

Risk-Constrained Multi-Objective Arctic Route Planning under Sea-Ice Uncertainty Using a Time-Dependent Multi-Label an Algorithm: A Dalian–Rotterdam Container Shipping Case Study

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Abstract: The geographical advantage of the Northern Sea Route (NSR) is readily quantifiable, whereas its operational reliability for scheduled container transportation remains highly uncertain. To address this challenge, this study develops an artificial intelligence (AI)-based, uncertainty-aware, multi-objective route-planning model for a container voyage from Dalian to Rotterdam. Arctic navigation is formulated as a time-dependent network in which each edge represents a dynamically evolving navigational state. The intelligent cost model integrates sailing distance, sea-ice concentration, sea state, vessel ice-class capability, fuel consumption, carbon emissions, operational cost, and navigational risk. A modified multi-label A* algorithm is developed as the core AI search mechanism. The algorithm dynamically eliminates infeasible waters, maintains non-dominated route labels, imposes a route-level risk ceiling, and automatically replans the uncompleted route when updated environmental information becomes available. This architecture enables adaptive decision-making under changing sea-ice and weather conditions and provides a computational interface for future integration with deep-learning-based sea-ice prediction and neural-network-based vessel performance models. Three Arctic alternatives and the conventional Suez route are evaluated under a controlled September 2026 scenario. Environmental and operational uncertainties are further propagated through 3,000 Monte Carlo simulations. The low-risk Arctic route covers 8,021.95 nautical miles in 19.32 days. Compared with the Suez route, it reduces distance, voyage time, and fuel consumption by 20.03%, 19.37%, and 18.41%, respectively, corresponding to a CO₂ reduction of 1,284.72 tonnes. However, its simulated on-time arrival probability is only 78.8%, compared with 94.9% for the Suez route. The results demonstrate that the proposed AI-based planning framework can generate adaptive and interpretable route alternatives while explicitly balancing efficiency, environmental performance, schedule reliability, and navigational risk.

1. Introduction

1.1 Background and significance

The established Asia-Europe container corridor runs through Malacca, the Indian Ocean, and Suez. Its distance is considerable, but operators benefit from familiar ports, regular services, and mature rescue and support arrangements. Congestion, geopolitical disruption, and volatile fuel costs nevertheless expose the concentration risk of relying on one corridor. Reduced summer sea ice has consequently renewed interest in the Northern Sea Route (NSR) as a second connection between the Pacific and Atlantic [1–3].

The NSR's attraction follows from geometry, although geometry alone does not establish commercial value. Smith and Stephenson and Melia et al. projected longer periods of Arctic accessibility as sea ice declines [1,2]. Aksenov et al. showed that the location and timing of navigable water remain sensitive to high-resolution ocean-ice evolution [3]. Economic comparisons have identified potential distance and fuel savings for Asia-Europe container movements, while Eddy et al. emphasized that uncertainty and additional operating costs can offset part of that advantage [4–6].

This tension motivates the present study. Ice concentration and distribution alter attainable speed and may require assistance or a detour; weather and limited emergency coverage add further exposure. A route that is shortest on departure can therefore become slower, more fuel intensive, or unacceptable by the time the vessel reaches it. Planning must compare efficiency with safety and service reliability instead of treating the Arctic as an ordinary open-water shortest-path problem.

1.2 Related research on Arctic route planning

Route quality depends first on the environmental state supplied to the planner. Passive-microwave products such as the NOAA/NSIDC climate data record provide consistent sea-ice concentration histories [7]. Those observations also document pronounced seasonal and interannual change; Stroeve and Notz describe an Arctic ice cover that is changing in every season [8]. For operations, this means that an ice field must carry both a valid time and an uncertainty description.

Navigation models have begun to account for this variability. Choi et al. planned against uncertain ice predictions rather than one deterministic future ice map [9]. Lee et al. incorporated POLARIS so that the same ice condition can be evaluated differently for vessels with different ice capabilities [10]. These approaches show why accessibility cannot be inferred from concentration alone.

