next, define worst-case scenarios using interval uncertainty sets to assess plan resilience. then deconstructs the long-term feedback of human survival demands on the logistics system using machine learning algorithms, followed by quantifying the negative feedback of extraterrestrial exploration on Earth's ecology through a standardized life cycle assessment framework[7,8]. Finally, a multi-criteria decision model compresses multidimensional metrics and performs final plan ranking, aiming to provide scientific decision support for the sustainable operation of lunar bases[9].

MODELS

Discrete Resource Allocation and Pareto Optimization for Earth-Moon Logistics Routes

Model Preparation

(1) Data Processing

This question needs to compare the completion time and total cost of transporting 100 million metric tons materials to the lunar base under three transportation scenarios. The key structure and scale are given in the stem: three equatorial ports (120°interval), the annual capacity of the elevator system is 179,000 metric tons/year, and a single load of 100-150 tons of the rocket, and it is assumed that the system is in perfect operation (no elevator swing, no launch failure) in this question[10-12]. This 100-million-ton supply target encompasses all the infrastructure materials, life-support components, and scientific research equipment required to sustain the long-term survival of 100,000 people—equivalent to approximately 1,000 tons of long-term resource reserves per person—and is designed to test the capacity of logistics systems under extreme conditions.

(2) Assumptions

In order to ensure that the model is computable and consistent with the title, we normalize the key engineering parameters under the nominal scenario, including the annual throughput capacity of the space elevator, the single payload of the rocket and the upper limit of the launch rhythm, and adopt “fixed construction cost and variable cost with transportation quality” as the unified cost structure, so as to ensure that the three types of Scenarios are fairly compared under the same caliber. The model assumes that all supplies are transported from Earth. Although in-situ resource utilization (ISRU) can effectively reduce the burden of Earth-based transportation, given the reliance on Earth-supplied materials during the initial construction phase and the uncertainty surrounding ISRU production capacity, this model prioritizes assessing the baseline capacity of the Earth-based supply transport system to ensure the robustness of the logistics chain. To ensure comparability across different scales, this model employs a static total cost assessment and does not currently account for inflation or learning curve effects over a century-long period; its purpose is to reflect the pure engineering cost investment required at the system’s initial scale.

(3) The Foundation of Model

In this study, the discrete configuration problem for lunar base transportation needs to be optimized simultaneously under the upper limit of capacity, construction period constraints and cost structure. In order to ensure the engineering feasibility of the solution, we use integer programming to describe the 0-1/integer decisions such as facility activation, launch number and capacity allocation, and their capacity constraints. At the same time, a genetic algorithm is introduced to perform global search in a high-dimensional combination space, and the time-cost Pareto frontier is output to support the Scenario trade-off. IP provides strict constraints and feasible domains, and GA provides multi-solution exploration and compromise solution selection, which can stably provide interpretable optimization results under complex constraints[13].

Model Establishment

To optimize the transportation allocation for lunar base construction, we formulate a bi-objective 0-1 mixed-integer programming model. The continuous variables x_e and x_r denote the annual payload delivered by the space elevator and by rockets, respectively, while the discrete variables characterize the launch organization: l_j is the number of launches assigned to launch site j and y_j indicates whether site j is activated. Feasibility is ensured by capacity and launch-resource constraints, and the rocket unit cost is modeled as a function of the launch-organization state S (determined by y_j and l_j), which links payload allocation, launch planning, and cost within a single framework[14-16].

$$\min T = \frac{M}{x_e + x_r}, \min Cost = F + M\left(\frac{x_e}{x_e + x_r}c_e + \frac{x_r}{x_e + x_r}c_r(s)\right) \tag{1}$$

Here, M is the total payload demand, C_e and C_r are the annual capacity limits of the elevator and rockets, $L_{\max}$ and $L_j^{\max}$ are the global and site-level launch-count limits, P_j is the effective payload per launch at site j, F is the fixed system cost, c_e is the elevator unit cost, and $c_r(s)$ is the rocket unit cost induced by the chosen launch organization[17,18].

Because the model is a constrained bi-objective mixed-integer program, we use a GA–IP hybrid to search for non-dominated solutions and construct the Pareto front, yielding a Pareto set that quantifies the time–cost trade-off among elevator-only, rocket-only, and hybrid strategies.

Baseline Logistics Planning under Ideal Operations

Under ideal operating conditions, the optimization results clearly reveal the structural distribution between different modes of transport. Space elevators always operate at their maximum annual capacity, while rocket launches are only enabled when elevator capacity cannot meet demand. This allocation model stems from the elevator's lower unit transportation cost and its strict annual capacity limits, rather than relying on any established priority rules.

Figure 1 quantitatively compares the construction performance of the three candidate strategies, summarizing the completion time and total cost. Scenario B, which relied entirely on rocket launches, performed poorly on both indicators, took about 400 years to complete, and cost more than $40 trillion in total. In contrast, Scenario A (using elevators only) achieved the lowest total cost of all strategies, but its limited capacity resulted in an extension of completion time to over 186 years. These contrasting results show that cost-effectiveness alone is not enough when system capacity is severely limited[19,20].

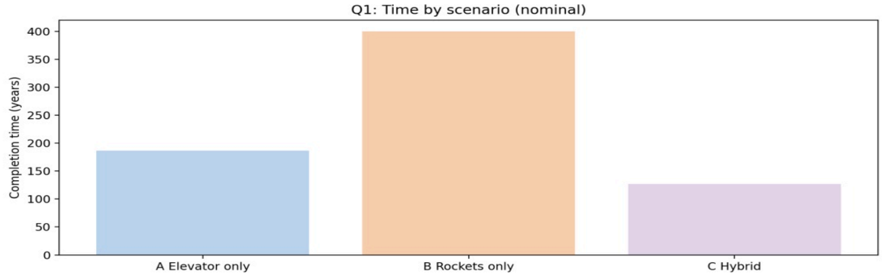

Figure 1. Time by scenario (nominal)

Scenario C combines the full use of space elevators with rocket launches, which can significantly reduce the completion time to 127.1 years, as shown in Figure 1. However, the total cost of Scenario C is higher compared to Scenario A, indicating an inherent trade-off between time and cost. Thus, Figure 1 reveals that under normal conditions, neither a pure space elevator nor a pure rocket can provide a completely satisfactory solution.