Uncertainty also enters through events outside the ice forecast. Delays in support, communication failure, and route closures affect a transport service even when the expected environmental state is favorable. The maritime-resilience framework of Omer et al. provides a system-level basis for considering such disruptions [11]. A useful Arctic planner should therefore return not only a nominal path but information about its sensitivity and reliability.

Graph search supplies the computational basis. Dijkstra's algorithm solves a weighted shortest-path problem [13], whereas A* uses a heuristic estimate of the remaining cost to guide the search [12]. Later work strengthened heuristic shortest-path computation on large networks [14]. Standard forms, however, usually assume stable edge weights and one dominant cost. Arctic edges are time dependent and carry safety, fuel, and reliability consequences that cannot be represented adequately by distance alone.

1.3 Research gaps and motivation

The literature leaves four connected issues for an operational route decision.

First, a single forecast field understates the consequences of ice error. Spatial shifts in an ice band

can change speed, assistance requirements, or route feasibility. Planning should therefore propagate environmental variation into voyage outcomes rather than report only the route obtained from the mean forecast [3,9].

Second, commercial preference is multi-dimensional [12]. A shorter voyage can reduce fuel and charter time yet expose the service to delay or a higher probability of encountering unacceptable ice. The preferred path depends on cargo commitments, risk appetite, insurance conditions, and schedule recovery options. No one of these quantities is a sufficient objective on its own.

Third, the cost of an Arctic edge depends on when the vessel reaches it. A* can search efficiently, but a static implementation assigns the same weight regardless of arrival time. When ice and weather evolve during the voyage, the planner must evaluate an edge against the forecast valid at its anticipated traversal time and be able to restart from the current vessel position.

Fourth, the environmental comparison should include emissions. Operational measures and voyage optimization are recognized routes to lower shipping greenhouse-gas output [15]. The Arctic case is therefore evaluated for fuel and CO₂ as well as distance and time, without assuming that a geographic shortcut is automatically environmentally preferable.

1.4 Objectives and contributions

We develop a time-sensitive, risk-constrained planning method and apply it to a container movement from Dalian to Rotterdam. The experiment is designed to separate average efficiency from schedule reliability under perturbed ice and weather conditions.

The work makes four contributions:

(1) It represents the corridor as a dynamic network whose nodes and edges combine geography, forecast time, ice state, vessel capability, and operating restrictions.

(2) It evaluates candidate paths using travel time, fuel, risk, and cost while retaining a separate hard ceiling for accumulated risk.

(3) It modifies A* to reject inadmissible water, maintain non-dominated partial labels, and recalculate the uncompleted route after an environmental update.

(4) It estimates on-time probability through 3,000 Monte Carlo trials and compares three Arctic operating preferences with the Suez baseline.

Section 2 specifies the voyage, inputs, and feasibility rules. Sections 3 and 4 define the route model and adapted search. Section 5 reports the corridor comparison and uncertainty experiment, Section 6 discusses operational use, and Section 7 states the conclusions and limitations.

2. Planning problem and data requirements

2.1 Route and vessel

The origin is Dalian (approximately 38.92 degrees N, 121.65 degrees E) and the destination is Rotterdam (approximately 51.95 degrees N, 4.14 degrees E). Arctic candidates proceed past Japan through the Bering Strait, Chukchi, East Siberian, Laptev, Kara, Barents, and Norwegian seas. The baseline instead follows the East China Sea, Malacca, Indian Ocean, Bab el-Mandeb, Suez, Mediterranean, and Gibraltar corridor.

A representative 12,000-TEU, Polar Class 6 container vessel is used. Open-water service speed is set to 18 knots and base daily fuel consumption to 92 tonnes. These are modeling assumptions for the comparison and should not be interpreted as the particulars of an identified ship. The main vessel parameters and simulation settings are summarized in Table 1.