In order to explore whether there is a better compromise structure, we further study the hybrid strategy through the two-objective optimization framework, and obtain the Pareto trade-off curve as shown in Figure 2.

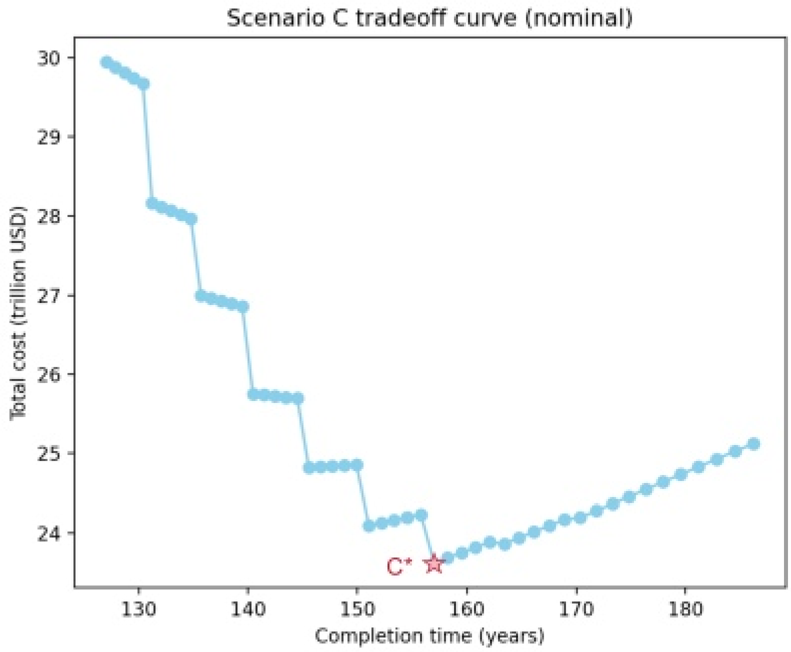

Figure 2. Scenario C trade-off curve (nominal)

Figure 2 presents the time-cost trade-off curve for Scenario C, i.e., the Pareto frontier obtained by combining integer programming with a systematic search over rocket deployment patterns. The curve shows a clear diminishing-returns effect: beyond a certain level of rocket utilization, further reductions in completion time become marginal, while total cost rises sharply. In this context, C^* lies near the "knee" of the frontier and thus serves as a practical decision anchor, capturing most of the achievable time savings without entering the steep cost-escalation region.

Moreover, Figure 2 highlights C^* as a Pareto-optimal operating point with the minimum total cost on the frontier. At C^* , the project can be completed in 156.99 years at a total cost of $23.62 trillion. Operationally, this solution corresponds to running the space elevator at full annual capacity while deploying rockets only from the lowest-cost launch sites, each operated at its maximum feasible launch frequency. Relative to Scenario A, C^* achieves a shorter completion time at a lower total cost, thereby strictly dominating the elevator-only strategy under ideal conditions.

Table 1. Comparison of completion time and total cost for different scenarios

Scenario Name	Completion Time	Total Cost
Scenario A (Elevator only, 3 harbors fully utilized)	186.2 years	25.12 trillion USD
Scenario B (Rockets only, 10 sites+200 launches/year)	400.0 years	40.17 trillion USD
Scenario C (Hybrid full, Elevator full + Rockets full)	127.1 years	29.94 trillion USD
Scenario C*	156.99 years	23.62 trillion USD

From Table 1, we can directly compare the completion time and total cost of the four alternatives, which yields a clear decision logic. Scenario B is dominated in both time and cost and can be excluded. Scenario A achieves the lowest cost, but its strict capacity limit leads to an excessively long construction period and thus poor time efficiency. Scenario C (full hybrid) substantially shortens the schedule, yet its cost increases noticeably relative to Scenario A, indicating that simply intensifying rocket usage comes with a considerable economic penalty. In contrast, Scenario C^* preserves a clear scheduling advantage while keeping the total cost at a more reasonable level, making it a more balanced choice under the time-cost trade-off. Moreover, the ranking implied by the discrete optimization results is consistent with the overall pattern revealed by the Pareto trade-off structure, confirming that the proposed model not only generates feasible engineering solutions but also provides clear and interpretable support for decision-making.

Stability and Robustness Audit of Transport Capacity Under System Uncertainty

Model Preparation

(1) Data Processing

The second question requires discussing how solutions evolve when system uncertainties exist. Collected uncertainty data-such as elevator capacity reduction ranges, rocket failure rate intervals, payload fluctuations, delays, and cost overrun ranges-are mapped as follows: Capacity reduction factor (affecting schedule T); Unit cost increase + payload reduction (affecting total cost).

(2) Assumptions

In robust assessment, we characterize uncertain parameters like capacity degradation, downtime, and cost overruns as interval sets. When monotonicity holds, we use the worst-case endpoint to represent the worst-case scenario, thereby obtaining conservative upper bounds for time and cost. Extreme catastrophic events like "complete system failure" are excluded from the deterministic robustness set and treated separately as scenario/probabilistic risks. This prevents pushing the problem into infeasibility while maintaining the operability of engineering decisions. Specifically, the uncertainty set U is constructed based on the following intervals: the elevator capacity loss coefficient $\alpha_e \in [0.7,1.0]$, and the rocket unit cost increase factor $\delta \in [0,0.5]$. These boundary values were set with reference to conservative forecast ranges for extreme weather conditions and technical failures.

(3) The Foundation of Model

The essence of the second question is: even without reliable probability distribution information, we must still provide feasible guarantees and upper bounds for the schedule and cost of the three Scenarios under uncertain perturbations. Robust optimization is precisely suited for early-stage engineering scenarios where only bounds/upper limits are known. By solving for the worst-case scenario within the uncertainty set U, it directly outputs upper bounds for time and cost that remain feasible under worst-case conditions. This enables consistent, verifiable calculation and interpretation of the increase between nominal and robust results (risk premium). In contrast, Monte Carlo simulation leans more toward evaluation than solution, while stochastic programming heavily relies on distribution assumptions. Neither approach offers the robustness and defensibility of robust optimization under the information constraints of this problem.

Model Establishment

This study employs robust optimization to address uncertainties in transportation systems. First, to account for capacity degradation, the effective capacities of the space elevator and rocket are defined as $C_e^{rob} = \alpha_e C_e$ and $C_r^{rob} = \alpha_r C_r$, respectively, where α_e and α_r represent potential capacity loss coefficients, and α_e , $\alpha_r \in (0,1)$.

Second, the unit cost of the rocket is adjusted based on capacity loss, expressed as $c_r^{rob} = c_r(1+\delta)$, where δ denotes the cost increase factor due to capacity degradation.

Regarding the objective function, we minimize both the project duration and total cost. The project duration $T^{rob} = \frac{M}{x_e^{rob}+x_r^{rob}}$ is determined by the total transport demand and effective transport capacity. The cost formula is:

$$Cost^{rob} = F + M\left(\frac{x_e^{rob}}{x_e^{rob} + x_r^{rob}} c_e^{rob} + \frac{x_r^{rob}}{x_e^{rob} + x_r^{rob}} c_r^{rob}(s)\right) \quad (2)$$

where F is the fixed cost, c_e^{rob} and $c_r^{rob}(s)$ are the adjusted unit costs, and l represents the number of launches.

This robust optimization model incorporates a risk premium for uncertainty, ensuring stable plan execution even under worst-case scenarios. The model's robustness not only enhances plan reliability but also provides decision-makers with stable optimization outcomes.

Robust Construction Logistics under System Uncertainty

When system-level uncertainty is incorporated, the feasibility and performance of all transportation strategies undergo fundamental changes. Compared to ideal operating conditions, the reduction in elevator throughput and rocket operation interruptions collectively reshape achievable construction schedules and associated cost structures.

The impact of system uncertainty on construction performance is first reflected in the overall schedule deterioration shown in Table 2. Across all scenarios, robustness requirements lead to varying degrees of schedule extension. The scenario employing only the elevator strategy experiences the most severe delays, with the construction period extending from 186.2 years under expected conditions to 263.1 years in the worst-case scenario. This sensitivity stems from the elevator's reliance on continuous operation, making it particularly vulnerable to performance degradation and maintenance downtime. In contrast, the pure rocket strategy inherently operates at a slower pace even under expected conditions, and robustness considerations further extend its schedule to 476.0 years, significantly diminishing its competitiveness.

Table 2. Cost and duration comparison for robust scenarios

Scenario Name	Completion Time(nominal)	Completion Time(robust)	Total Cost(nominal)	Total Cost(robust)
Elevator only	186.2 years	263.1 years	25.12 trillion USD	25.12 trillion USD
Rockets only	400.0 years	476.0 years	40.17 trillion USD	54.27 trillion USD
Hybrid full	127.1 years	169.5 years	29.94 trillion USD	35.55 trillion USD

Table 2 also summarizes costs under robustness assumptions, revealing distinct risk profiles across strategies. The pure elevator approach exhibits minimal cost volatility due to fixed unit prices, but its schedule reliability declines significantly. The pure rocket approach shows the opposite trend: its schedule extension is relatively moderate, but total costs surge to $54.27 trillion due to launch failures and redundancy requirements. The hybrid approach occupies the middle ground, achieving 169.5 years and total costs of $35.55 trillion. This strategy retains most of its time advantage.

Figure 3 further quantifies these starkly contrasting impacts, illustrating the relative changes in schedule and total cost driven by uncertainty. The figure highlights a pronounced structural asymmetry: the primary risk for elevator-dominant approaches lies in schedule sensitivity-robust schedules increase by approximately 41% relative to nominal schedules while costs remain nearly unchanged. Conversely, the main risk for rocketdominant approaches manifests in cost sensitivity-robust costs rise by about 35% relative to nominal costs, accompanied by a 19% schedule increase. The hybrid strategy disperses uncertainty impacts across both dimensions: a 33% increase in schedule and a 19% increase in cost. This approach avoids both steep cost escalation and excessive delays. This balanced response to uncertainty explains why the hybrid remains viable even under robust assumptions.

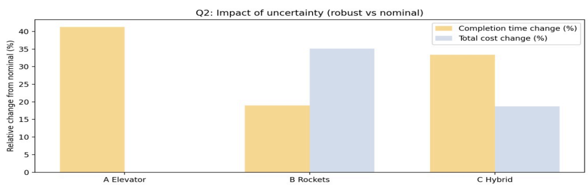

Figure 3. Impact of uncertainty (nominal vs robust)

We conducted a time–cost scan under worst-case assumptions to obtain the robust Pareto frontier, from which the corresponding key operating point C^* can likewise be identified. This conclusion aligns closely with the nominal Pareto-optimal solution, further demonstrating that the proposed modeling framework not only produces feasible robust solutions but also provides stable and interpretable decision logic across different uncertainty conditions.

Machine Learning-Based Water Demand Forecasting and Supply Scheduling for Lunar Bases

Model Preparation

(1) Data Processing

This question uses the Water_Intake_Dataset collected from the open-source website Kaggle to train a regression model predicting individual daily water intake. Features include age, gender, weight and height, temperature and humidity, activity level, exercise duration, and health status. During preprocessing, categorical variables like Activity_Level and Health_Condition were one-hot encoded, while numerical features retained their original scales for interpretability. The dataset was split into training (80%) and testing (20%)

sets, with 5-fold cross-validation employed to measure generalization error using RMSE. The final output provides stable predictions suitable for annual demand estimation.

(2) Assumptions

When extrapolating the model-predicted "individual daily water consumption" to the base scale, we used the given population $N = 100,000$ and selected a set of representative living pod conditions and typical individual characteristics to generate input samples. Simultaneously, mass conversion was performed at a rate of 1 L≈1 kg. Since this question focuses on the timeline and incremental costs of "additional water replenishment," fixed construction costs are treated as given investments, with only the variable costs of water transportation included. It should be noted that, although the model uses Earth-based drinking water datasets, the low gravity and radiation present in the actual lunar environment may alter physiological metabolism. This study treats this as a baseline prediction bias and mitigates potential fluctuations in demand caused by environmental differences by introducing P90 and P95 safety factors.

(3) The Foundation of Model

The task explicitly requires predicting water consumption, necessitating the use of regression-based machine learning to learn the mapping relationship between hydration levels and multidimensional physiological, environmental, and behavioral variables. This approach avoids the systematic bias introduced by constant per capita averages and ensures reproducible results. By incorporating the ML-generated annual water demand W_{year} as additional logistics load into the capacity and unit cost models of three transportation Scenarios, the required replenishment time and cost can be directly calculated. This generates a timeline starting from 2050, thereby closing the loop between "data-driven forecasting" and "engineering decision accounting" within a single chain.