Table 1. Main simulation settings

Setting	Symbol	Value	Purpose
Open-water speed	v_0	18 kn	Service speed
Base fuel use	F_0	92 t/day	At-sea operation
CO ₂ factor	κ	3.114 t/t fuel	Emission estimate
Ice class	—	PC6	Summer and autumn case
Trials	N	3,000	Random seed: 20260731
Departure period	—	September 2026	Late-summer case

2.2 Data and preparation

An operational implementation would merge bathymetry and coastline, ice concentration and type, wind, waves, current, protected areas, rescue resources, navigation warnings, and vessel operating limits. Official services such as NSIDC can supply ice observations, while forecast or reanalysis systems can supply meteorology and sea state [7]. All layers must be projected to a common grid and queried at the vessel's expected time of passage, not merely at departure.

For this experiment, the ice fields are synthetic but geographically constrained. Maximum concentration is 0.34 on the shortest Arctic corridor, 0.27 on the time-oriented corridor, and 0.18 on the low-risk corridor; Suez is ice free. The construction is a controlled response test rather than a reconstruction of a historical daily ice chart.

2.3 Conditions that determine whether an area is usable

Feasibility is decided before economic ranking. An edge is unavailable if it crosses land, violates depth or prohibition rules, exceeds the vessel's approved ice capability, misses a permit window, or leaves insufficient fuel or emergency margin. Icebreaker-dependent edges may remain in the network only after waiting time, service cost, and added uncertainty are included. Thus, a low modeled cost cannot make an illegal or unsafe segment selectable.

3. Route-planning model

3.1 Network representation

For computation, the sailing domain is discretized as the directed graph $G = (V, E)$. A node carries position, anticipated arrival time, ice concentration, sea state, and depth. A directed edge exists only when the vessel can proceed between its endpoint nodes. Edge length follows the great-circle expression: $d_{ij} = 2R \operatorname{atan2}(\sqrt{a}, \sqrt{1-a})$, where $a = \sin^2(\Delta\phi/2) + \cos\phi_i \cos\phi_j \sin^2(\Delta\lambda/2)$, and R is 3,440.065 nautical miles.

3.2 Speed under ice and sea conditions

The vessel's effective speed is estimated as $v_{ij} = \max[v_{\min}, v_0(1 - \alpha\bar{c}^\beta - \gamma\bar{w})]$. In this relation, $\bar{c}$ is average ice concentration on the route section, $\bar{w}$ is a scaled measure of sea conditions, and $v_{\min}$ is the minimum permitted planning speed. Parameter values in the experiment are $\alpha = 0.70$, $\beta = 1.35$, $\gamma = 0.15$, and $v_{\min} = 8$ knots. The nonlinear ice term makes the speed loss grow once concentration is no longer light. Traversal time is then obtained from edge length and this effective speed.

3.3 Fuel, emissions, and risk

Fuel assigned to an edge is computed from $f_{ij} = (t_{ij}/24)F_0(1 + \eta\bar{c} + \mu\bar{w})$, with $\eta = 0.28$ and $\mu = 0.08$. A factor of 3.114 converts fuel mass to modeled CO₂ emissions [15]. The risk record includes ice, sea state, remoteness from support, and forecast error. Before aggregation, every component is normalized to $[0, 1]$. The components are then combined using weights that reflect the operator's priorities.

3.4 Objective and safety limit

Candidate path P is ranked by $J(P) = \lambda_t\hat{T}(P) + \lambda_f\hat{F}(P) + \lambda_r\hat{R}(P) + \lambda_c\hat{C}(P)$. Its components are normalized time, fuel, risk, and monetary cost. The four coefficients are constrained to sum to one. Independently, cumulative route risk is bounded by a specified ceiling. Separating this constraint prevents a hazardous path from winning simply because the objective assigns risk a low coefficient.

3.5 Uncertainty and schedule reliability

Forecast error and unplanned operational delay are represented explicitly rather than absorbed into the mean edge cost [9,10]. Each trial samples bounded ice and sea-state perturbations together with a non-negative delay. Reliability is the share of trials arriving within two days of the nominal plan. Operational calibration would require observed forecast errors and delay records for the vessel or service concerned.

4. Adapted A* search method

4.1 Basic approach

A* ranks each partial path by incurred cost plus a lower bound on the remaining cost. Here, great-circle distance to Rotterdam divided by the maximum feasible speed supplies the time component of that bound, and unobserved future ice risk is set to zero. This deliberately optimistic estimate guides the search toward the destination without excluding a lower-cost candidate prematurely.