Model Establishment

To establish a prediction model for annual water consumption, we compared four regression models: LinearRegression, Ridge, RandomForest, and GradientBoosting. We calculated their RMSE/MAE using 5-fold cross-validation. After evaluation, the Ridge model was selected as it yielded the lowest RMSE on the test set. The model's objective is to predict annual water consumption $\hat{y} = f(x)$ using input feature x , and to select the optimal regression model based on performance.

Annual water consumptions W_{year} predicted using the following formula:

$$W_{year} = 365N\hat{w} \tag{3}$$

where $N = 100,000$ represents the total population of the lunar base. Due to inherent uncertainty in water demand data, safety margin factors P90 and P95 were incorporated into the model to ensure coverage of extreme demand scenarios.

To evaluate the time and cost of different transportation Scenarios, we define three scenarios: elevator-only, rocket-only, and a hybrid elevator-rocket approach. The unit variable cost c_s for each scenario is set based on transportation capacity $Caps$. Depending on the annual transportation capacity of the selected Scenario, the time and cost required for water replenishment are:

$$T_s = \frac{W_{year}}{Caps}, Cost_s = W_{year}c_s \tag{4}$$

Transport capacity and costs for elevators and rockets are configured according to different Scenarios. In the defined Scenario, elevators operate at full capacity across three ports, while rockets utilize ten launch sites conducting 200 launches annually, each transporting 125 tons. The elevator-rocket combination achieves optimal results through optimized capacity allocation.

Additionally, we assume construction material transport (10^8 tons) commences in 2050. The projected completion time of the construction period can be calculated using the following formula:

$$Year_{build} = 2050 + \frac{M_{build}}{Caps_{build}} \tag{5}$$

Where M_{build} represents the volume of construction materials, and $Caps_{build}$ denotes the transport capacity during the construction period.

Operational Water Demand and Guaranteed One-Year Resupply

To ensure the long-term habitability of lunar bases, annual water resupply during the operational phase constitutes a periodic and critical logistical task. The analysis first evaluated the predictive performance of different demand estimation models. As shown in Figure 4, Ridge regression demonstrated one of the lowest prediction errors on the test set ($RMSE = 4.054 \quad L/day$, $MAE = 3.190$ L/day) and exhibited more stable generalization capabilities. However, the corresponding coefficient of determination remains low, indicating substantial individual variation in water consumption likely influenced by behavioral differences, environmental conditions, and unobserved factors.

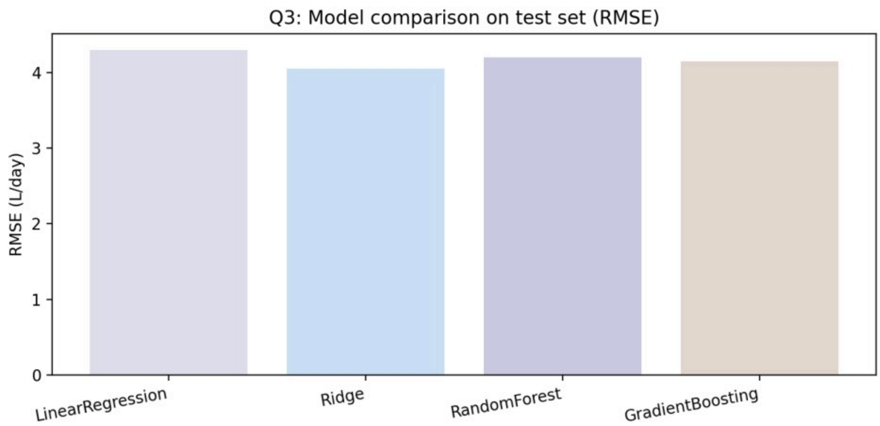

Figure 4. Model comparison on test set (RMSE)

The empirical distribution of daily water consumption shown in Figure 5 further illustrates this inherent variability, exhibiting pronounced right skewness and long-tailed characteristics. While the predicted average daily per capita water consumption of 4.818 L/day/person serves as a useful point estimate for baseline planning, relying solely on average demand exposes the system to a non-negligible risk of life-sustaining resource shortages. To mitigate this risk, higher demand quantiles (P90 and P95) are introduced as conservative planning benchmarks, shifting the modeling objective from average efficiency to reliability assurance.

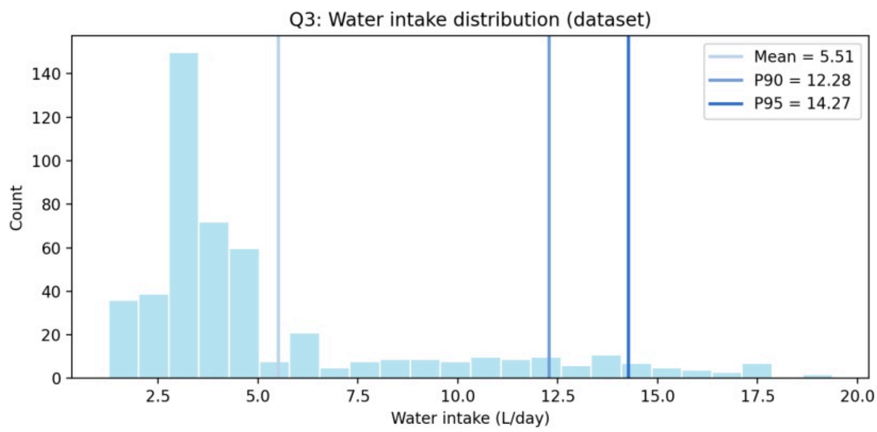

Figure 5. Water intake distribution (dataset)

Figure 6 quantifies the operational impact of this modeling choice, illustrating how the time required to deliver one year's water supply varies with increasing demand percentile. It reveals highly nonlinear sensitivity: a moderate increase in demand leads to disproportionately extended delivery times, particularly under capacity-constrained strategies. This outcome demonstrates that selecting demand percentiles is not merely a statistical optimization but a decision with direct engineering implications for scheduling feasibility.