4.2 Risk limit and changing information

Each active label stores arrival time, cumulative fuel, accumulated risk, and its predecessor. An extension is discarded if the next edge violates an operating rule or if route risk passes the specified ceiling. Dominance pruning removes a label when another reaches the same node with no worse time, fuel, and risk. When a forecast update is received, the vessel's current position and time replace the original start and the untraveled portion is searched again.

4.3 Procedure

The algorithm proceeds in seven stages. It first builds the time-indexed network from vessel limits and environmental layers, then removes land, shallow water, prohibited zones, and inadmissible ice. The start label enters a priority queue. At each iteration, the best-ranked label is extended using conditions forecast for its arrival time; time, fuel, and risk are updated, and infeasible or dominated labels are deleted. Search ends when Rotterdam is reached. Runs with different objective weights retain several interpretable alternatives instead of presenting one opaque optimum.

4.4 Computing requirements

For a single label per node, a priority-queue A* implementation is of order $O((|V| + |E|) \log |V|)$. Multi-criteria labels can increase time and memory because several non-dominated states may reach the same node. The risk ceiling, dominance test, and an explicit cap on retained labels control this growth. Grid resolution should be no finer than the environmental data justify; additional nodes do not create additional forecast skill.

5. Dalian–rotterdam simulation

5.1 Experimental design

Four route policies are compared. Route A minimizes Arctic distance, Route B accounts for ice-related speed loss and minimizes time, and Route C gives greater weight to safety under a maximum-risk constraint. Route D is the Suez reference. Scenario costs are USD 42,000 per operating day, USD 650 per tonne of fuel, and USD 480,000 for Suez transit; Arctic preparation, permits, and an allowance for ice support are added separately. These figures are experimental inputs, not market quotations. The geographical layouts of the three Arctic alternatives and the Suez reference route are illustrated in Fig. 1.