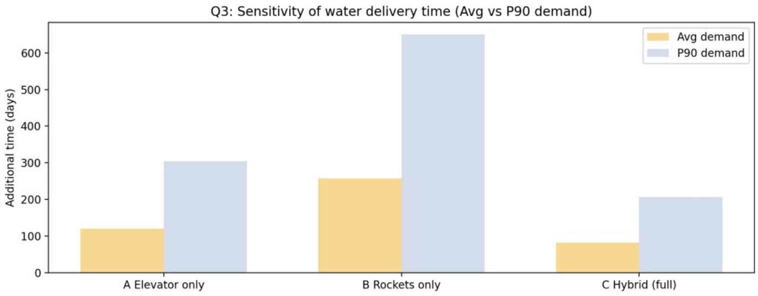

Figure 6. Sensitivity of water delivery time to demand level (Avg vs P90 demand)

Given this sensitivity, comparing different transportation strategies at representative demand levels is critical for operational decisions. Using machine learning-predicted average demand as a baseline, Figure 7 illustrates the additional time required for each strategy to complete a full year of water supply. The hybrid strategy significantly outperforms alternatives, completing the task in just 81.56 days due to its higher effective throughput. In contrast, the elevator-only strategy incurs longer transport times despite lower unit costs, while the rocket-only strategy suffers from both extended transport times and increased costs. Combined with analyses from Figures 5 and 6, these results demonstrate that the hybrid approach achieves the optimal balance between demand uncertainty and transportation efficiency.

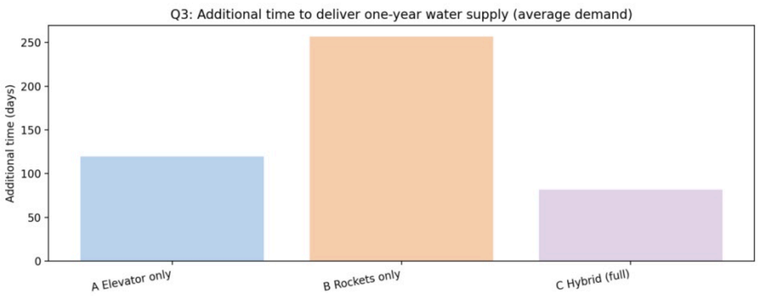

Figure 7. Extra delivery time for one-year water supply (average demand)

Crucially, these resupply outcomes are fully consistent with the robust logistics framework. All delivery times were calculated using the same worst-case effective transport capacity, ensuring the 81.56-day completion time represents a feasible subinterval within the robust operational range rather than an optimistic estimate. Figure 8 visually illustrates this consistency by embedding the one-year water supply cycle within the overall project timeline starting in 2050. The resulting schedule demonstrates that annual water supply requirements can be reliably met during the post-construction operational phase without violating robustness constraints.

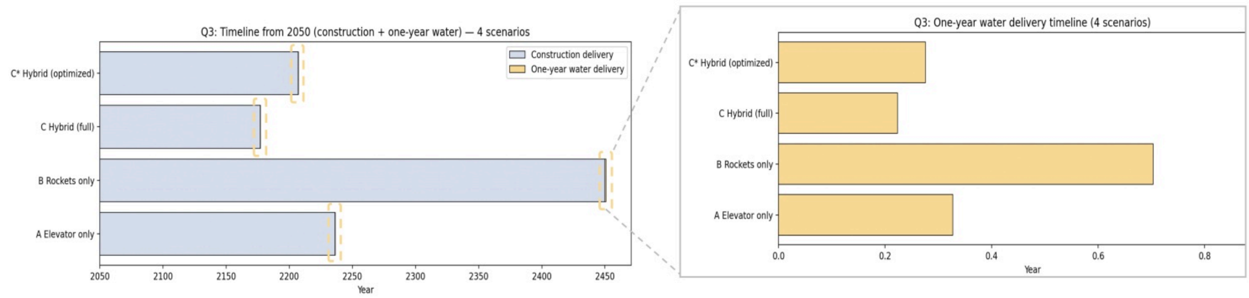

Figure 8. Timeline from 2050 (build materials + one-year water)

Figures 4 through 8 collectively form a closed-loop decision framework linking stochastic demand estimation, conservative planning based on quantile selection, and deterministic transportation capacity constraints. By integrating machine learning-based demand forecasting with a robust multimodal logistics model, the proposed method translates uncertain human consumption behavior into actionable, engineering-grade water supply plans. This integration not only fulfills the problem requirement of constructing a clear operational timeline but also provides a reliable basis for long-term life support planning under uncertainty.

Life Cycle Assessment of Space Transportation Systems' Environmental Impacts on Earth

Model Preparation

(1) Data Processing

Collect and organize four sets of environmental data: obtain unit payload carbon emissions, water consumption per kilogram of payload, energy consumption, land use, and noise levels. Compile these into unit impact vectors for each system (elevator, rocket): $e = (e_{CO_2}, e_{water}, e_{energy}, e_{soil})$.

(2) Assumptions

To ensure comparability among the three scenarios under the same metrics, we assume that environmental indicators exhibit near-linear amplification with payload capacity, meaning total impact can be characterized as “unit impact intensity and total transported mass.” Emissions, water consumption, and energy consumption for the hybrid scenario are aggregated by weighting according to mass share. Soil or ecological disturbance is constructed as a composite index of “land use and noise” and aggregated based on “elevator contribution and rocket contribution”. The evaluation boundary is restricted to Earth-based environmental impacts to align with the question's requirements.

(3) The Foundation of Model

The fourth question requires a quantitative comparison of environmental impacts on Earth, where environmental costs inherently involve multidimensional externalities such as emissions, water consumption, energy use, and ecological disturbance. A single metric cannot support meaningful comparisons between solutions. LCA (Life Cycle Assessment) provides a unified metric for multi-indicator impact intensity, enabling standardized and verifiable side-by-side comparisons of environmental burdens across different transportation systems. AHP (Analytic Hierarchy Process) transforms multi-indicator trade-offs into a weighting system with testable consistency, compressing LCA's vector results into a rankable comprehensive environmental score. This directly provides actionable inputs for subsequent integrated decision-making.

Model Establishment

In this study, LCA indicators are defined as four key environmental impact factors: CO_2 emission intensity, water use intensity, energy intensity, and soil and ecological disturbance index. CO_2 emission intensity reflects greenhouse gas emissions from different transportation modes, water use intensity accounts for water resource consumption, energy intensity involves energy consumption during transportation, while the soil and ecological disturbance index measures the ecological impact on the environment during transportation. Based on these indicators, we applied AHP to assign weights to each environmental criterion and conducted consistency tests to validate the model. In this study, the calculated consistency ratio (CR) yielded a result of $CR = 0.022$, meeting the consistency requirement ($CR < 0.1$).