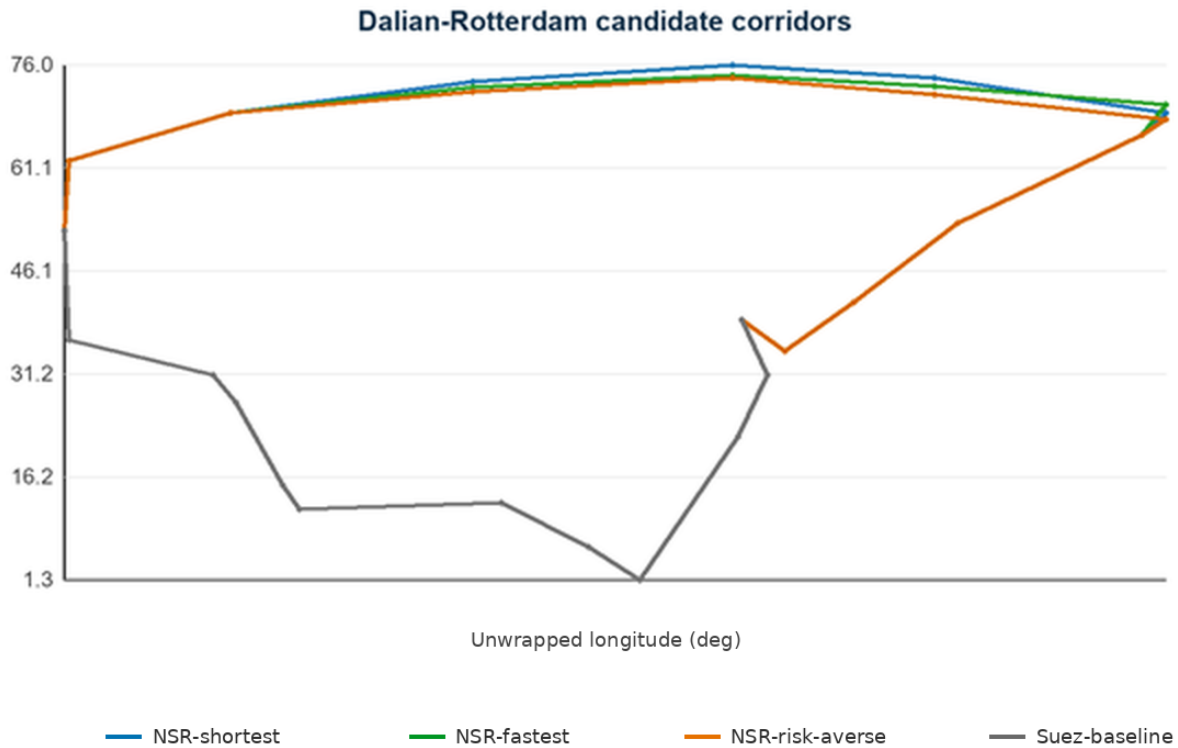


Fig. 1 Candidate route corridors between Dalian and Rotterdam (longitude shown continuously)

5.2 Baseline results

Table 2 summarizes the distance, average speed, voyage time, fuel consumption, risk, and on-time arrival probability of the four route alternatives. Route C, the low-risk Arctic option, is 8,021.95 nautical miles versus 10,031.51 for Suez. The 2,009.56-nautical-mile difference equals 20.03%.

Modeled duration declines from 23.97 to 19.32 days (4.64 days), and fuel use from 2,241.45 to 1,828.89 tonnes. Applying the emissions factor gives 6,979.89 and 5,695.17 tonnes of CO₂, respectively. Route C is 141.60 nautical miles longer than the geometric Arctic minimum, yet its avoidance of heavier ice produces higher average speed and lower fuel consumption. The result illustrates why minimum distance and minimum operating burden need not coincide. The baseline performance comparison is illustrated in Fig. 2.

Table 2. Results for the four route alternatives

Route	Distance (n mile)	Speed (kn)	Time (days)	Fuel (t)	Risk	On time
Shortest Arctic	7,880	16.96	19.37	1,857	0.282	79.3%
Fastest Arctic	7,999	17.09	19.50	1,860	0.240	80.1%
Lower-risk Arctic	8,022	17.30	19.32	1,829	0.181	78.8%
Suez baseline	10,032	17.44	23.97	2,241	0.037	94.9%

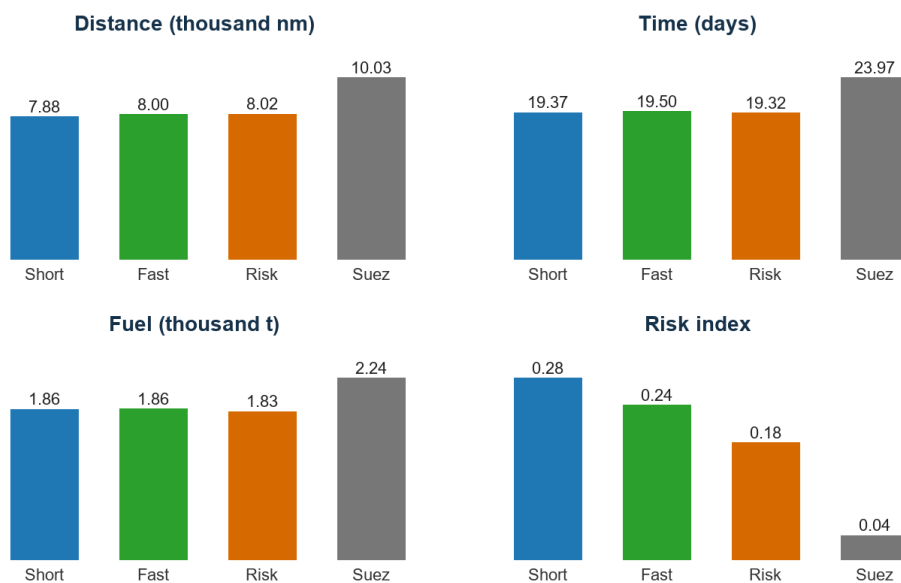


Fig. 2 Performance under the baseline September scenario

Modeled total cost is about USD 2.55 million for Route C, USD 2.62 million for the fastest Arctic alternative, USD 2.64 million for the shortest Arctic alternative, and USD 2.94 million for Suez. Fuel price, permit charges, support requirements, and insurance can readily change this order. The figures test the internal behavior of the planning model and should not be read as a current freight-market forecast.