Subsequently, we applied a standardization method, performing min-max normalization on each environmental indicator to ensure all metrics were compared on the same scale, thereby avoiding evaluation biases caused by differing scales. Based on the normalized data, we calculated the comprehensive environmental score for each Scenario. The final environmental evaluation result can be expressed by the following formula:

$$EnvScore = \sum_{k} w_k e_k \tag{6}$$

where w_k denotes the weight of the environmental indicator, e_k represents each Scenario's performance on indicator k, and the resulting environmental composite score reflects the environmental impact of each Scenario. AHP weights for environmental criteria is shown in figure 9.

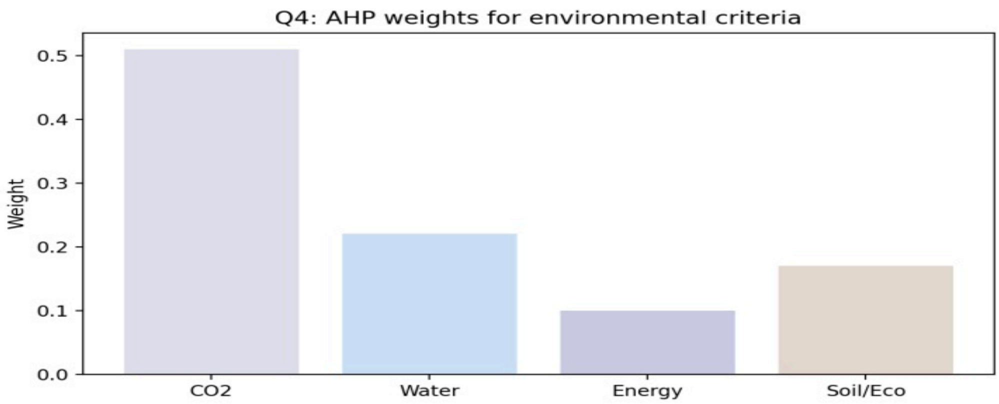

Figure 9. AHP weights for environmental criteria

Environmental Impact Assessment and Low-Impact Transport Decisions

Beyond cost and schedule considerations, the construction and operation of large lunar bases will inevitably impose externalities on Earth's environment. To quantify and compare these impacts across different transportation strategies, this paper combines LCA framework with AHP, synthesizing multiple environmental indicators into a single, decision-oriented impact index.

Figure 10 displays the final composite scores, where lower values indicate reduced environmental impact. According to this metric, the strategy relying solely on the elevator achieves an environmental impact score of 0.000, demonstrating optimal environmental benefits. It is important to emphasize that a score of 0.000 simply indicates that, among the current set of candidate proposals, the elevator proposal has the lowest relative environmental impact (a relative measure), rather than being completely pollution-free in a physical sense. This outcome reflects the elevator's consistently low unit emissions, minimal water consumption, and lower energy requirements per unit transported mass. Conversely, the strategy using rockets alone receives the highest normalized environmental impact score of 1.000, corresponding to the greatest environmental burden. This outcome primarily stems from the inherently high energy consumption of rocket launches, which generate significantly higher emissions and resource consumption per ton of transported mass compared to the elevator.

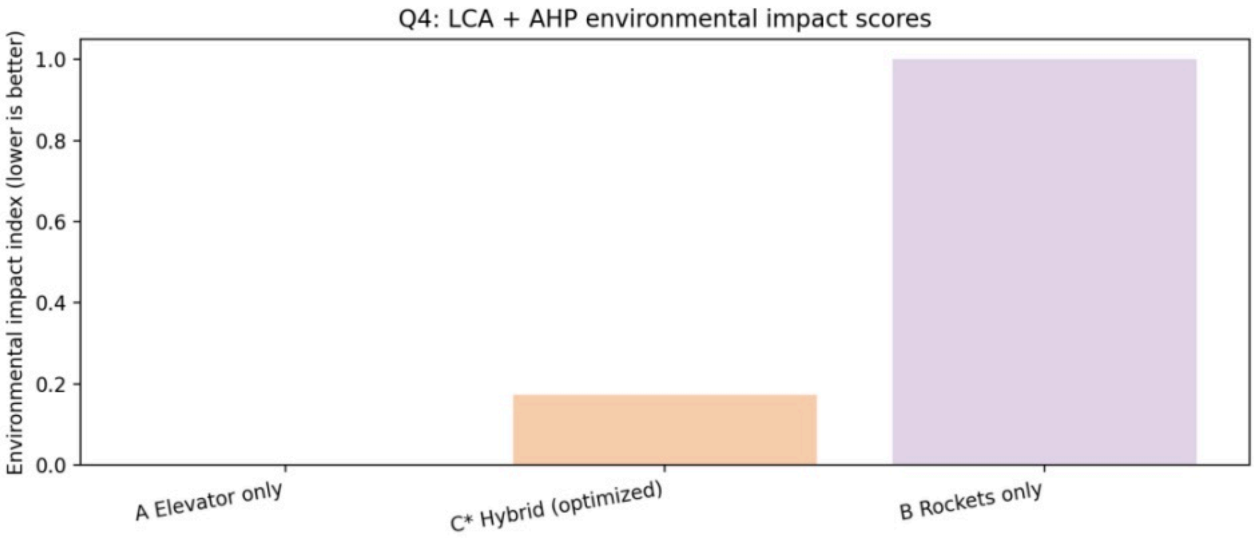

Figure 10. LCA+AHP environmental impact scores

It should be emphasized that an environmental impact score of zero does not imply that the elevator-only strategy causes no environmental burden in absolute terms. Rather, this result arises from the min-max normalization adopted in this study, where all environmental indicators are treated as cost-type metrics and evaluated on a relative basis within the candidate solution set. As the elevator-only strategy consistently exhibits the lowest impact across all considered environmental dimensions, it serves as the baseline reference, yielding a normalized composite score of zero. This formulation ensures meaningful comparison among strategies and allows the environmental score to function as a relative decision metric rather than an absolute measure of environmental load.