5.3 Schedule reliability

Schedule performance is estimated from 3,000 trials per route. Arctic trials perturb ice, sea state, and operational delay; Suez trials perturb sea state and delay only. An arrival within two days of plan is counted as on time. The three Arctic probabilities cluster near 79-80%, whereas Suez reaches 94.9%. Route C retains the best mean time, fuel, and combined cost but not the best service reliability. Reporting only its 19.32-day mean would therefore conceal a material part of the operational

comparison. Figure 3 presents the empirical cumulative distributions of voyage time obtained from 3,000 Monte Carlo trials for each route.

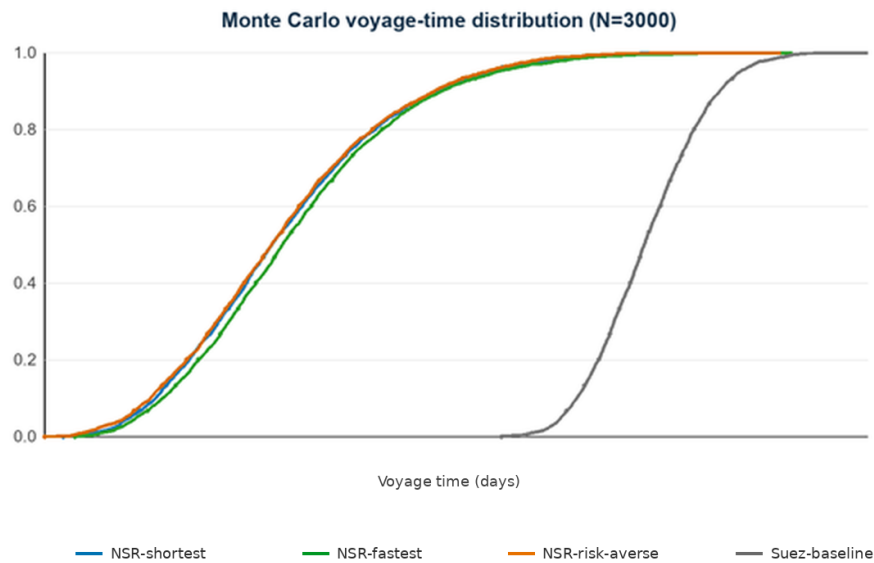


Fig. 3 Empirical cumulative distributions of voyage time based on 3,000 Monte Carlo trials.

5.4 Sensitivity to the importance of risk

The route-risk weight is swept from 0 to 0.8 while the relative shares assigned to time and fuel decline. Low values favor the faster or lower-fuel candidate; higher values shift preference toward Route C. The switch point is more informative than a claim that one weight is universally correct. An operator can compare that point with cargo value, arrival commitments, insurance terms, and the company's tolerance for delay and ice exposure. Figure 4 illustrates how the evaluated objective values of the Arctic alternatives change as the risk weight increases from 0 to 0.8.