The optimized hybrid strategy C^* achieved an environmental impact score of 0.173, substantially lower than the rocket-only approach. By prioritizing elevator transport and restricting rocket use to selected low-cost launch sites, the hybrid approach preserves most of the elevator's environmental advantages while ensuring acceptable construction and operational timelines. Thus, the relative ranking of strategies in Figure 10 reflects a structural conclusion rather than a scenario-specific outcome: greater reliance on rocket launches leads to higher environmental impacts, while maximizing elevator utilization yields significant environmental benefits. Crucially, the environmental impact index serves not only as an evaluation metric but also as a controllable design variable within an optimization framework. One approach involves incorporating the composite environmental score as an additional objective, forming a three-objective optimization problem alongside cost and time. An alternative method imposes an explicit environmental constraint and optimizes cost and schedule within this constraint. Both methods empower policymakers to translate environmental priorities into transparent, quantifiable decision rules.

In summary, environmental performance is strongly tied to the transportation mix: the elevator-only strategy yields the lowest environmental burden, the rocket-only strategy the highest, and the optimized hybrid strategy offers a pragmatic compromise that substantially reduces impacts while remaining operationally feasible. It should be noted that the environmental impact score reported here is a cost-type metric (lower is better), whereas the TOPSIS comprehensive score in the next section is converted into a benefit-type rating after normalization (higher is better). Consequently, the elevator strategy receives a higher TOPSIS score because it corresponds to the lowest environmental impact. Under this TOPSIS scoring Scenario, the environmental ratings for the elevator, rocket, and hybrid strategies are 1.000, 0.000, and 0.827, respectively.

Comprehensive Evaluation and Trade-offs of Heterogeneous Transport Capacity Scenarios Under Multi-Criteria Constraints

Model Preparation

(1) Data Processing

This study constructs a TOPSIS decision matrix based on the previously calculated time, cost, stability penalty, and environmental impact metrics. These metrics serve as evaluation criteria for each Scenario and are all cost-based indicators. Specifically, they include the number of years required for completion during the construction period, the total construction cost, the average deterioration percentage from the ideal to the robust Scenario in the second question, and the comprehensive environmental score derived from the fourth question using AHP. These metrics are used as inputs to form the standardized matrix required for TOPSIS.

(2) Assumptions

To ensure transparent and reproducible results, this study assumes equal weighting for all evaluation criteria. The solution set comprises Solutions A, B, and the improved Solution C (main elevator trunk supplemented by a small number of low-cost rockets), where Solution C^* is an interpretable solution derived from the Pareto frontier. All criteria share a unified directionality, where “lower values are better,” enabling TOPSIS to explicitly identify the column minimum as the positive ideal solution.

(3) The Foundation of Model

The fifth question requires integrating multiple outcomes-including time, cost, stability, and environmental impact-into a final recommended solution, constituting a Multi-Criteria Decision Making (MCDM) problem.

TOPSIS calculates the relative proximity of each solution to the ideal solution and its negative counterpart, thereby generating a ranking. This approach condenses multi-dimensional metrics into a single interpretable ranking, facilitating concise and clear presentation of recommended results in academic papers. Compared to simple weighted summation, TOPSIS offers greater control over dimensionality and normalization dependencies. Its distance-based approach mitigates the dominance of extreme values in outcomes. TOPSIS also supports flexible weighting configurations, making it particularly suitable for synthesizing existing quantitative metrics. Additionally, it facilitates weight sensitivity analysis, enhancing the model's adaptability and interpretability across varying decision preferences.

Model Establishment

In the preceding analysis, different transportation strategies have been quantitatively evaluated from the perspectives of cost, project duration, environmental impact, and robustness. To integrate these high-dimensional performance metrics into results directly applicable for decision-making, this section employs the TOPSIS method to construct a multi-criteria comprehensive evaluation model.

Considering uncertainties in system operation, the effective transport capacity and equivalent cost derived from robustness analysis are directly incorporated into the decision-making indicator system. The effective capacity of elevators and rockets under worst-case scenarios is defined as $C_e^{rob} = \alpha_e C_e$, $C_r^{rob} = \alpha_r C_r$ where $\alpha_e, \alpha_r \in (0,1)$ represents capacity reduction caused by performance degradation and operational interruptions. The robust unit cost of rockets is further adjusted to $c_r^{rob} = c_r \cdot (1+\delta)$ to account for equivalent cost increases resulting from failures and payload losses.

A decision matrix $X = [x_{ij}]$ is constructed based on cost, schedule, environmental impact, and robustness, and vector normalization is applied:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_i x_{ij}^2}} \tag{7}$$

After applying given weights w_j , a weighted matrix $v_{ij} = w_j r_{ij}$ is obtained. For cost-type indicators, the positive ideal solution and negative ideal solution are respectively set to the minimum and maximum values, and the distance from each Scenario to these two values is calculated:

$$S_i^+ = \sqrt{\sum_j \left(v_{ij} - A_j^+\right)^2}, S_i^- = \sqrt{\sum_j \left(v_{ij} - A_j^-\right)^2} \quad (8)$$

The final proximity coefficient is defined as $C_i = \frac{S_i^-}{S_i^+ + S_i^-}$, where a higher C_i indicates superior overall performance of the solution.

This model achieves multidimensional metric compression into a single ranking while maintaining robust consistency in constraints. Weight sensitivity analysis further characterizes the transition range of optimal solutions under varying policy preferences.

Comprehensive Decision-Making under Multiple Criteria

To provide actionable recommendations that balance economic efficiency, construction time, environmental impact, and system robustness, this study employs a multi-criteria decision-making framework based on TOPSIS. This framework converts the high-dimensional performance metrics of each transportation strategy into a single proximity coefficient, enabling direct comparison while maintaining transparency of decision preferences.

With equal weighting assigned to cost, time, environmental impact, and robustness, the resulting proximity coefficients are shown in Figure 11. Scenario A (Elevator Only) achieved the highest score of 0.9407, followed by the optimized hybrid strategy C^* with 0.8583, while Scenario B (Rocket Only) ranked last with 0.0000. This outcome primarily stems from Scenario A's significantly superior environmental performance compared to other Scenarios, as confirmed by the Life Cycle Assessment-Analytic Hierarchy Process (LCA-AHP). Although Scenario A is not the fastest choice, its near-zero environmental impact grants it a decisive advantage when sustainability is weighted equally with other criteria.