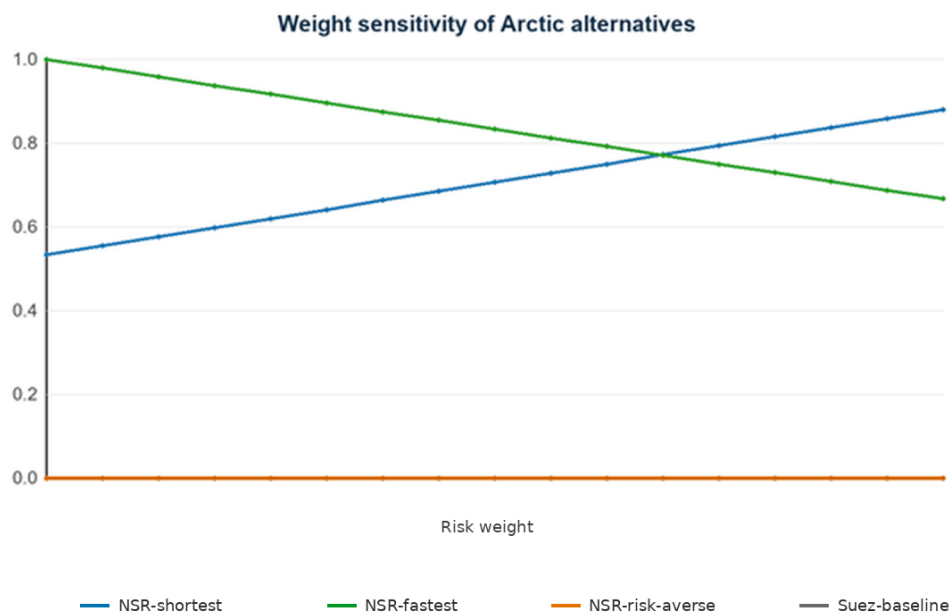


Fig. 4 Sensitivity of Arctic alternatives to the importance assigned to risk

5.5 Interpretation

Four observations emerge. The Arctic corridors provide a substantial geographic saving. Within the Arctic set, a modest diversion around heavier ice can reduce both fuel and risk despite adding distance. Average voyage-time savings do not eliminate a markedly wider delay distribution, which matters to berth windows, inland connections, and subsequent liner rotations. Finally, uncertain permit, support, and insurance costs can reverse the economic ranking. Route selection should therefore be based on a set of environmental and commercial scenarios rather than on one deterministic forecast.

6. Practical implementation

6.1 System structure

A deployable system would separate data ingestion, preprocessing, vessel performance, route search, and presentation. The ingestion service receives ice, weather, sea state, warnings, and vessel position. Preprocessing reconciles coordinates, valid times, and uncertainty. The vessel module stores approved limits and speed-fuel response. The route engine returns several safe, non-dominated options. The bridge interface then allows the master to impose waypoints, prohibited areas, and safety margins and to inspect why the alternatives differ.

6.2 Route revision during the voyage

Recalculation is appropriate before the Bering Strait, after entry into higher-latitude ice, and after a material forecast revision. Illustrative triggers include a change above 0.1 in expected concentration over the next 48 route hours, a predicted arrival shift above 12 hours, loss of an existing edge, or a changed icebreaker schedule. The interface should overlay old and proposed routes and state the change in time, risk, and the observation responsible for the recommendation.

6.3 Safety and legal limits

The model provides decision support rather than navigational authority. The master's judgment, coastal-state rules, navigation warnings, official charts, and the Polar Water Operational Manual prevail. Statistical risk is not permission, and no objective weight may relax the ship's certified ice limit. Additional margins are required where bathymetry, communications, or rescue coverage are weak.

7. Conclusions and future work

7.1 Main conclusions

The study combines a time-indexed Arctic network with a risk-constrained A* search. Operating restrictions remove infeasible edges, accumulated risk is bounded independently of its objective weight, and edge cost is evaluated at expected arrival time. In the Dalian-Rotterdam scenario, Route C reduces distance by about 20.0%, time by 19.4%, and fuel and CO₂ by about 18.4% relative to Suez. Its small detour from the geometric Arctic minimum avoids the denser modeled ice and improves operating performance.

The uncertainty trials qualify this average advantage. Arctic on-time probability is roughly 79-80% in the model, compared with 94.9% for Suez. The planning question is therefore not whether the Arctic path is shorter, but whether its expected efficiency compensates for a larger schedule tail under

the operator's service commitments.

7.2 Limitations and future research

The conclusions are bounded by a synthetic ice field and a simplified vessel response. Ice thickness, age, ridging, current, hull condition, engine load, and actual icebreaker queues are omitted, and the cost inputs are scenarios rather than quotations. Further work should use daily satellite products and ensemble weather forecasts, calibrate speed and fuel response with ship-position and machinery records, incorporate port and liner-network effects, and test objectives that penalize severe delay more strongly than average delay.

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