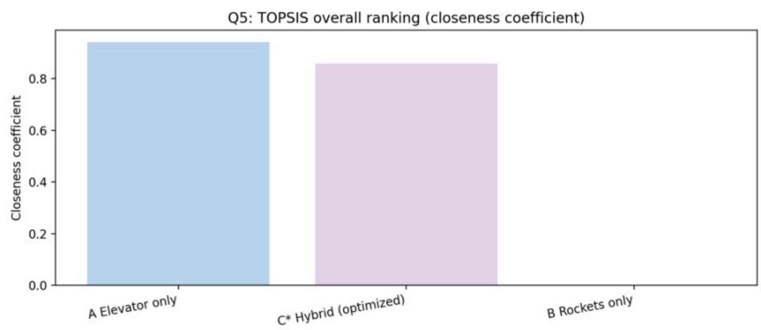

Figure 11. TOPSIS overall ranking (closeness coefficient)

However, equal weighting fails to reflect shifting strategic priorities under different policy objectives. To address this, we conducted a sensitivity analysis by incrementally increasing the weight of construction time while proportionally decreasing other criteria weights. The results, shown in Figure 12, reveal a distinct preference shift: when the time criterion's weight exceeds 0.48, the optimized hybrid strategy C^* surpasses Scenario A in proximity coefficient. This inflection point quantitatively demonstrates how policy emphasis on accelerated timelines can alter the baseline ranking.

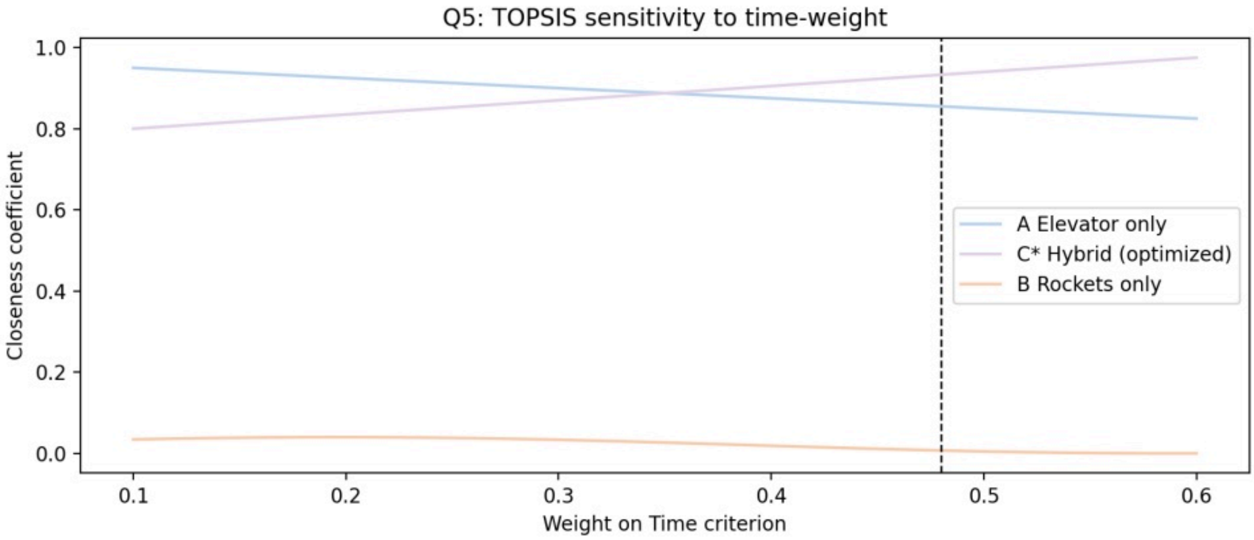

Figure 12. TOPSIS sensitivity to time weight

This shift can be understood by comparing each Scenario's performance across dimensions. While Scenario A has the lowest environmental score, its construction cycle is significantly longer. In contrast, C^* achieves shorter completion times and lower total costs than Scenario A, while its environmental impact remains substantially lower than a strategy relying solely on rockets. As time becomes the primary consideration, these advantages outweigh Scenario A's relative environmental strengths, making C^* the superior choice.

From a decision-making perspective, the integrated TOPSIS results support robust and easily interpretable recommendations. If minimizing environmental impact is the primary policy objective (e.g., under stringent sustainability mandates), Scenario A should be selected. Conversely, if the project must balance environmental responsibility, accelerated construction speed, and cost-effectiveness, Scenario C^* emerges as the optimal compromise, significantly reducing construction time at an acceptable environmental cost. Scenario B remains disadvantaged under all reasonable weight settings and should therefore not be considered a viable long-term strategy.

Overall, the TOPSIS framework effectively condenses multiple performance dimensions into a single ranking usable for decision-making, while the corresponding sensitivity analysis clarifies the weight thresholds influencing preference shifts. This combination ensures the final recommendation is grounded not in heuristics or subjective judgment, but in transparent trade-offs and clear policy priorities.

CONCLUSIONS

This study systematically deconstructs the decision logic for large-scale lunar logistics missions by integrating discrete optimization, robustness analysis, machine learning prediction, and sustainability assessment. It demonstrates that the hybrid teaching-education approach possesses unparalleled structural advantages in balancing efficiency, cost, and risk. The research not only identifies the C* operating point with Pareto-optimal characteristics but also establishes reliability boundaries for long-term operations through risk premium calculations and environmental footprint audits. However, the model in this section retains certain limitations. First, to maintain computational feasibility, the model linearizes the transportation process, potentially underestimating the complex effects of nonlinearities—such as learning curves, economies of scale, and queuing windows—on actual project duration and variability. Second, robust optimization heavily relies on predefined interval boundaries, leaving room for improvement in capturing extreme tail risks or systemic correlated failures. Furthermore, weight allocation in multi-criteria decision-making retains subjective elements. Future research should focus on incorporating dynamic nonlinear evolutionary models to more accurately characterize construction cycle fluctuations. Integrating reinforcement learning algorithms to optimize scheduling strategies under real-time volatility could establish an adaptive deep-space logistics intelligent decision-making system. Furthermore, although a construction period of 156.99 years may seem lengthy under the current technological framework and carries the risk of technological obsolescence, this result provides a baseline assessment of the physical limits for lunar base construction. Future research could incorporate a technological progress factor into the model to further optimize life-cycle predictions for long-term projects.

Author Contributions

Shuran Lei: Conceptualization; Methodology; Formal analysis; Supervision; Writing - original draft; Writing - review & editing

Xinjue Che: Methodology; Project administration; Resources; Writing - review & editing

Conflicts of Interest

The authors declare no conflict of interest.

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